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A Systematic Approach To Manage Missing Data In Pavement Management Systems

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Dedication

To my beloved parents; to my loving wife; to my precious sons: Mohammad, Faleh, and Ali; to my dear daughters: Debae, Lemar, and Almas; to all members of my family. Without your inspiration, encouragement, support and prayers, this work would not be.

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PAVEMENT MANAGEMENT SYSTEMS

by

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Abstract

Pavements are an important part of the highway transportation infrastructure, accounting for the largest share of the overall investment. A tremendous amount of time and money is spent each year on the construction of new pavements, as well as on the maintenance and rehabilitation of existing pavements.

Transportation agencies use pavement management systems (PMS) for their maintenance and rehabilitation planning, programming, and budgeting. PMS are used to make decisions regarding when maintenance and rehabilitation should be applied. The systems also select what type of treatment should be applied for each pavement section in the network with clear estimations of the cost for different scenarios. To support these decisions, it is important to have reliable data on pavement conditions and accurate performance models for predicting pavement condition. The data on pavement condition typically comes from regular annual field surveys resulting in distress, condition, and ride scores. PMS datasets are often incomplete (for some locations and some years) because they could not be rated, measured, collected, saved, and managed correctly. The PMS missing data reduce the predictive power of the pavement performance models.

Model-free and model-based replacement techniques for estimating missing data points have been designed and successfully used in other application areas like statistics, economics, marketing, medicine, psychometrics, political science, etc. It is therefore reasonable to apply these methods to the PMS databases. Statistical techniques are assembled and used in a robust approach to systematically analyze the effect of applying these techniques to rebuild missing performance data.

The dissertation is planned as follows. Chapter one is the introduction. Chapter two provides a comprehensive overview of the pavement performance measures in PMS. Chapter three is an extensive literature review of the statistical techniques to handle missing data. Chapter four is a comprehensive description of a systematic statistical approach to populate missing performance data. In addition, several statistical techniques and methods for handling missing data in PMS are discussed.

Chapter five is a technical paper entitled "A Systematic Statistical Approach to Populate Missing Performance Data in Pavement Management Systems," submitted to the *Journal of Infrastructure Systems*. It includes a case study, Continuous Reinforced Concrete Pavement (CRCP) sections were selected to test the statistical systematic approach from Pavement Management Information System (PMIS) maintains by the Texas Department of Transportation (TxDOT). A major impact was observed in the results of predicting the distress scores due to applying the developed approach. Finally chapter six summarizes the obtained conclusions and recommendations to extend the future works related to this study.

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Chapter 1: Introduction

Pavements are an important part of the highway transportation infrastructure, accounting for the largest share of the overall investment. A tremendous amount of time and money is spent each year on the construction of new pavements, as well as on the maintenance and rehabilitation of existing pavements.

Pavement Management Systems (PMS) are complex sets of processes that need to be dealt with in a scientific and efficient manner so that accurate results are achieved. The PMS program generally focuses on improving pavement management through the analysis of pavement data sets. Moreover, it aims to improve the durability, safety, and efficiency of pavement materials and structures bearing in mind both economic and environmental constraints. The main objective of pavement management is to maintain and improve the overall condition of the pavement network and to maximize the performance of the network, while keeping the costs to a minimum.

Most highway agencies use their PMS data at the network level for programming, planning, and budgeting. It is used to determine both short-term and long-term maintenance funding requirements and to examine the consequences it has on network condition, if insufficient funding is available. PMS are now used in all 50 states, as well as other countries worldwide, in order to manage efficiently the maintenance of paved roadway surfaces. PMS frequently face Missing Data Problem (MDP) in its databases. Missing data occurs for several reasons. There is no specific reason for missing data in PMS, but rather a variety of odd conditions that lead to missing data for completely unrelated reasons "but rather a variety of odd conditions, all of which lead to missing date for completely unrelated reasons".

This chapter's objectives are to state the missing data problem, to identify its impact on PMS, and to state the null hypothesis. The main thrust of the study focuses on statistical techniques of addressing missing data and the impact that missing data has on prediction of pavement performance future conditions.

1.1. Motivation for the Study

A considerable amount of research has been taking place in Civil Engineering and a major amount of it has even been going into infrastructure engineering, with an emphasis on PMS. It is driven by longitudinal studies that collect repeated data and observations over time. Most PMS have a yearly pavement ranking and condition evaluating of distresses, ride quality, deflection, and skid resistance taken to estimate pavement conditions. An almost unavoidable complication in drawing inferences is that some data will be missing in PMS. Missing data in management systems are frequently results of chance and other processes that are well characterized as event times. Therefore, methods for modeling repeated measures and pavement age play a central role. Despite the available literature and recent advances in statistical software packages, treatment of missing data in PMS still remains a problem, and has enough complexity to make it a worthy topic for the study. Consequently, a systematic approach to manage missing PMS data properly and efficiently is needed.

1.2. Statement of the problem

Missing data has been a ubiquitous problem in data analysis since the origin of data collection. Since the beginning of the 1980s time of past century, data volumes have grown exponentially and continue to do so. More historical data is being collected today due to the proliferation of computer software and the high capacity of storage media. Missing data, accordingly, is growing in proportion and, as such, remains a problem today on a much larger scale. In turn, the issue of

missing data becomes an even more pervasive dilemma. Hence, the more data that is collected, the higher the likelihood of missing data.

The problem missing data occurs frequently in several types of datasets in different databases, and it can be considered a part of almost all databases. Missing data is common in different types of studies such as engineering, environmental, statistics, medical, nursing, social sciences, geology, biological and others.

Similarly, PMS databases frequently face missing data within their datasets in different modules and at various levels; it can be considered a serious problem in systems. Despite the experts' efforts to enhance PMS by yearly evaluating various distresses, ride quality, deflection and skid resistance to estimate pavement conditions, the problem of missing data arises by chance. The missing data problem frequently appears in PMS for different reasons. PMS data may be missing from the database because it could not be rated, measured, collected, saved, or managed correctly.

Missing data creates various problems in PMS applications and affects pavement performance predictions, treatment selection, and budget estimates. It is significant because it can change the decision making processes through the types and costs of pavement treatment to be applied and may also alter budget amount and allocation.

Proper handling of missing data is important in all analyses and is serious in PMS. Improper handling of missing data will distort pavement need estimates, cost estimates and budget allocations of the PMS. The problem occurs due to missing data in any module of PMS that not only impacts that module, but also has a greater impact on other modules. In order to manage effectively the missing data in the databases, one must examine the characteristics of the missing data in terms of type, amount, mechanism, and pattern.

This problem arises in almost all database analyses and the researcher has to decide how this information should be managed. Missing data creates various problems in analyzing and processing data in PMS databases. The most important problem with missing data is the pavement performance condition trend analysis. The historical data of pavement performance condition shows three forms of trends: increasing, constant, and decreasing trends. The increasing trend is a result of applying efficient maintenance and rehabilitation. The constant trend results when applying no treatment or inefficient maintenance and rehabilitation, and a decreasing trend results when applying no treatment or inefficient maintenance and rehabilitation.

Accurate prediction of pavement deterioration is the most important factor in the determination of pavement repair years and optimization programming of highway network maintenance.

Historical data is used to predict performance condition for both rigid and flexible pavements. These predictions are based on regression models using data available from databases to predict the future pavement performance with reasonable accuracy to be able to plan future maintenance and rehabilitation needs cost effectively.

The problem of missing data shall be addressed properly and this is possible only if there is a systematic approach to manage the missing data. There are a number of ways to deal with missing data. Statistical techniques exist to manage incomplete data, avoid biased estimates, and to rebuild the missing values of the datasets to improve their accuracy and precision (i.e. when using the rebuilt datasets to predict the future performance). Statistical methods are efficient when compared to traditional methods, such as the analysis of the sub-sample of complete observations.

Statisticians have attempted to address the impact of missing data on different applications. Statistical techniques for estimating missing data points have been designed and successfully used in other application areas like statistics, economics, marketing, medicine, psychometrics, political science, etc. It is therefore reasonable to apply these methods to the PMS databases.

These research efforts aim to develop a systematic statistical approach to populate missing data in pavement management systems reliably and efficiently, by thoroughly examining several missing data techniques and placing them in context. The various missing data techniques are applied to rebuild the missing data sets and, in doing so, endeavor to improve the prediction of pavement conditions of the PMS. Therefore, by utilizing statistical techniques, the systematic approach not only improves the quality of dataset by rebuilding the missing datasets, but also improves the prediction of pavement conditions.

The developed systematic approach to managing missing data in pavement management systems procedures will be started by identifying the most sensitive pavement performance variables to be included in the approach, and then evaluate different methods to manage missing data. Finally, the approach will evaluate the impact of missing data and its consequences on PMS. A comprehensive guideline for implementing the systematic approach is constructed; it describes in detail the implementation procedures for different dataset types in PMS.

This research offers a new approach to populate missing data for pavement management applications, one that acknowledges and examines missing data, informs the user of its presence and significance, and allows the user to manage the situation in a more informed and intelligent manner.

1.3. Research Hypotheses

The hypothesis of the study is that rebuilding the missing data should improve the prediction of pavement performance. The null and the alternative hypothesis are as follows:

H_0: Rebuilding the missing data using statistical techniques will improve the prediction of pavement performance.

H_a: Rebuilding the missing data using statistical techniques should not improve the prediction of pavement performance.

It is also hypothesized that certain statistical techniques should be more efficient than others in rebuilding the missing data, depending on pavement age, pavement condition, and the rate of deterioration. The null and the alternative hypothesis are stated as follows:

H_0: certain statistical techniques should be more efficient than others in rebuilding the missing data, depending on pavement age, pavement condition, and rate of deterioration.

H_a: certain statistical techniques should not be more efficient than others in rebuilding the missing data, depending on pavement age, pavement condition, and rate of deterioration.

In order to test these hypotheses, statistical techniques are used to rebuild the pavement performance missing datasets. The prediction efficiency of different statistical techniques is then quantified. A non-parametric Mann-Whitney statistical test is used to check the statistical significance of the prediction improvement.

1.4. Description of the topics

1.4.1. Missing Data Strategies

Missing data has been in existence as long as data has been in existence. In fact, the literature suggests the amount of missing data will grow in proportion to the amount of data in general (Ritzmann, 2010). Generally, that data is growing exponentially, as the amount of missing data does as well. The impact of missing data (and ways to manage it) seems to be an area that has been understudied. The literature also states that the two most widespread missing data techniques – case deletion and mean/mode imputation – are generally the least effective techniques to manage missing data.

In order to manage effectively the missing data, one must look at the characteristics of the missing data in terms of amount, mechanism and pattern. One must then make an informed decision as to how to approach the management of missing data and which technique is the most appropriate for populating missing data. The approaches to managing missing data can broadly divide into two basic categories: heuristic-based and statistical-based. Heuristic approaches function similarly to expert systems and may be domain specific. Statistical methods rely upon examination of the data and the drawing of statistically based, sound conclusions aimed at imputing missing values. This study adopted the statistical category to develop the new systematic approach for handling missing data in PMS.

To explain different possible ways of utilizing the approach, it is necessary to enumerate different known missing data techniques. The selection of the method for populating missing data depends on the field of application. The following three possible approaches to the handling of missing data have been investigated (Tsikriktsis, A review of techniques for treating missing data in OM survey research, 2005):

Deletion of datasets that contain the missing data; (i.e. this approach is currently used when predicting pavement performance in PMS),

Use model-free methods to replace the missing data with estimated values, and

Model the distribution of missing data and then to fill it in with new estimates based on the resulting model(s).

1.4.2. Pavement Performance Models

The accurate prediction of pavement performance is important for the efficient management of road infrastructure. At the network level, pavement performance prediction is essential for rational budget and resource allocation. At programming level, pavement performance prediction is needed for adequate activity planning and project prioritization, while at the project level, it is needed for establishing and designing the necessary corrective actions such as maintenance and rehabilitation.

Pavement performance models exist in various forms to provide the pavement management agencies' needs and resources. Performance models are needed to predict accurately future pavement conditions, to forecast confidently, and prioritize the future rehabilitation and maintenance expenditures. Many highway agencies use project and network level pavement performance models to predict their short-term and long-term maintenance and rehabilitation treatment needs.

Several performance prediction models have been developed over the years and grouped into main classes as follows: empirical, mechanistic, mechanistic-empirical, and probabilistic.

These models are either based on mechanistic principles, field observations or a combination of both. An empirical approach is usually followed for network level analyses, while a mechanistic or mechanistic-empirical approach is preferred for project level assessments. Regression

analyses are frequently used for fitting model equation parameters to a dataset. Probabilistic models have recently received considerable attention from pavement engineers and researchers.

The approach and techniques used for the development of pavement performance models vary according to the management level and data availability (i.e. presence of missing data within the database). Statistical tools are universally used to improve the performance models.

1.4.3. Distress Score as a Measure of Pavement Performance

Pavement condition is a function of exhibited distress types, the severity of these distress types, and the density of these distress types (i.e. extent of occurrence in surveyed pavement area) (Shahin, Darter, & Kohn, Pavement Condition Evaluation of Asphalt Surfaced Airfield Pavements, 1978; Shahin, Darter, & Kohn, Condition Evaluation of Jointed Concrete Airfield Pavement, 1980)Pavement distress indices are used to evaluate the pavement's condition integrity by aggregating several distress types (i.e., cracking, rutting, bleeding, etc., in asphalt pavement, and cracking, faulting, spalling, etc., in concrete pavement). There are also global indices that combine pavement roughness and distresses to measure the overall condition of the pavement. These are used to describe the current and future quality of pavement network health, in order to identify maintenance and rehabilitation treatment needs, and to estimate investments in the short and long term. (McNeil S. M., Emerging Issues in Transportation Facilities Management, 1992).

To predict the future pavement performance, it is necessary to know the current pavement condition and the future deterioration rate. To estimate how fast the pavement deteriorates, it is desirable to know the pavement condition history.

Pavement structural and material condition is determined by exhibited distress types (i.e., cracking, faulting, spalling, etc.), the severity of these distress types, and the density of these

distress types (i.e., extent of occurrence in surveyed pavement area) (Shahin, Darter and Kohn 1978) (Shahin, Darter and Kohn 1980). To evaluate the pavement condition, TxDOT has combined these characteristics into a single distress index, such as the Distress Score (DS), since the late 1980s. Distress scores range from 1 to 100, with 1 representing the worst pavement and 100 representing a pavement section with no distresses (Stampley & Miller, 1995).

1.4.4. Continuously Reinforced Concrete Pavement (CRCP) Models

Continuously Reinforced Concrete Pavement (CRCP) was first introduced in the United States in 1921. It started to gain popularity in the 1960s with the construction of the U.S. Interstate Highway System. The design viewpoint behind CRCP is to reduce maintenance, and increase pavement serviceable life and performance (Gallegos, Chang, & Nazarian, 2013).

Models for predicting CRCP performance have adopted different types of equations. Network level models are simple and usually follow a sigmoidal form; project level models are more complex and usually utilize mechanistic, empirical and/or hybrid mechanistic-empirical models that may take various forms (e.g. power functions and logarithmic).

A sigmoidal model, also known as an S-shaped model, shows a curve that has an inflection point and upper and lower asymptotes. This type of model is adequate for modeling pavement condition, which is usually bounded by upper values that are set according to acceptable pavement conditions. The inflection point of the model can also be used to represent effectively the different deterioration rate stages present during the pavement service life (Sadek et al. 1996). CRCP network level performance models usually predict distresses and ride quality service through pavement age or traffic. Common distresses in CRC pavements are punchouts, spalling, pumping and faulting (Choi & Chen, 2005).

1.5. Case Study

A case study was conducted to test the efficiency of the systematic statistical approach in predicting the distress scores. The pavement data was taken from TxDOT database. TxDOT divides Texas into 25 districts, out of which 23 have Continuous Reinforced Concrete Pavement (CRCP). This case study used all the distress records related to CRCP pavements in the 23 districts from 1993 to 2010.

Ideally, each 0.50 mile pavement section should have 18 distress scores corresponding to all 18 fiscal years from 1993 to 2010. In practice, some of these data points are missing. Since accurate predictions are only possible when there are a sufficient number of data points, this study only considers road segments where at least 10 distress scores out of 18 possible are available. Also, this study only considers road segments that exhibit at least 10% distress score deterioration from 1993 to 2010. Overall, there are 491 pavement sections that fit these requirements.

1.6. Significance of the Study

This study provides insight into missing data techniques as applied to serious and practical areas of infrastructure and pavement management systems. First, in terms of impact, missing data can reduce the pavement performance in regards to predictive accuracy.

Unfortunately, little or no research has been conducted to explore systematically the impact of PMS missing data, especially for the pavement performance missing data handling point of view. Second, this study, in a very practical manner, aims to improve the prediction accuracy of the pavement performance data in management systems. The study endeavors to accomplish this by developing and applying the systematic statistical approach for a more accurate pavement performance prediction.

Lastly, the conclusions are used to develop a future approach for the effective management of missing data. This approach can be further developed and employed to address the ultimate goals, which are better, more informed pavement management systems, assisted decision making, and budget allocations.

This study is a new contribution for PMS, which helps in handling missing data problems efficiently. It highlights the missing data within PMS databases and defines it as a serious problem. It will identify and evaluate the bias of the predicted future pavement conditions and it will estimate the absent type of applied treatments caused by MD. It will investigate the disturbance of the need estimates, cost estimates and budget allocations due to MD. The study develops a systematic approach to managing the missing data of pavement management systems. The developed approach is expected to be adopted by decision makers to manage missing data problem for different PMS data sets in order to make decisions.

1.7. Scope and Purpose

1.7.1. New Promising Work

This work starts and builds upon no previous work conducted on managing PMS missing data. The systematic statistical approach applied on CRCP distress score as pavement performance data. The future condition of the pavement is predicted using the developed and traditional approaches. The resulted distress score values are compared to quantify the improvement for the future prediction process by reason of applying the systematic approach. The obtained results raise the overall accuracy of the decision making and budget allocation.

1.7.2. Research Objectives

There are three main areas to this research. The first is to address the problem of missing or incomplete data and present strategies to overcome the problem. Several factors affect this

problem. Data volumes are exploding and, as data volumes increase, so too does the amount of missing data found in any given PMS database. In order to maximize the accuracy for decision making verification and identifications systems, strategies and methods must be in place to manage the missing data in a wise manner.

The second area of research concerns the endeavor to improve the prediction accuracy of the pavement performance in PMS by applying and testing the developed systematic statistical approach with the CRCP pavement performance data. To improve pavement performance predictions, and to attain more accurate treatment and budget needs analyses, the approach is applied by utilizing statistical techniques for rebuilding missing data to predict pavement performance. In many situations, the prediction accuracy is improved by rebuilding the missing data points and then using the rebuilt datasets make the predictions. Techniques for rebuilding missing data have been successfully applied in tested pavement performance datasets. Tests were then conducted to determine if the obtained improvements in prediction accuracy are statistically significant and, if so, which technique demonstrated the most improvement.

The third area regards the conclusions of the research and how they will apply to other types of pavement and their performance measures by applying the developed systematic approach, specifically for different infrastructure applications. This element of the research is critical as infrastructure applications gain more and more popularity. Ever increasingly, automated systems (nonhuman beings) are making decisions. This is primarily occurring in the area of infrastructure and pavement management systems. Yet, many of these systems do not adequately account for missing or incomplete data. And if they do, it is usually via a rudimentary, unsophisticated method, such as case deletion or use of mean/mode. However, these techniques – almost brute force in nature – do not lead to better information and better decision making. They neither

assign value nor benefit from the information that can be derived from the missing data. The expected results of applying the new approach on PMS will be:

Minimize the bias of the dataset

Improve the accuracy of the predicted pavement conditions

Enhance the decision making process

Enrich the budget allocations

1.7.3. Research Limitations

There are several limitations to this study that are taken into account. First, to test the efficiency of the missing data approach in predicting the distress scores, this study only considers pavement sections in which at least 10 distress scores out of 18 possible are available. Also, this study only considers pavement sections that exhibit at least 10% distress score deterioration from 1993 to 2010. Overall, there are 491 pavement sections that fit these requirements.

Second, the actual pavement age is completely missing from the investigated datasets because of the flaw in the design of the database. The study used the available performance data and fiscal year to estimate the age of the selected pavement sections.

Lastly, regarding practical applications, the systematic approach is offered that incorporates the findings and major conclusions from this work. This contribution, however, is limited to a

CRCP pavement performance, and although neither asphalt concrete pavement nor a jointed concrete pavement has been tested, it is recommended for future work.

1.7.4. Research Approach

The primary research approach employed by this study is missing data techniques. A sub-discipline employed is pavement performance in management systems, specifically distress score as a measure of performance.

1.8. Dissertation Organization

The balance of this dissertation is organized as follows. ***Chapter One*** is the introduction of the study. ***Chapter two*** provides a comprehensive overview of the pavement performance measures in Pavement Management Systems (PMS). Section two briefly introduces PMS. Section three introduces pavement performance prediction models. Section four includes a description of the type of PMS pavement performance prediction models and general approaches of predicting pavement performance using the defined models. Section five introduces measurements of pavement performance includes definitions of pavement distresses, indices and scores, which are mainly used to evaluate the pavement functional and structural condition.

Section six classifies the pavement performance prediction models and provides a synopsis and categorization of prediction models discusses according to the assumptions and methods upon which they are based. Section seven focuses on factors affecting pavement performance and identifies the factors that affect life cycle performance of pavement structures and their importance for developing performance models. Section eight briefly reviews deterioration of the prediction models. Section nine overviews the pavement performance indices, defines the pavement indices and scores and classifies them into three categories according to their characteristics and usage by the agencies: Direct Panel Rating, Utility Functions (i.e. TxDOT's Approach), and Deduct Values and Weighting Factors. Section ten discusses cost-benefit models, optimization techniques, and funding allocation methods, which defines the use of tools to support pavement management decisions variety, from ranking methods to optimization techniques. It also suggests that the assimilation of these tools by PMS are needed to know the estimated budget and the consequences of the different budget levels. Section eleven on data sources at Texas Department of Transportation TxDOT's, lists the five pavement-related

databases that could provide information for TxDOT's pavement management efforts: the Pavement Management Information database (PMIS), the Road Life database (RL), the Maintenance Management Information System (MMIS) database, the Texas Reference Marker databases (TRM), the Design and Construction Information System (DCIS) database, and the Site Manager database (SM). Section twelve discusses Pavement Management Information System (PMIS) and explains the PMIS five modules: utility curves, performance curves, needs estimate program, optimization program, and impact analysis program. Finally section thirteen reviews the original performance prediction models, which are coded in PMIS, were developed in the 1980s-1990s, and based on the engineering judgment of experienced engineers (Stampley B. , Miller, Smith, & Chang, 1995).

Chapter three is an extensive literature review of the statistical techniques to handle missing data. Section one provides reviews of the historical evolution of missing data estimation methods. Section two identifies the reasons for missing data in different types of datasets within the research, studies and systems. Section three identifies the reasons for missing data in PMS. Section four characterizes missing data into a number of patterns. Section five differentiates three missing data mechanisms: Missing Completely At Random (MCAR), Missing At Random (MAR), and Missing Not At Random (MNAR). Section six reviews the common missing data imputation techniques. Section seven discusses the three groups of statistical methods used to manage missing data: (a) to delete it, (b) to replace the missing data with estimated scores and (c) to model the distribution of missing data and estimate it based on certain parameters. Section eight presents the findings of ~~in~~ the chapter by summarizing tables to show the advantages and disadvantages of each statistical missing data technique. It also shows which techniques utilize in the systematic approach developed in this study.

Chapter four is a comprehensive description of a systematic statistical approach to populate missing performance data. In addition, several statistical techniques and methods for handling missing data in PMS are discussed. Section two describes the developed systematic statistical approach and illustrations and the detailed eleven steps of the approach by schematic diagram. Each step is listed in a sequence series and then is extensively explained. The non-parametric Mann-Whitney test is performed to check whether the prediction improvement efficiency of the distress score is statistically significant. The final step of the approach identifies the better/best prediction techniques to be used to populate missing performance data in PMS. The last section lists the conclusions of applying the systematic approach on CRCP.

Chapter five is a technical paper entitled "A Systematic Statistical Approach to Populate Missing Performance Data in Pavement Management Systems," submitted to the ***Journal of Infrastructure Systems***. It has been assigned the manuscript number ISENG-532 and has been forwarded to the editor to begin the review process.

Chapter six lists the obtained conclusions and recommendations to extend the future works related to this study. ***Appendices*** are included in the last part of the study.

Chapter 2: Pavement Performance Measures in Management Systems

2.1. Introduction

The objective of this chapter is to conduct a review of the literature on Pavement Management Systems (PMS), including distress data, scores and indexes, and performance prediction models. Pavement is an important part of the highway transportation infrastructure. A great amount of time and money is spent each year on the maintenance and rehabilitation of existing pavements. Most highway agencies use PMS data at the network level for programming, planning, and budgeting. Pavement management systems are used in 50 states as well as other countries worldwide in order to manage efficiently the maintenance of paved roadway surfaces. This chapter includes a comprehensive review focusing on pavement performance and its importance in pavement management. This chapter concentrates on the importance of pavement performance models, their impacts on PMS at different levels, and the decision making concerning the allocation of the funds on the network and the project budgeting levels. Previous researchers have explored various pavement performance prediction models (Salem, 2003).Traditionally, these pavement performance models have been categorized as being either project-level or network-level models. The following section provides a synopsis and categorization of prediction models according to the assumptions and methods upon which they are based.

2.2. Brief Overview of Pavement Management Systems

The objective of pavement management is to maintain or improve the condition of the pavement network and to maximize the performance of the network while minimizing cost. Pavement management is a complex set of processes that need to be dealt with in a scientific and efficient manner so that accurate results are achieved. The Pavement Management Systems (PMS) and

Programs generally focus on improving pavement management through the analysis of pavement data, which evaluates the condition and the ride quality of the pavement. Moreover, it aims to improve the durability, safety, and efficiency of pavement materials and structures within both economic and environmental constraints.

PMS includes pavement evaluation as an essential component. Pavement evaluation, whether at the network or project level, invariably includes the pavement's ride quality or roughness and some measure of surface distress. In addition, other data elements such as structural adequacy and rut depth, together with skid resistance, may also be incorporated. Pavement evaluation is used to assess the present condition of the pavement, and plan any necessary rehabilitation treatments. Pavement distress appearances are used to determine the sources of pavement deterioration and to select the most appropriate maintenance and rehabilitation treatments to renovate pavement serviceability.

In quantitative terms, the pavement surface condition is generally expressed as a Pavement Condition Index (PCI), or some other similar index such as Distress Score (DS) and Condition Score (CS). These composite indices are derived from the pavement distress present, their extent, and severity. The contribution of individual elements to the overall index depends on their weights assigned in the equations for calculating the composite index. Within the Texas Department of Transportation (TxDOT) Pavement Management Information System (PMIS), the indices are accounted for in the DS and CS (Gharaibeh, et al., 2012).

Ride quality, structural strength, and rut depth can be measured rather accurately and objectively using automatic or mechanical methods such as profiler device. However, these measurements are also subject to variability and uncertainty that need to be quantified using different statistical

techniques such as visual inspection and automated measurements. The most common method of evaluating surface distress is through visual inspection of the pavement; however, this method of measurement is also subject to uncertainty and prone to subjectivity. The visual inspection method of estimating distress quantities is subjective and prone to personal bias, data collection inconsistency, and is missing data collection reproducibility. The training of the evaluators and the standardized inspection methods used are designed to control and minimize inaccuracy and bias. Although the preceding factors are well recognized, there is little information available about their impact on the variability in a visual pavement distress survey. The variation in distress evaluation will affect the overall PCI, or other indicators of pavement condition used in PMS, in proportion to the respective weights assigned to the constituent elements of the index.

A PMS also requires reliable assessments of ride quality, based on either response-type roughness measurements or longitudinal profile measurements. These are often used to characterize pavement condition and predict future needs. Over the years, a number of vehicle-mounted devices, designed to measure riding quality, were used to support an agency's PMS. One of the problems encountered is the stability of the device over a period of years. This problem, along with actual fluctuations in pavement roughness, introduces variability in the roughness measurements. To determine successfully changes in pavement roughness, the measurement equipment must provide accurate and repeatable results and be stable over time. Records of pavement profile taken at intervals form a basis on which changes in roughness can be deduced, whether by calculation of International Roughness Index (IRI) or some other roughness characteristic or statistic. For this reason, measurements of longitudinal profile are a key component of any PMS (Project No. 0-6386 Exhibt B, 2010).

2.3. Pavement Performance Prediction Models

Pavements are complex physical structures that respond to the influence of numerous environmental, subsurface, and load-related variables and their interactions. Subsequently, the task of predicting the multi-faceted responses of pavements to the series of interrelated variables is complex and must be addressed by using a number of assumptions and simplifications.

The accurate prediction of pavement performance is important for efficient management of road infrastructure. At the network level, pavement performance prediction is essential for rational budget and resource allocation. At the programming level, pavement performance prediction is needed for adequate activity planning and project prioritization; while at the project level, it is needed for establishing and designing the necessary corrective actions such as maintenance and rehabilitation.

Previous researchers have explored various pavement performance prediction models (Salem, 2003).Traditionally, these pavement performance models have been categorized as being either project-level or network-level models. The following section provides a synopsis and categorization of prediction models according to the assumptions and methods upon which they are based.

Several performance prediction models have been proposed over the years. The models vary greatly in their comprehensiveness, their ability to predict performance with reasonable accuracy, and input data requirement. Most of these models are empirical and were developed for use under particular traffic and climatic conditions; others are of the mechanistic – empirical type in which some of the input parameters are calculated using mechanistic models. The other two models are mechanistic and probabilistic.

Pavement condition is a function of exhibited distress types, the severity of these distress types, and the density of these distress types (i.e. extent of occurrence in surveyed pavement area) (Shahin, Darter, & Kohn, 1978); (Shahin, Darter, & and Kohn, "Condition Evaluation of Jointed Concrete Airfield Pavement.", 1980). Pavement distress indices are used to evaluate the pavement's condition integrity by aggregating several distress types (i.e., cracking, rutting, bleeding, etc. in asphalt pavement, and cracking, faulting, spalling, etc. in concrete pavement). There are also global indices that combine pavement roughness and distresses to measure the overall condition of the pavement. These are used to describe the current and future quality of pavement network health in order to identify maintenance and rehabilitation treatment needs, and to estimate investments in the short and long term. (McNeil & Markow, 1992).This study reviews available pavement performance models.

2.4. Pavement Performance Models in Pavement Management Systems

Preservation of road infrastructure asset requires a systematic approach involving condition assessment and performance modeling, program optimization and development of tactical and strategic plans. An important part of such approach is the use of pavement performance models, which predicts the future road conditions based on their present conditions under a defined range of future loading and maintenance scenarios.

The successful implementation of road asset management systems or pavement management systems (PMS) is strongly dependent upon how well future pavement condition, as predicted by the performance prediction models, agrees with observed behavior and local engineering knowledge of the road network under consideration.

Pavement materials will deteriorate under the influence of loads and climatic effects. The stresses caused by heavy loads may result in micro cracking in materials and may also cause permanent deformation in pavement layers. Skid resistance will be reduced as a result of changes in surface texture due to aggregate polishing or bleeding. Frost heave may cause cracking and deformation, while spring thaw can considerably reduce the permissible stresses in the unbound materials. With time, micro cracking can develop into macro cracking, allowing water to penetrate into the pavement. Ideally a pavement performance model should capture this deterioration process in a comprehensive manner and consider all influencing factors. Unfortunately, the process of material deterioration is quite complex and difficult to model.

A large number of different pavement performance models are already available, but given the same input data they tend to produce different output (predictions). Pavement performance models should be based on fundamentally correct standard engineering principles to be reliable and acceptable. It is also important that these models are easily adjustable in accordance with available historical data and the engineer's knowledge of materials, environmental effects, construction and maintenance practices, etc.

In spite of an enormous effort that has been made in the pavement engineering field, it still is not possible to make accurate and precise prediction of pavement life (Molenaar, 2003). This is due to the fact that it is very difficult to predict many of the factors that influence the pavement performance. For instance, unusually hot summers, cold winters, wet springs etc. cannot be predicted. Traffic forecasts are mostly unreliable and there is a large variation in the characteristics of pavement materials and structures. The available performance prediction models have several limitations in that most of them involve large simplifications (e.g. in

material behavior), some of them contain input factors that are difficult to quantify, and most are not comprehensive enough (do not consider all influencing factors). Figure 2.1 illustrates the complexity of the performance prediction problem.

2.5. Measures of Pavement Performance

Pavement performances have been expressed in terms of individual pavement distress (such as rutting, cracking etc.), pavement condition index, which is often a composite measure involving the pavement's functional and structural condition, and pavement serviceability index, which includes the user's evaluation of the condition of the pavement.

At the project level it might be appropriate to evaluate the distresses individually, but at the network level, definition of some kind of composite measure of performance (performance indicator) is necessary.

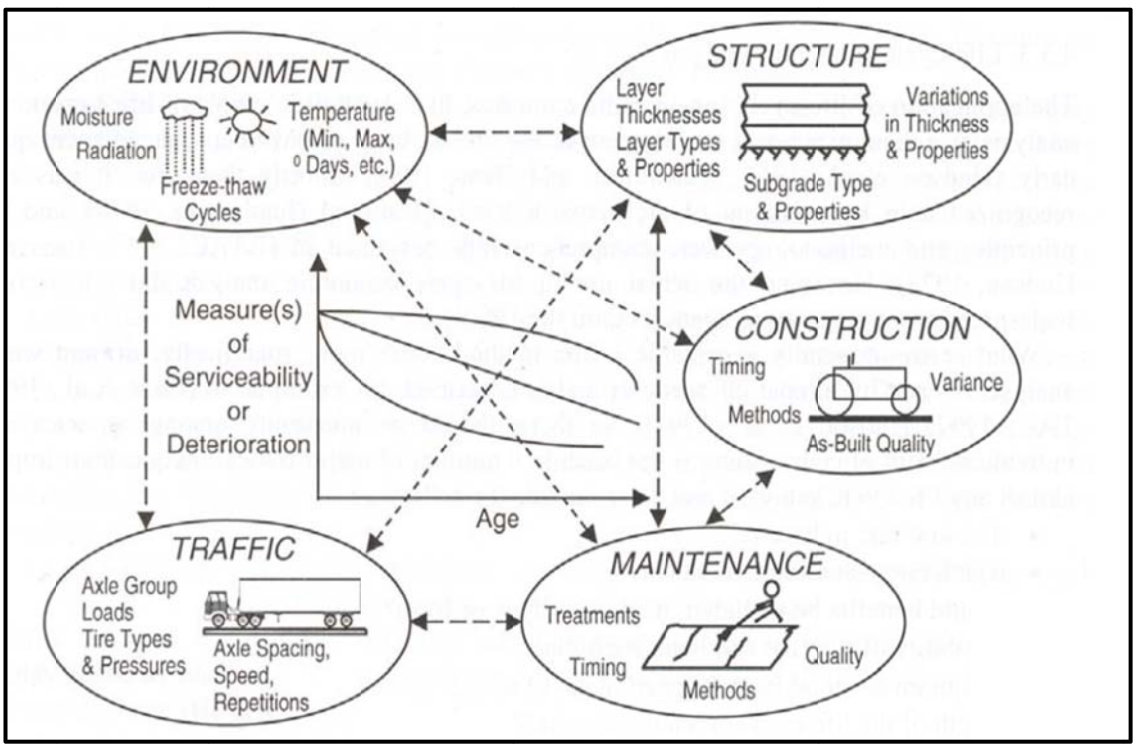

Figure 2.1: Factors affecting pavement performance (Haas 2003)

2.6. Classes of Pavement Performance Prediction Models

Previous researchers have explored numerous pavement performance prediction models in the past (Alsherri and George, 1988; Butt et al., 1994; Davis and Van Dine, 1988; Hutchinson et al., 1994; Lee et al., 1993; Zhang et al.,1993). Traditionally, these pavement performance models have been categorized as being either project-level or network-level models. The following section provides a synopsis and categorization of prediction models according to the assumptions and methods upon which they are based.

One of the most profound challenges facing pavement managers and engineers has been the development of pavement performance models and/or prediction of deterioration rates and values. Several performance prediction models have been proposed over the years, some of which are simple while others are more complex. Pavement performance prediction models grouped into various classes according to their characteristics as follows (Haas, 2003): Empirical, mechanistic, mechanistic-empirical, and Probabilistic models

2.6.1. Empirical Models

Empirical, where certain measured or estimated variables such as deflection, accumulated traffic loads etc. are related to loss of serviceability or some other measure(s) of deterioration and pavement age, usually through regression analysis.

Various equations, mostly based on regression analysis, were developed for predicting pavement performance. The usefulness of these empirical equations is limited by the scope of the database that were used in their development. These kinds of regression equations are valid only under certain conditions and should not be applied when the actual conditions are different. One of the best known examples of the empirical models is the Highway Design and Maintenance Standards Model (HDM – 4) developed by the World Bank.

The World Bank developed the Highway Design and Maintenance Standards Model (HDM-III) over two decades ago for use in infrastructure investment planning in developing countries. However, in recent years some industrialized countries have shown interest in the model and this further led to development of the model. In order to extend the scope of HDM-III and include additional capabilities such as models for traffic congestion, cold climate effects, road safety and environmental effects, the International Study of Highway Development and Management (ISOHDM) was conducted. This project produced the Highway development and Management Tool, HDM-4 (Kerali 2000). The HDM-4 has applications at the strategic, program and project levels and includes deterioration models for various types of distresses.

Most of DOT's in the U.S. and in other countries have developed performance models for the various performance indicators such as: roughness, crack initiation, plastic deformation, longitudinal profile, transverse profile, surface cracking, structural cracking, structural adequacy (deflection), surface defects, and skid resistance. The majorities of these models are empirical and are mostly based on one independent variable such as the number of repetitions of load or age. Some of the countries use a composite index that combines the various indicators.

2.6.2. Mechanistic Models

Mechanistic models can either yield pavement serviceability predictions directly (Queiroz, 1983), or they may predict pavement distresses which are then synthesized and related to serviceability. Over the past three decades, considerable effort has been devoted to the development of deterministic-based prediction models (Sobanjo, 1993; Feighan, 1988; Sobanjo, 1993). As a result, various deterministic models have been developed for regional or local pavement management systems. However, it is not adequate to apply deterministic models to all

situations of pavement management due to the following: 1. the uncertainties in pavement behavior under changeable traffic load and environmental conditions; 2. the difficulties encountered in quantifying the factors or parameters that substantially affect pavement deterioration; and 3. the errors associated with measuring pavement condition and the bias from subjective evaluations of pavement condition.

2.6.3. Mechanistic- Empirical Models

In the mechanistic - empirical models, calculated response variables, such as pavement layer stresses and strains etc., tensile strain at the bottom of the asphalt layer and vertical strain at the top of subgrade, are used in addition to other parameters such as accumulated traffic loading to predict performance of the pavement structure and loss of serviceability or some other measure(s) of deterioration through regression analysis, or a model which that is calibrated (i.e. the coefficients are determined) by regression analysis.

The performance is often expressed in terms of the individual distresses such as fatigue cracking, rut depth etc. The responses, such as the strains and the stresses resulting from axle loading are calculated using linear elastic multilayer theory, or, in some cases, finite element method. The material properties, such as the elastic moduli for the various layer materials, are taken into account in the response calculation. The environmental effects, such as the effects of temperature and moisture, can also be taken into account through their effect on the material properties.

Performance prediction models incorporated into the 2002 mechanistic – empirical design guide, developed in USA under the National Cooperative Highway Research Program (NCHRP) 1-37A, are typical examples of this group of models. The pavement performance measures considered in the guide include permanent deformation (rutting), fatigue cracking (both bottom-up and top-down), thermal cracking and smoothness (International roughness index, IRI).

Pavement response is calculated using either the elastic multilayer theory or the finite element method. Fig 2.2 shows the mechanistic – empirical design guide.

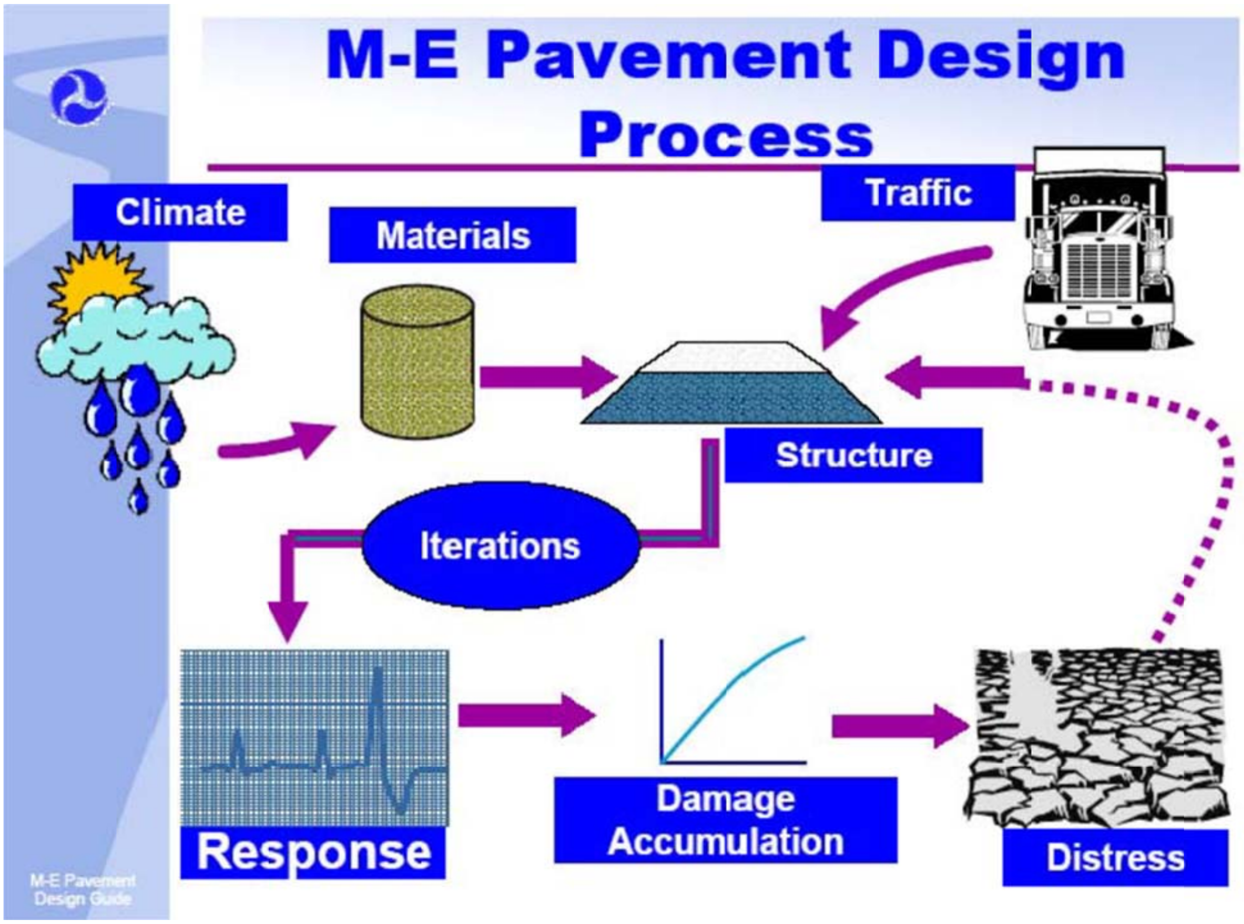

Fig 2.*2*: Mechanistic – Empirical Design Guide (M-E Design Guide Web Site)

2.6.4. Probabilistic Models

Probabilistic models have recently received considerable attention from pavement engineers and researchers. Darter (1973) and Hudson (1975) -(Darter, 1973)-(Hudson W. , 1975) extensively discussed the principles of applying probabilistic models for the prediction of pavement deterioration versus time in the 1970's. In their studies, a quantitative relationship between reliability and the four basic elements involved in pavement system design-- probability,

performance, time, and environment-- has been developed on the basis of substantial investigations and statistical analysis of all types of variations between design and actual values. The deterioration of pavements is affected by several factors some of which are difficult to observe. Traffic load and environmental conditions change over time and are difficult to predict. This causes the performance or deterioration of pavements to vary greatly, showing uncertain or random characteristics. Furthermore, uncertainty can arise from the inspection or measurement process and from the inability to quantify the factors that affect the deterioration process, and from modeling the true deterioration process of the materials. Thus, pavement deterioration process shows stochastic characteristics.

Probabilistic models attempt to tackle the stochastic characteristics of the pavement deterioration process. Most of the proposed probabilistic models are based on Markov process modeling. A Markov chain is considered as a special type discrete-time stochastic process where the state of the system (for example pavement condition) (X_{t+1}) at time t+1 depends on the state of the system (X_t) at some previous time t but does not depend on how the state of the system (X_t) was obtained. In mathematical form this can be expressed as:

$$P\,(X_{t+1=j}/\,X_{t=i}) \qquad \text{Eq (1)}$$

Where (P) is the probability of the state at time t + 1 being j given that the state at time t was i, assuming that the probability is independent of time. This assumption is known as the stationary assumption and it represents a major limitation for most of the probabilistic models because it implies that the rate of deterioration of pavements is independent of time. Few models use so-called non-homogenous (time dependent) Markov chains to overcome this limitation (Zhen, 2005). Some of the probabilistic models are developed based on econometric methods.

Although great progress has been made in the development of probabilistic modeling of pavement performance, the applicability of many existing probabilistic models is limited to local or regional pavement networks, which are classified on the basis of traffic level, subgrade condition, and pavement thickness. One of the major challenges facing existing probabilistic models is the difficulty in establishing the Transition Probability Matrices (TPMs). A TPM is a square [sxs] matrix where *(s)* is the number of possible states in the system. The matrix contains the probabilities of transitioning from state *(i)* to state *(j)*, i.e., the probability of something being in one state and then changing into another state over a fixed time interval. The TPM can be established using historical data or subjective opinions of experienced engineers through individual interviews and questionnaires, which takes considerable time and expenses. Most TPMs of the existing probabilistic models are built using either Markov process modeling or regression analysis through a large amount of observed long-term pavement performance data.

Karan investigated pavement deterioration functions by means of Markov process modeling for maintaining the pavement covering the Waterloo, Ontario regional road network (Karan M.A., 1979). In his study, pavement performance deterioration versus age was modeled as time-independent using the Markov process with a constant TPM throughout the programming period. Each element of the TPM is built on the basis of the average subjective opinions of experienced engineers through individual interviews and questionnaires. It should be noted that considerable time and expenses were incurred to develop the TPM through subjective information collection and processing.

An example of such models is the Highway Investment Planning System (HIPS) used widely in Finland and Norway. These models usually group the pavements into families (group of

pavement sections with similar characteristics) and as such are suited for network-level pavement management systems or strategic investment analysis for the road network. However, they are not suitable for project-level analysis.

2.7. Factors Affecting Infrastructure Performance

Identifying and analyzing the factors that affect life cycle performance of pavement structures are essential for developing performance models. These factors can be ~~either~~ identified from either historical performance data or from accelerated failure tests. Factors affecting infrastructure deterioration can be divided into five categories (Hudson W. H., 1997). These categories are: load/usage, environment, material, construction quality, and interaction effects. Several factors affecting pavement deterioration were considered ~~in~~ when constructing the transition probability matrices for a Markov process in order to predict deterioration (Turay, 1991).

The proposed stratification process utilizes the pavement performance factors, which are considered when formulating the design formula, which is in the widely used "AASHTO Guide for Design of Pavement Structures" (AASHTO, 1986). As for the pavement thickness factor, the AASHTO procedure for designing pavement structures recommends similar pavement thickness for the same level of traffic (i.e., low, medium, high) (AASHTO, 1986; AT&U, 1997). This was verified through the correlation analysis performed between traffic volume and pavement thickness.

2.8. Deterioration Prediction Model Development

A single prediction model cannot provide enough accuracy to capture the variety of conditions that occur in a pavement network including pavement types, soil types, climatic regions, and Equivalent Single Axel Load (ESAL). Therefore, the prediction approach was not limited to

developing one model representing the entire network, but rather the concept of a "family of curves" was adopted. This approach consisted of developing a model for each of the previously defined eight groups.

2.9. Overview of Pavement Performance Indices

Researchers and highway agencies around the country have developed a host of pavement distress indices to measure the pavement's structural and materials integrity by aggregating several distress types (i.e., cracking, rutting, bleeding, etc. in asphalt pavement, and cracking, faulting, spalling, etc. in concrete pavement). Additionally, there are a host of broader indices that combine pavement roughness and distresses to measure the overall condition of the pavement.

Traditionally, these indices have been used by engineers to describe the current and future quality of pavement networks, provide a warning system for early identification of maintenance and rehabilitation requirements, and estimate future funding needs (McNeil & Markow, 1992). The asset management paradigm, along with the increasing demand for accountability in infrastructure management, have promoted strategic decision making approaches for the preservation, operation, expansion, and improvement of transportation infrastructure systems (AASHTO, 2002). This has motivated researchers, practitioners, and public officials to use existing pavement conditions indices for strategic decision making. For example, these condition indices are increasingly being used by policy makers and legislators to set state-wide goals for infrastructure conditions and compare the performance of highway systems among the states.

Pavement structural and material condition is a function of exhibited distress types, the severity of these distress types, and the density of these distress types (i.e. extent of occurrence in surveyed pavement area) (Shahin, Darter, & Kohn, 1978); (Shahin, Darter, & and Kohn, “Condition Evaluation of Jointed Concrete Airfield Pavement.”, 1980). The main challenge is how to combine these characteristics into a single distress index. The development of an overall condition index is even more challenging because surface roughness is also considered, adding an extra dimension to the index. Existing pavement performance indices combine these characteristics through: Direct Panel Rating, Utility Functions (i.e. TxDOT’s Approach), and Deduct Values and Weighting Factors. The methods are further reviewed in the following paragraphs.

2.9.1 Indices Determined Based on Direct Panel Ratings

Early efforts in developing pavement condition indices used direct panel ratings. This approach involves a panel that drives the surveyed pavement (normally at posted speed) and subjectively rates the pavement sections either using a numeric scale or verbal descriptions such as good, fair, poor etc. based on observed distress types and ride quality.

Subjective panel ratings date back to the AASHO Road Tests in the 1950s (Carey, “The Pavement Serviceability Performance Concept.”Billiton 250, 1960). A panel subjectively rated sections of differing pavement types in Ottawa, Illinois on a 0-5 scale known as the Present Serviceability Rating (PSR). Since PSR depends on passenger perception of ride quality, it generally has a stronger correlation with road roughness measurements than with distress measurements. This review of ~~the~~ literature revealed that the following DOTs currently use distress indices that are derived from direct subjective panel ratings as shown in Table 1.

Table 2.1 State DOTs use Direct Subjective Panel Ratings

Department Of Transportation	Distress Index	Abbreviation
Oregon	Oregon's Good-Fair-Poor	GFP
Michigan	Michigan's Sufficiency Rating (SR)	SR

While panel ratings have the advantages of being simple and representative of the perception of roadway users, they are inherently subjective and do not provide sufficient engineering data that can be used to identify effective repair alternatives.

2.9.2 Indices Computed Based on Deduct Values

The deduct values method captures the effect of distress type, severity, and extent, and ride quality on the total score through deduct values. The general expression for computing a distress index using deducts values is as follows in Equation 1:

$$CI = C - (a_1\, d_1 + a_2\, d_2 + a_3\, d_3 + \ldots + a_n\, d_n + a_r\, d_r) \qquad \text{Eq 1}$$

Where:

CI = Condition Index

C = maximum value of the distress/condition index (perfect score)

$a_1, a_2, a_3, \ldots, a_n$ = adjustment factors for roughness (for overall indices) and distress types *1* through *n*

$d_1, d_2, d_3, \ldots, d_n$ = deduct values for distress types *1* through n. normally, *d* depend on distress type, severity, and extent (i.e., density) and roughness level (for overall indices).

a_r = adjustment factors for roughness.

d_r = deduct value for roughness.

A widely used distress index that is derived from deduct values is the Pavement Condition Index (PCI), which was developed in the late 1980s by the U.S. Army Corp of Engineers. The PCI scale ranges from 0-100, with 100 representing the perfect score (i.e., a pavement in excellent condition). In 2000, the American Society for Testing of Materials (ASTM) adopted the PCI method as a standard practice for roads and parking lots' pavement condition index surveys (ASTM Standard D6433-99). The general expression for computing PCI is as follows in Equation *2* (Shahin, Darter, & Kohn, 1978) (Shahin, Darter, & and Kohn, "Condition Evaluation of Jointed Concrete Airfield Pavement.", 1980).

$$PCI = C - \sum_{i=1}^{P} \sum_{j=1}^{m_i} a(T_i, S_j, D_{ij}) F(t, q) \quad \text{........................Eq 2}$$

Where:

PCI = Pavement Condition Index

C = maximum value of the condition index (perfect score)

a (T, S, D) = deduct value function that varies with distress type (*T*), severity (*S*), and density (*D*).

F(t,q) = is an adjustment function that varies with total deduct value *(t)* and number of deducts *(q)*. *i* and *j* are counters for distress types and severity levels, respectively.

p = total number of observed distress types.

m_i = number of severity levels for the *i* th distress type. Typically, three levels of severity are used (low, medium, and high).

Most state DOTs use distress indices that are derived from deduct values. Examples of these DOTs and their indices are listed below in Tables 2 and 3. Table 2 shows the state DOTs which currently use distress indices that are derived from distress only. However, Table 3 shows the DOTs which currently use distress indices that are derived from both distress and roughness.

Table 2.2 Examples of State DOTs Use Distress Indices (Distress only)

Department Of Transportation	Distress Index	Abbreviation
Iowa	(ASTM Standard D6433-99)	PCI
Oregon	Overall Index	OI
Minnesota	Surface Rating	SR
Tennessee	Pavement Distress Index	PDI
Ohio	Pavement Condition Rating	PCR

Table 2.3 Examples of State DOTs Using Condition Index (Distress and Roughness)

Department Of Transportation	Distress Index	Abbreviation
Pennsylvania	Overall Pavement Index	OPI
South Dakota	Surface Condition Index	SCI
Illinois	Condition Rating Survey	CRS
Texas	Condition Score	CSc

2.9.3. Indices Computed Based on Utility Values (TxDOT's Approach)

The utility values method was developed by TxDOT in the late 1980s (7) and resulted in two primary pavement performance indices:

- Distress Score (DS): a 1-100 index (with 100 representing no or minimal distress). DS considers various sets of distress types for various pavement types.
- Condition Score (CS): a 1-100 index (with 100 representing no or minimal distress and roughness). CS considers the pavement's DS and roughness (measured in IRI).

The utility value Equation *3* U_i is used to convert the level (i.e. density) of distress or ride quality loss (Li) values to become utility values that can be used to calculate PMIS distress score DS, and condition score CS.

$$U_i = \begin{cases} 1.0 & when\ L_i = 0 \\ 1 - \alpha e^{-\left(\frac{\rho}{L_i}\right)^{\beta}} & when\ L_i > 0 \end{cases} \qquad \text{……………………………………………………Eq 3}$$

Where:

U = utility value

i = a PMIS distress type (e.g., Deep Rutting or Punch outs) or ride quality

e = base of the natural logarithms ($e \approx 2.7182818\ldots$)

α = Alpha, a horizontal asymptote factor that controls the maximum amount of utility that can be lost

β = Beta, a slope factor that controls how steeply utility is lost in the middle of the curve

ρ = Rho, a prolongation factor that controls "how long" the utility curve will "last" above a certain value

L = level of distress (some distress types must be "normalized") or ride quality lost

The utility value equation produces an S-shape curve, as shown in Figure 2.3. U_i values range between zero and 1.0 and represents the quality of a pavement in terms of overall usefulness (e.g., a U_i of 1.0 indicates that distress type i is not present and thus is most useful).

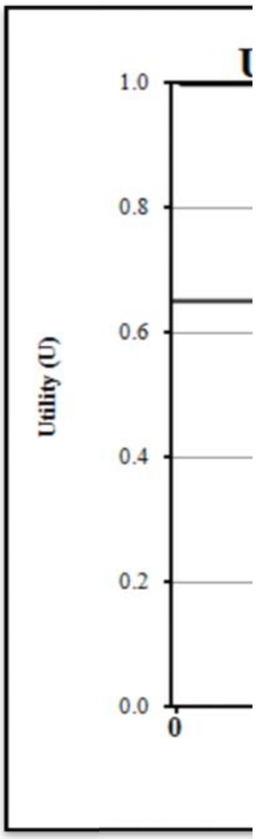

Figure 2.3 General Shape of Utility Curves used for Computing TxDOT's Pavement Performance Indices

Both DS and CS are implemented in TxDOT's Pavement Management Information System (PMIS) and are computed in Equations 4 and 5 as follows:

$$DS = 100 * \prod_{i=1}^{n} U_i \qquad \text{……………………Eq 4}$$

$$CS = URide * DS \qquad \text{…………………Eq 5}$$

The coefficients for CRCP Type 01 are shown in Table 4, as an example. Different pavement types have different utility curve coefficients.

Table 2.4 Example Distress Types and Utility Curve Coefficients CRCP Type 01

Distress	(Maximum Loss factor) α	(Slope factor) β	(Prolongation factor) ρ
Spalled Cracks	0.9369	1.0	62.70
Punchouts	0.9849	1.0	5.14
Asphalt Patches	0.9849	1.0	5.14
Concrete Patches	0.8649	1.0	8.20
Ride Quality (CS only)	1.818 (Low Traffic) 1.76 (Medium Traffic) 1.73 (High Traffic)	1.0	58.50 (Low Traffic) 48.10 (Medium Traffic) 41.00 (High Traffic)

2.10. Cost-Benefit Models, Optimization Techniques, and Funding Allocation Methods

The use of tools to support pavement management decisions varies from ranking methods to optimization techniques. The assimilation of these tools by the PMS is needed to know the budget needed and the consequences of the different budget levels.

A cost-benefit ranking procedure was analyzed to prioritize needs for TxDOT. Other procedures were also studied for TxDOT in order to provide their PMS with the capability to estimate network level maintenance and rehabilitation requirements over a given planning horizon, and to determine the consequences of varying fund levels on network condition and the level of service (Livneh, 1994). Further research was conducted by TxDOT to compare ranking and optimization procedures. Alternative optimization procedures were considered to perform prioritization. A multi-year optimization procedure with multiple treatments was studied for implementation (Zambrano, 1995).

The Metropolitan Transportation Commission in the San Francisco Bay area of California uses a ranking method, based on a weighted cost-effectiveness ratio, in its PMS (MTC-PMS) to rank the sections and prioritize the allocation of funds when the budget is constrained. Ratios have

been proposed to analyze the impact of maintenance and rehabilitation strategies, such as the ratios of agency costs over expected life, and agency costs over the performance period reflect the variation due to the implementation of a pavement management scenario (MTC, 1986). The use of these ratios can show the consequences of deferring treatments in the asset value and the future funds needed (Chang, 1999). Optimization techniques based on integer programming and "near optimization" methods have also been analyzed for integration into MTC-PMS. Near optimization methods provide feasible options when compared to optimization techniques. If multiple objectives are set by the agency, "near optimization" techniques can simplify the procedures and still produce similar results to optimization. Findings using these methods in a case study indicate that timing in applying the "right treatment" makes a difference in future investment needs and the future condition of the pavement network. Applying preventive maintenance at the "right time" reduces future investment needs and increases overall effectiveness (Chang-Albitres, 2007).

Approaches to handling multiyear maintenance and rehabilitation optimization programming for pavement management have been discussed in several papers. Some approaches use a Markov transition process to model pavement deterioration over time, combined with cost effectiveness integer programming. for the preservation of pavements when subjected to budget limitations and a required pavement serviceability level (Li, 1998).

A study to enhance the Arizona Department of Transportation's PMS was developed in the 1990s. The study recommended Markov transition matrices to model the transition process of pavement condition states and a linear optimizer tool based on Chapman-Kolmogorvo equations for solving the problem (Wang, 1992). Dynamic programming and the use of knowledge based

expert systems has also been proposed to develop a network optimization model for the Iowa Department of Transportation's PMS (Smadi O. , 2000), (Smadi O. , Development a Network Optimization Model for Pavement Management Using Dynamic Programming. Master Thesis, 1993). There are also methods that use life-cycle cost analyses to select projects and treatment alternatives. Life-cycle cost is primarily used at the project level, but the concept is also used at the network level when associated with remaining service life and strategy analysis concepts (Novak, 1992).

2.11. Data Sources at Texas Department of Transportation TxDOT's

There are five pavement-related databases that could provide information for TxDOT's pavement management efforts: the Pavement Management Information database (PMIS), the Road Life database (RL), the Maintenance Management Information System (MMIS) database, the Texas Reference Marker databases (TRM), the Design and Construction Information System (DCIS) database, and the Site Manager database (SM).

2.12. Pavement Management Information System (PMIS)

According to TxDOT, "PMIS is an automated system for storing retrieving, analyzing and reporting information to help with pavement related decision making processes" (Stampley B. M., 1995). The PMIS five modules are: utility curves, performance curves, needs estimate program, optimization program, and impact analysis program. Figure 2.4 describes the modules schematically.

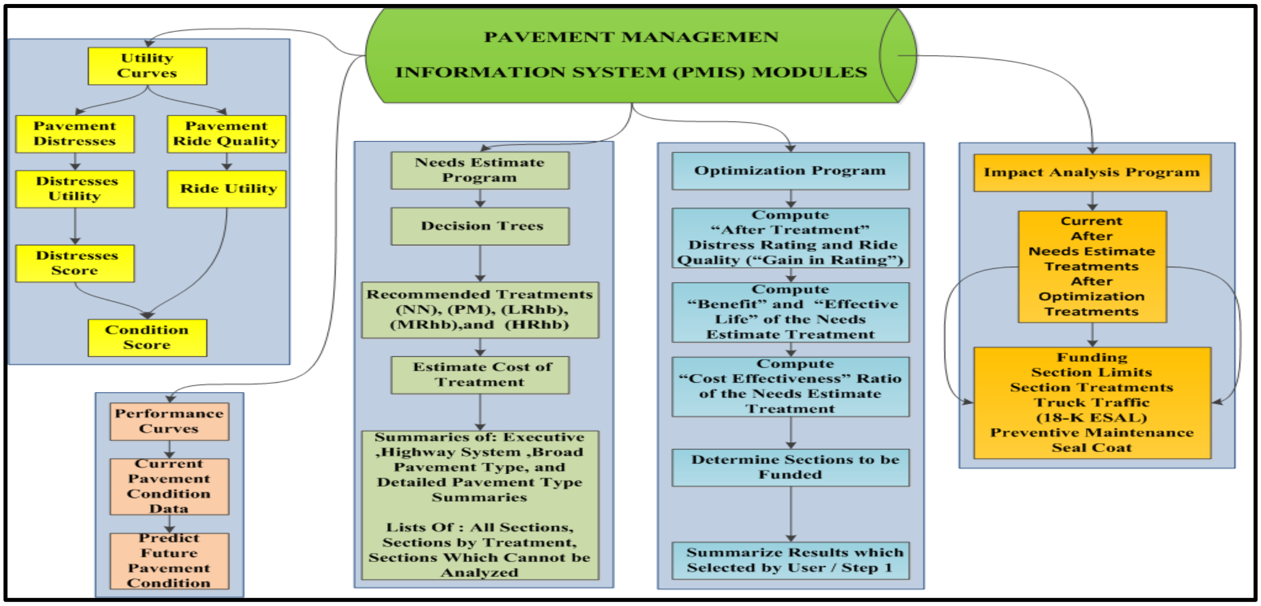

Figure 2.4 Pavement Management Information PMIS Modules

The following surveys are conducted for pavement sections in Texas:

1) Visual and automated distress evaluations.
2) Ride quality and automated rut data.
3) Deflection data (optional).
4) Skid Resistance (optional)

Deflection surveys are optional. Skid resistance surveys are required annually on 50% of the interstate highway mileage and 25% of all other highway mileage. Distress and ride quality are currently being conducted on 100% of the network annually.

2.12.1 Visual Distress Data

At TxDOT, trained raters conduct visual distress surveys each year from September to December on the following pavement types:

01 – Continuously Reinforced Concrete Pavement (10,534 estimated lane miles)

02 – Jointed Reinforced Concrete Pavement (2,636 estimated lane miles)

03 – Jointed Plain Concrete Pavement (1,705 estimated lane miles)

04 – Thick Asphaltic Concrete Pavement (ACP) greater than 5-1/2” (5,148 est. lane miles)

05 – Intermediate Thickness ACP, 2-1/2” to 5-1/2” (54,856 estimated lane miles)

06 – Thin Surfaced Flexible Base Pavement, less than 2-1/2” ACP (27,681 est. lane miles)

07 – Composite pavement (541 estimated lane miles)

08 – Overlaid and/or Widened Old Concrete Pavement (9,595 estimated lane miles)

09 – Overlaid and/or Widened Old Flexible Pavement (3,135 estimated lane miles)

10 – Thin Surfaced Flexible Base Pavement, Surface Treatment-Seal Coat Combination

(78,096 estimated lane miles)

The distress types rated for flexible pavements (pavement types 04 through 10) are shallow rutting, deep rutting, patching, failures, block cracking, alligator cracking, longitudinal cracking, and transverse cracking. Shallow rutting and deep rutting distress data collection is automated using rut bars mounted on TxDOT profiler vehicles. Raveling and flushing are collected but not used in the distress and condition score calculations. CRCP (pavement type 01) and JCP (pavement types 02 and 03) are defined as rigid pavements. The CRCP distress types are spalled cracks, punchouts, asphalt patches, concrete patches, and average crack spacing. The JCP distress types are failed joints and cracks, failures, slabs with longitudinal cracks, shattered slabs, concrete patches and apparent joint spacing. The ACP distress types are Shallow Rutting, Deep

Rutting, Patching, Failures, Block Cracking, Alligator Cracking, Longitudinal Cracking, and Transverse Cracking.

2.12.2. Ride Quality and Rut Data

Ride quality, along with automated rut data, is collected on a yearly basis. Currently, TxDOT uses vehicle mounted laser inertial profilometers to measure pavement roughness. Through reduction of the raw profiles to a ride score, TxDOT has the ability to report ride scores for the whole network. Ride scores are reported in a scale from 0.1 (very rough) to 5.0 (very smooth), and are subdivided in five discrete classes. The same vehicle is fitted with a rutbar that allows automated measurement of rutting. The rutting measurements are used in the calculations of the distress score for flexible pavements previously discussed.

2.12.3. Deflection Data

The Deflection survey is an optional survey that helps TxDOT's pavement managers determine the structural integrity of the pavement. Deflection data is collected throughout the Fiscal Year and stored in PMIS; the Falling Weight Deflectometer (FWD) collects this data. TxDOT operates thirteen FWDs for the collection of deflection data. A parameter called SSI (Structural Strength Index) score summarizes the deflection data. The SSI score varies from 1 (very weak) to 100 (very strong). A SSI score below 80 shows that the pavement has a weak structure and may require extensive monitoring and frequent maintenance to maintain suitable driving conditions. The range of SSI scores is divided in five classes ranging from very strong to very weak.

2.12.4. Skid Resistance

As mentioned earlier, skid resistance surveys are required annually on 50% of the interstate highway mileage and 25% of all other highway mileage. This data can be collected throughout

the Fiscal Year and stored in PMIS. TxDOT's Pavement Management Engineers use this information to evaluate the surface friction properties of surveyed pavement sections. A locked-wheel skid trailer and a tow vehicle collect these data. The data is collected at a constant speed. The tow trailer's wheel locks at periodic intervals while a standardized amount of water is sprayed on the pavement surface. The score that classifies skid resistance data is the Skid score. The Skid score ranges from 1 (very poor) to 100 (very good).

2.13. Review of PMIS's Pavement Performance Prediction Models

The original performance prediction models, which are coded in PMIS, were developed in the 1980s-1990s (Stampley et al. 1995), based on the engineering judgment of experienced engineers due to lack of field data at that time. These models predict distress density (*Li*) as a function of pavement age, climatic region, traffic loading level, and subgrade quality using sigmoidal functions. The general form of this function is shown in Equation 6.

$$L_i = \alpha e^{-\left[\left(\frac{\chi\varepsilon\sigma\rho}{Age_i}\right)^{\beta}\right]} \qquad \text{.................................Eq 6}$$

Where, Li represents the density of the distress in the pavement section. Age_i represents the age of the pavement since original construction or last maintenance or rehabilitation activity. The χ, ε, σ, coefficients represent traffic loading, climatic region, and subgrade type, respectively. The α coefficient (Maximum Loss factor), β coefficient (Slope factor), and , ρ coefficient (Prolongation factor) control the location of the *Li* curve's inflection point and the slope of the curve at that point, as illustrated in Figure 2.5.

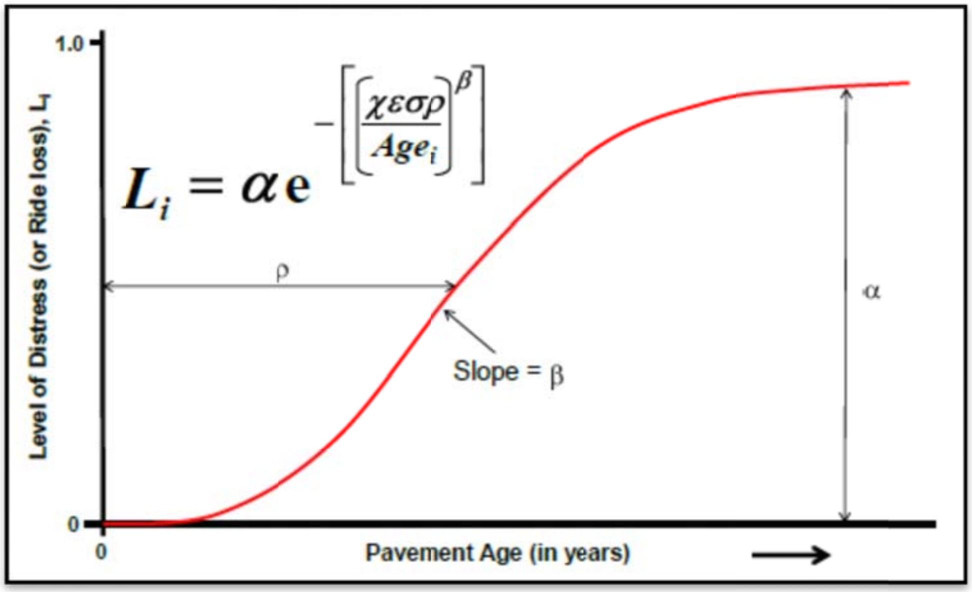

Figure 2.5 General Shape of TxDOT's Existing Pavement Performance Prediction Model

Once the *Li*'s are predicted over time, using Equation 6, they are combined, using Equations 3 and 4, to predict DS over time. Once DS is predicted over time, it is used to predict CS over time, using Equation 5. The default coefficients (χ, ε, σ, α, β, and ρ) that exist in PMIS were determined in the past based only on engineering judgment, and this was due to the missing data at that time. An analysis evaluation of the performance models used by Dr. Chang's approach in PMIS report 0-6386 (unpublished) revealed that the original values of these coefficients result in wide differences between predicted performance and actual performance of all types of pavements in PMIS and within all districts in Texas. Thus, it was concluded that the performance model coefficients require calibration to minimize the wide difference between predicted performance and actual performance (Gharaibeh, et al., 2012).

Each combination of pavement type and rehabilitation or maintenance types can potentially have a different set of model coefficients. PMIS has 10 pavement types and four maintenance and rehabilitation (M&R) types. The pavement types are continuously reinforced concrete pavement

(CRCP), jointed plain concrete pavement (JPCP), and hot-mix asphalt concrete pavement (ACP) (divided into seven sub-types of ACP). The M&R types are preventive maintenance (PM), light rehabilitation (LR), medium rehabilitation (MR), and heavy rehabilitation (HR).

Due to the lack of pavement age (i.e., construction history) data in PMIS, it is necessary to estimate the pavement age based on performance data. Year of construction or last maintenance and rehabilitation can identify based on sudden decrease in *Li*'s.

Chapter 3: Statistical Techniques to Handle Missing Data Literature Review

The purposes of this chapter are to conduct a comprehensive review of several statistical techniques and methods for handling missing data and to familiarize the Pavement Management Systems (PMS) researchers with the key issues of dealing with missing data in their own research. Its main goal is not to provide a step-by-step guide of how to use each statistical technique, but instead, to provide a review of techniques for treating missing data for those PMS researchers who are not very familiar with them.

The chapter performs an extensive literature review of the statistical techniques to handle missing data. The implications of missing data, types of missing data and techniques for improving the management of missing data are discussed. It discusses the situations in which some data is missing from the datasets rather than the total lack of data from the whole survey.

The chapter is organized as follows. Section one provides reviews the historical evolution of missing data estimation methods. Section two identifies the reasons for missing data in different types of datasets within the research, studies and systems. Section three identifies the reasons for missing data in PMS. Section four characterizes missing data into a number of patterns. Section five differentiates three missing data mechanisms: Missing Completely At Random (MCAR), Missing At Random (MAR), and Missing Not At Random (MNAR). Section six reviews the common missing data imputation techniques. Section seven discusses the three groups of statistical methods used to manage missing data: (a) to delete it, (b) to replace the missing data with estimated scores and (c) to model the distribution of missing data and estimate it, based on certain parameters. Finally, section eight presents the finding of the thorough literature review performed in the chapter by providing two summary tables show the advantages and dis

advantages of each statistical missing data technique. It also shows which techniques utilize in the systematic approach developed in this study.

3.1. The Historical Evolution of Missing Data Estimation Methods

Missing data is a very common problem in empirical research (Lepkowski, 1987) (Downey, 1998) and especially in survey research because it usually involves a larger number of observations and a larger number of measurements (Kim, The treatment of missing data in multivariate multivariate analysis, 1977; Quinten, 1999)

Missing data is a common problem in most research studies. Yet, no commonly agreed upon solution for addressing this problem and/or preventing this in the future exists. Consequently, researchers have developed a wide variety of techniques for handling missing data. However, no single technique is without pitfalls. Thus, researchers facing a missing data problem should thoroughly investigate the sources of the missing data as well as the options for handling missing data. Most studies and research (e.g., survey studies and field experiments) contain some missing data. However, most standard statistical methods have been designed to analyze data sets with no missing data. Consequently, the researcher has two scenarios: (a) to delete those cases which have missing data, or (b) to fill-in the missing values with estimated values (Anderson, 1983).

The following paragraphs are going to discuss the methods that delete those cases which have missing data; the methods are listwise and pairwise. Listwise deletion is the first method included. Listwise deletion is the first method included. Pairwise deletion is the second method covered.

The listwise deletion method sacrifices a large amount of data (Stumpf, 1978; Malhotra, Analyzing marketing research data with incomplete information on the dependent variable,

1987). The large loss of data will reduce the statistical power (Cohen, 1983; Gilley, 1991), and may reduce the precision of the parameters being estimated (Donner, Missing value problems in multiple linear regression with two independent variables, 1982; Little R. R., 1987) additionally, when data is missing at random, "type II error rates may artificially inflated" (Raymond M. , 1986). Thus, listwise deletion is not a generally adequate method for handling the missing data problem (Cohen, 1983).

In pairwise deletion, it is unclear what sample size to use for computation of standard error and tests of statistical significance (Orme, 1991). Other problems associated with the use of pairwise deletion are that the correlations being estimated may lie outside the acceptable range (-1, 1), and that R2 may be less than zero or larger than one (Cohen, 1983; Little R. R., 1987). Additionally, as pointed out by (Kim, The treatment of missing data in multivariate multivariate analysis, 1977), "the matrix generated by pairwise deletion may not be consistent ([not positive definite]) (p.222)."

By imputing the missing values, the researcher is then able to use statistical techniques that require complete data sets. Additionally, the recovery of the sample size and statistical power is a motivational factor in imputing values (Raymond M. R., 1987). Imputation of missing values by sensible estimates, although widely used, has some pitfalls (Little R. R., 1987).

According to Dempster and Rubin (1983), the idea of imputation is both seductive and dangerous. It is seductive because it can lull the user into a pleasurable state of believing that the data is complete after all. It is dangerous because it lumps together situations where the problem is sufficiently minor that it can be legitimately handled in this way and situations where standard estimators applied to the real imputed data have substantial biases.

According to Raymond (1986), “The most widely used estimation technique is probably the mean substitution method”. Because the means are replacing the missing values, variances and covariance will be downwardly biased (Little R. R., 1987). Additionally, the confidence interval may not be as precise as expected (Little R. , 1988).

In the regression imputation, the imputed data will preserve deviation from the mean as well as the shape of the distribution (Little R. , 1988). Thus, the imputed data “will not attenuate correlations as much as mean substitution” according to (Roth P. , 1994).

Missing data has received no coverage in pavement management systems (PMS) research. On the other hand, certain fields such as marketing (Kaufman, 1988), organizational behavior (Roth P. S., 1999), economics, statistics and psychometrics have paid more attention to the issue.

Before the 1970s, missing data problems were resolved through editing, whereby missing variables were logically inferred from additional data that had been observed. The literature on the statistical analysis of data sets with missing data has grown since the early 1970s, spurred by advances in computer technology that made previously laborious numerical calculations a simple matter. A method for inference from incomplete data was only developed in 1976. Immediately afterwards, Dempster, Laird, and Rubin invented the Expectation Maximization (EM) algorithm in 1977 that resulted in the use of the Maximum Likelihood (ML) methods for missing data estimation. Despite recent advances in the analysis of data sets with missing data, weaknesses in the literature still remain, and these weaknesses are reflected in the research.

Later, (Little & Rubin, 1987) acknowledged the limitations of case deletion and single imputations and then introduced Multiple Imputations (MI). Tests and interval estimates from small samples with missing data have had limited development. Very little work has been done

on diagnostic tests ~~of~~ concerning the validity of models when data are missing and incomplete, or on the robustness of estimates derived from the proposed models (Marwala, 2009). The literature on the analysis of partially missing data is comparatively recent; review papers include Alfifi and Elashoff (1966), Hartley and Hocking (1971), Orchard and Woodbury (1972), Dempster, Laird, and Rubin (1977), and Little (1982). Methods proposed in this literature can be grouped into the following categories: Procedures based on completely recorded units, imputation-based procedures, weighting procedures, and model-based procedures (Little & Rubin, 1987).

Missing data are a problem in many data sets. Early documents include Rubin (1977a, 1977b, 1978, 1980, 1983), Herzog and Rubin (1983), Rubin and Schenker (1986), and Rubin (1987). There are situations where the multiple imputation method is appropriate, and, as with any statistical tool, there are others where its application is more questionable. Originally it was viewed as being most appropriate in complex surveys that are used to create public-use data sets to be shared by many ultimate users, although, over the years it has proven valuable in other settings as well.

The general location model of Kin & Tate (1961) and extensions introduced by Krzanowski (1980, 1982) form the basis for methods. Maximum likelihood estimation with incomplete data is achieved by an application of the EM algorithm (Dempster & Rubin, 1977). Special cases of the algorithm include Orchard & Woodbury's (1972) algorithm for incomplete normal samples, Fuchs's (1982) algorithms for log linear modeling of partially classified contingency tables, and Day's (1969) algorithm for multivariate normal mixtures. Applications include: (a) imputation of missing values, (b) logistic regression and discriminate analysis with missing predictors and

unclassified observations, (c) linear regression with missing continuous and categorical predictors, and (d) parametric cluster analysis with incomplete data.

3.2. Reasons for Missing Data in Datasets

There are several reasons for missing data in different types of datasets within the research, studies, and systems. Knowing the reasons for missing data helps in identifying and understanding the mechanism, which is the crucial key in deciding how to manage and handle missing data. The main reasons for missing data in datasets are study design, participant characteristics, measurement characteristics, data collections, management conditions, and chances. It is important to note that these reasons can occur individually or simultaneously within datasets. Furthermore, data missing for different reasons at once are additive. Although reasons for missing data may help explain a missing data mechanism, knowing the reason does not automatically indicate the ignitibility of missing data. Some reasons may provide a more likely situation for a particular mechanism. Figure 4 shows the main reasons for missing data in datasets (McKnight, McKnight, Sidani, & Figueredo, 2007).

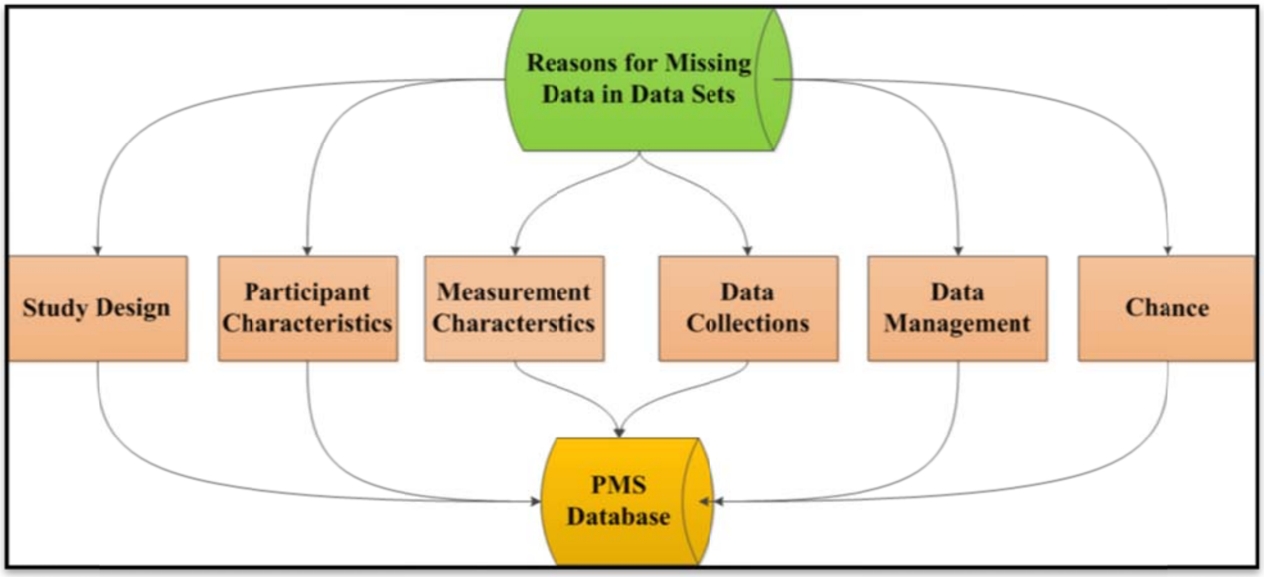

Figure 3.1 The Reasons Causes Missing Data in Data Sets

One source of missing data is simply the study design. Campbell and Stanly (1966) stated that no research design is without flaws. Similarly, no research design eliminates missing data altogether. However, different study designs yield different probabilities of missing data. Rubin (1987) identified two general reasons for non-response to items: processing of information, and refusal to provide information. These two reasons are associated with personal characteristics of the participants. Missing data can be due to characteristics of the measures used in the study. The measures mean the tools or instruments used to quantify the concept of interest. In some instances, the conditions under which observations are made can increase the probability of missing data. Investigators can also lose data due to poor data management. Many investigators rely on transferring data into different formats (e.g., entering paper-and-pencil questionnaires into a computer database). Data can be lost in the transfering process. Despite the investigator's efforts to design the study well and measures taken to reduce the likelihood of missing data, missing data still occurs by chance.

3.3. Reasons for Missing Data in Pavement Management Systems

This part of the literature review tries to shed light on the MDP and identify the most common reasons for missing data in PMS. The reasons for missing data are varied. Pavement raters and engineers may not provide the complete information that is required, observers might fail to record all of the 0.5 mile section information, or they may not have all data for pavement sections properly coded and/or transferred throughout the duration of collecting data for evaluating the condition of the pavement. This matter is stated as, “If there are any ways in which data can be missing, they will be” (19) (p.275).

It is significant to know why the data is missing; this can help with finding a solution to the problem. If the values are missing at random there is still information about each variable in each data set, but if the values are missing systematically, the problem is more severe because the sample cannot be representative of the population. Because of these problems, methodologists routinely advise researchers to design research so as to minimize the occurrence of missing values. Sometimes missing values are caused by the researchers themselves. In addition, missing data may be caused due to data collection that was not done properly, or if mistakes were made with the data entry and storage (20).

Dropout is a type of missing data that occurs mostly when studying development over time. In this type of study the measurement is repeated after a certain period of time. Missing data occurs when data drops out before the test ends and one or more measurements are missing. A great deal of missing data arises in cross-national research in: economics, sociology, and political science because government agencies choose not to, or fail to, report critical statistics for one or more years.

PMS data may be missing because it could not be rated, measured, collected, saved, and managed correctly. Some of the missing data cases in pavement management systems fall under the following categories: missing data in pavement distress, ride, and condition scores and their performance curves; as well as missing the type of treatments applied to the pavement, the thicknesses of the pavement layers and the age of pavements are also a factor. Before any missing data remedy can be implemented, one must first diagnose and understand the processes underlying the missing data (11). Several reasons cause missing data in PMS datasets. Knowing the causes of the problem helps in identifying and understanding the system, which is crucial in deciding how to manage it. It is important to note that these reasons can occur individually or simultaneously within the data sets. Some remedy techniques may better apply than others for a particular MDP case (21).

1) This study tries to shed light on the MDP and identify the most common reasons for missing data in PMS which are: Restricted access to a number of pavement sections. This is primarily caused by maintenance, rehabilitation, and reconstruction works in these parts of network during the period of yearly evaluations. The pavement evaluators and the measuring vehicles cannot get on these sections to evaluate the distresses or ride quality, so the data for that portion will be missed from the dataset;
2) Location characteristic restrictions of the road alignment. The location of the evaluated pavement section along the road alignment may cause missing data for that section. The data refers to the boundary of the inspected highways or roads usually missed at both the beginning and the end of the road.
    a) Beginning of road. At the beginning of the evaluated pavement section, the vehicle used is unable to get up to the speed limit required to measure ride or

rutting; as a consequence, the data for that portion will be missing from the database..

b) End of road. At the end of the evaluated pavement section, the vehicle used needs to slow down to the speed limit, which is slower than the required speed, to measure ride or rutting before the end of the road, so the last evaluated portion is missed.

3) Equipment limitations and sensor errors. The equipment, devices, and sensors used in pavement evaluations may possibly cause losing the targeted data. The missing data usually caused by measurements out of range is occasionally caused by actual instrument failure during the measurement process.

4) Data extracted from several sources. A number of PMS using more than one data source to manipulate indices, scores, parameters, and other values for their pavements. Some of the pavement data are not available in the main sources. Occasionally data, such as scores, ADT, 18-k ESALs, number of lanes, length, etc. are also not there, so they show up as missing in that data set. In addition, the data can also be lost in the transfer process such as importing or exporting.

5) Database Design. One source of missing data is the database design itself. Since no database design is without flaws, sometimes pavement indices, scores parameters, treatments, ages and/or other variables are not built-in in the main pavement database design skeleton. These entities, which are not integrated within the main database body, will show up as absent data.

3.4. Missing Data Patterns

Missing data can be characterized into a number of patterns, as is shown in Figure 5. In this figure, the rows match up to observational units whereas the columns correspond to different data variables. A univariate pattern is a case wherein data and observations are only missing in one variable, as indicated by *(Y)* in Figure 5 (a). A Monotone pattern occurs when data is missing from a number of data variables and, in addition, missing data entries pursue a particular pattern that can easily be noticed, as shown in Figure 5(b). Finally, an arbitrary pattern occurs when data is missing in accordance with some random pattern, as is shown in Figure 5(C). The pattern that the data follow depends on the manner in which data become missing and on the particular application. Wasito and Mirk (2006) used the nearest-neighbors least squares data imputation method to analyze three missing data showing different patterns, and observed that the nearest neighbors method performed well on data that are missing in a random pattern. Yang and Shoptaw (2005) assessed the impact of missing data in longitudinal studies of smoking cessation. Gad and Ahmed (2006) used a stochastic EM algorithm to analyze longitudinal data with intermittent missing values, which are missing values that are followed by observed values (Marwala, 2009).

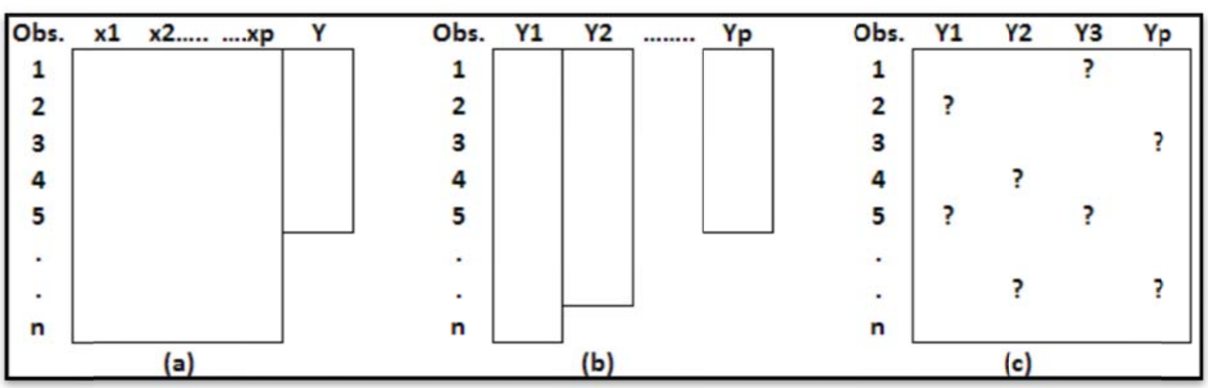

Figure 3.2 Patterns of missing data in rectangular databases: (a) uni-variant pattern; (b) monotone pattern, and (c) arbitrary pattern (Schafer & Graham, 2002)

3.5. Missing Data Mechanisms

It is vital to identify the reason why the data missing. When the explanation is known, a suitable method for missing data imputation may then be chosen or derived, resulting in higher effectiveness and prediction accuracy. In many situations, data collectors may be conscious of such reasons, whereas statisticians and data users may not have that information available to them when perform the analysis. In such scenarios, data users may have to use techniques that can assist in data analysis to comprehend how missing data is related to observed data and, as a result, possible reasons may be derived (Marwala, 2009).

Little and Rubin (1987) differentiate among three data missing mechanisms. These mechanisms are: Missing Completely At Random (MCAR), Missing At Random (MAR), and Missing Not At Random (MNAR).

3.6. Common Missing Data imputation Techniques

Many methods have been used to impute missing data because of their accessibility and computational efficiency. These techniques include, case deletion, list deletion, pair-wise deletion, mean substitution, hot/cold deck imputation, linear/nonlinear regression, regression-based nearest neighbor, stochastic imputation, maximum likelihood estimation, Markov Chain Monte Carol (MCMC), and weighted procedures.

The most commonly used method of dealing with missing data is to leave out those cases with missing data and to run the analysis on what remains. There are two methods that can be used for deleting data with missing entries, listwise-deletion and pair–wise deletion. Zhu et al. (2001) proposed case-deletion measures for models with incomplete data measures for evaluating the impact of an observation in complex models with real or assumed missing data corresponding to

latent random variables. On the other hand, Velilla (1993) proposed an approximation for evaluating the impact of deleting an observation on the Eigen values of the correlation matrix of a multiple linear regression model. List-wise deletion is a technique whereby only the complete data are retained (Tsikriktsis, A review of techniques for treating missing data in OM survey research, 2005). In the cases of missing entries in the respective observations, the entire observations are eliminated from the database. The major problem with this technique is the amount of information lost in the process. A further weakness with list-wise deletion is that it assumes that the observations with missing values are not significant and, therefore can be ignored. (Marwala, 2009)

Pair-wise deletion uses the incomplete record only if the missing variable is not needed in the calculation under consideration. In this case, the record with missing values is only used in the analyses that do not require the missing variable. Even though this technique appears to be better than list- wise deletion, it has been criticized by researchers such as Allison (2000), who noted that only if the data are MCAR does the pair-wise deletion method give biased estimates. When mean substitution is implemented, the missing entry is simply substituted by the historical mean of the observed data. This substitution, nevertheless, results in biased variances, which intensifies with an increase in the number of missing data records. Hot-deck imputation is a method in which missing data are substituted with data from similar cases that have been observed from the same dataset. Hot-deck imputation has two major steps. The first step records are divided into classes using techniques such as the nearest neighbor clustering techniques. During the second step, the incomplete entries are then imputed with values that fall within the same class. (Marwala, 2009).

The benefit of hot-deck imputation is that to estimate missing values, there is no need for robust model assumptions. Hot-deck imputations are also chosen for their theoretical simplicity. However, implementing them is difficult because of the complexity of characterizing the concept of similarity due to its subjectivity. In addition, in many cases, more than one value will be found suitable for imputing the missing value. A criterion for picking the most suitable value must be specified, as such, some approaches choose one value randomly or use an average of the candidate values. Cold-deck imputation is a case where missing values are substituted by constant values that are obtained from external sources such as previous observation or a modal value. Linear / Nonlinear regression imputations substitute the missing values with the values predicted from regression models constructed from the available data. Choosing a suitable regression imputation method is very reliant on the missing variable. Some regression imputation models begin by calculating estimates of the mean vector and co-variance matrix of the data from the sub-matrix from the data with no missing values. Linear/ nonlinear regression of the missing variables is then applied based on the observed data. Missing data are then replaced by the values obtained from the regression. This method, nevertheless, underrates the variance and the covariance of the data. The Regression-Based Nearest Neighbor hot-decking method (Huang and Zhu, 2002) is a mixture of the nearest neighbor hot-decking technique and the multivariate regression model. If the missing data are on continuous covariate, then the missing value is imputed as the mean of covariate values of the nearest neighbors. (Marwala, 2009)

Stochastic imputation is a type of regression imputation that replicates the uncertainty of the predicted values. It can be viewed as an extension of the simple-rule prediction. The distinction between stochastic imputation and decision tree based imputation is that, in place of using one variable, the multivariate rule prediction employs more than one variable. Neural networks

imputation can be considered ~~as~~ one example of a stochastic imputation class (Nelwamondo, 2008). This technique is also known as Multiple Imputation (MI), and was introduced by Rubin (1978). It merges statistical techniques by producing a maximum-likelihood based covariance matrix and a vector of means. Multiple imputations involve drawing missing values from the posterior distribution of the missing values, given the observed values, and is attained by averaging the posterior distribution for the complete data over the predictive distribution of the missing data. MI is related to hot-deck imputations, but its advantage over hot deck imputation is that it creates more than one imputation value. Its drawback is that it is computationally expensive. Maximum likelihood estimation (MLE) is a popular statistical method used for fitting a statistical model to data, and providing estimates for the model's parameters. Maximum-likelihood estimation was recommended, analyzed, and vastly popularized by R. A. Fisher between 1912 and 1922 (although it had been used earlier by Gauss, Laplace, Thiele, and F. Y. Edgeworth). Reviews of the development of maximum likelihood have been provided by a number of authors.

There are a number of ways to obtain maximum likelihood estimators, and one of the most common is called the Expectation-Maximization algorithm (EM). Schafer (1999) phrased the problem well when he noted, "If we knew the missing values, then estimating the model parameters would be straightforward. Similarly, if we knew the parameters of the data model, then it would be possible to obtained unbiased predictions for the missing values." An excellent discussion of the EM algorithm and its solution is provided by Schafer (1997, 1999) and Schafer & Olsen (1998). Schafer has also provided a program that will do the imputation. That program is named NORM that is freely available. Software specifically designed to implement EM estimation with missing data is available in both commercial and freely distributed statistical

software packages. Some of the most popular statistical software packages are SPSS, SAS (Yuan, 2000), and S- Plus (Schimert, Schafer, Hesterberg, Fraely, & Scheve, 2001) use the EM algorithm in their respective missing data packages. Stand-alone software packages including EMCOV (Graham & Hofer, 1991) and Amelia (King, Honaker, Joseph, & Scheve, 2001) implement the EM algorithm. SEM software packages like AMOS, EQS, LISREL, and Mplus offer ML estimation with missing data using the EM algorithms as well. The software automates the EM steps and produces the ML parameter estimates for the statistical models of interest.

One limitation of the ML model-based methods is that they are constrained by distributional assumptions (e.g., multivariate normality). The Markov Chain Monte Carlo (MCMC) procedure promises greater flexibility when underlying distributions are unknown. MCMC covers a diffuse set of procedures. Gibbs sampling is the most commonly used method for applying MCMC and the most available in terms of statistical software. MCMC is loosely allied with Bayesian estimation procedures, but Schafer (1997) argues that MCMC that might be mislabeled as Bayesian. MCMC was developed in the field of physics to investigate equilibrium distributions of interacting molecules. For statisticians, the MCMC process has the desirable quality of enabling parameter estimates under difficult data conditions, including when data are missing and when underlying distributions do not fit the assumptions of ML procedures. The process is characterized as Bayesian in that the ultimate goal is to obtain a desired probability distribution, known as a posterior distribution that can be used for parameter estimation. A posterior distribution is the distribution of unknown parameters after observing data and using the information gained from the data to update the statistical model (Gill, 2002).

In statistical situations with missing data, the goal is to generate unbiased parameter estimates. This can be difficult when using only the observed data. Thus, much like EM algorithm, with MCMC the observed data *(Y_{obs})* are augmented with simulated values of the missing data *(Y_{mis})* to handle this parameter estimation problem. One method for addressing the problems associated with deletion procedures is weighting cases or parameters based on the observed data. Randomization inferences from sample survey data without non-response are commonly based on design weights, which are inversely proportional to the probability of selection. Weighting procedures modify the weights in an attempt to adjust for non-response. Little and Rubin (1978) discuss several methods for estimating and applying weights for survey data. Schafer and Graham (2002) note a renewed interest in weighting procedures, particularly in the field of biostatistics, with new methods appearing for parametric and semi-parametric regression that extend generalized estimating equations. Schafer and Graham (2002) also note that weighting can eliminate bias associated with differential response rates for the variable used to estimate the response probabilities, but it cannot compensate biases related to unused or unmeasured variables.

3.7. Statistical Techniques to Manage Missing Data

According to Kline (1998), there are three ways to manage missing data: (a) to delete it, (b) to replace the missing data with estimated scores and (c) to model the distribution of missing data and estimate it based on certain parameters. Each one of these groups of methods is discussed further below.

3.7.1. Deletion Procedures

3.7.1.1. Listwise Deletion

This method eliminates from further analysis all cases [from PMS?] with any missing data. As a result, it loses a large amount of data (Malhotra, Analyzing marketing research data with incomplete information on the dependent variable, 1987). According to (Kim, The treatment of missing data in multivariate multivariate analysis, 1977), randomly deleting 10% of the data from each variable in a matrix of five variables can easily result in excluding 59% of cases from analysis. (Kaufman, 1988).

In spite of the fact that the large loss of data reduces statistical power and accuracy (Little R. R., 1987), listwise deletion is the default option for analysis in most statistical software packages. On the other hand, it is worth mentioning that listwise deletion gives very conservative estimates of the parameters. Empirical researchers usually want to find significance to support their theory. Listwise deletion results in conservative results, since by decreasing the sample size, it also results in a reduction in statistical power. Hence, it tends to make fewer variables statistically significant.

3.7.1.2. Pairwise Deletion

Pairwise deletion deletes cases only from those statistical analyses that require the information. For example, if a respondent is missing information on variable A, the respondent's data could still be used to calculate other correlations, such as the one between variables B and C. Compared to listwise deletion, pairwise deletion reserves much more information that would have been lost if the researcher was using listwise deletion (Roth P. , 1994). The most important problem with pairwise deletion is related to the interpretation of covariance or correlation matrices.

According to (Kim, The treatment of missing data in multivariate multivariate analysis, 1977), since different parts of the sample are used for each statistic, the correlations or covariances may be biased (mathematically inconsistent). This in turn could have serious negative effects on maximum likelihood-based programs such as the structural equation modeling statistical packages (e.g., LISREL, EQS, AMOS, etc.).

Researchers should also be mindful when using pairwise deletion in multiple-item scales with relatively low reliability (Roth P. S., 1999). One of the main reasons why survey researchers use multiple item scales is because scales enhance the reliability of the data. If a scale is reliable to begin with (e.g., it has a Cronbach's alpha of 0.90), then averaging fewer items (when one or more responses are missing) does not cause any major problem. However, if the Cronbach's alpha is marginal (about 0.60), then not using all the items in the scale, because of missing data, may result in an unreliable scale. Thus, pairwise deletion should be used only if a multiple-item scale is reliable to begin with.

Monte Carlo studies have shown that listwise deletion gives less accurate estimates of population parameters, such as correlations (Kim, The treatment of missing data in multivariate multivariate analysis, 1977) (Malhotra, Analyzing marketing research data with incomplete information on the dependent variable, 1987) (Raymond M. , 1986) (Raymond M. R., 1987) and regression weights (Kim, The treatment of missing data in multivariate multivariate analysis, 1977) (Raymond M. R., 1987). Pairwise deletion is consistently more accurate, though the differences can sometimes be small (Kim, The treatment of missing data in multivariate multivariate analysis, 1977) (Raymond M. , 1986).

3.7.2. Replacement Techniques

Prior to discussing replacement techniques in more depth, it is important to note that empirical researchers should be cautious before they start replacing data. Data replacement does not compensate for a badly designed instrument or for poor data collection. Overall, replacement procedures can be used in certain cases, as long as the researcher has a good reason for the replacement.

In general, the replacement techniques are easy to perform and some are included as options in statistical packages. The most important advantages of these procedures are the rebuilding of the sample size and, consequently, of statistical power in subsequent analyses. To a greater or lesser extent, all replacement techniques are biased if there is a non-random distribution of missing values. However, replacing missing data is appropriate when correlations between variables are low. Also, the problem of having missing data affects Likert-type scales, and replacement is suggested for the construction of scale scores (Quinten, 1999) (Little R. R., 1987).

Many different missing data replacement techniques have been developed over the years. In general, it has been found that the differences between the various methods decrease with: (a) larger sample size, (b) a smaller percentage of missing values, (c) fewer missing variables and (d) a decrease in the level of the correlations between the variables (Raymond M. , 1986). However, Kromrey and Heines (1994) reported that this is not the case if the effects of the treatments on the analytical statistics are taken into account. With larger sample sizes, in fact, the differences between the various replacement techniques are found to increase; this provides further evidence that in assessing the effectiveness of missing data treatments, both the accuracy of estimating the value of missing data and the accuracy of estimating the statistical effects have

to be considered. Three types of replacement techniques can be distinguished: mean-based, regression-based and hot-deck imputation.

3.7.2.1. Mean Substitution

There are three variants of mean substitution: total mean substitution, subgroup mean substitution and case mean substitution. Under total mean substitution, the missing value of a variable is replaced by the mean on the item for all respondents answering the question. According to the subgroup mean substitution, the missing value is replaced by the mean of the subgroup of which the respondent is a member. The third variant of mean substitution is the case mean substitution, which replaces missing values with the intra-individual mean of the respondent for all non-missing items.

Studies have been somewhat inconclusive regarding the effectiveness of mean substitution. Kim and Curry (1977) found mean substitution to be less accurate than listwise deletion in reproducing a correlation matrix, while others have shown that mean substitution is more accurate than listwise and pairwise deletion (Raymond M. R., 1987).

3.7.2.2. Regression Imputation

Regression Imputation is a two-step approach: first, the researcher estimates the relationships among variables, and then uses the regression coefficients to estimate the missing value. The underlying assumption of regression imputation is the existence of a linear relationship between the predictors and the missing variable. The technique also assumes that values are missing at random (i.e., a missing value is not related to the value of the predictors).

3.7.2.3. Hot-Deck Imputation

According to this technique, the researcher should replace a missing value with the actual score from a similar case in the dataset. A number of highly visible surveys have adopted hot-deck strategies such as the British Census, the U.S. Bureau of the Census, the Current Population Survey, the Canadian Census of Construction, the U.S. Annual Survey of Manufactures and the U.S. National Medical Care Utilization and Expenditure Survey (Roth P. S., 1999).

3.7.3. Model-based Techniques

3.7.3.1. Maximum likelihood

The maximum likelihood approach to analyzing missing data has many different forms. In its simplest form, it assumes that the observed data is a sample drawn from a multivariate normal distribution (DeSarbo, 1986). The parameters are estimated by available data, and then missing scores are estimated based on the parameters just estimated. Contrary to the techniques discussed above, maximum likelihood procedures allow explicit modeling of missing data that is open to scientific analysis and critique.

3.7.3.2. Expectation Maximization

The expectation maximization algorithm is an iterative process. The first iteration estimates missing data and then parameters using maximum likelihood. The second iteration re-estimates the missing data based on the new parameter estimates and then recalculates the new parameters estimates based on actual and re-estimated missing data (Little R. R., 1987). The approach continues until there is convergence between the parameter estimates.

3.8. The Findings of Reviewing the Statistical Missing Data Techniques

To achieve the purpose of this chapter and familiarize PMS researchers with the key issues of dealing with missing data in their own databases, a comprehensive literature review of statistical missing data techniques is conducted.

This section presents the findings of the thorough literature review performed in the chapter by providing two summary tables. Table 5 and Table 6 show the advantages and dis advantages of each statistical missing data technique. It also shows which techniques utilize in the systematic approach developed in this study.

Table 3.1 Statistical Technique for Handling Missing Data

Technique	Description	When to be used	Advantages	Disadvantages	References
Deletion-based					
List wise deletion / Case deletion	Eliminates from further analysis all cases with any missing data of the scores such as: condition, distress, and ride scores.	Better to be avoided as much as possible	Easy to use (default in most statistical packages) ‘‘Conservative’’: hard to find statistical significance	Sacrifices a large amount of data and has a negative impact on statistical power	Kim and Curry (1977), Raymond (1986), Malhotra (1987), Little and Rubin (1987)
Replacement-based					
Mean substitution	Missing value is replaced by the mean	When correlations between variables are low and less than 10% of the data are missing	Preserves the data and is easy to use	Negative impact on variance estimates and degrees of freedom	Ford (1976), Raymond (1986), Little and Rubin (1987), Kaufman (1988), Hawkins and Merriam (1991), Quinten and Raaijmakers (1999)
Total mean substitution / Series mean substitution	Missing value is replaced By the series mean of the scores such as: condition, distress, and ride scores.	When there are relatively low correlations between the missing variable and the other variables in the data	Easy to use (built-in in most statistical packages), sample retention	Downward biased variance/covariance estimates	Little and Rubin (1987), Quinten and Raaijmakers (1999)
Subgroup mean substitution	Missing value is replaced by the mean on the Subgroup of the scores such as: condition, distress, and ride scores.	When it is easy to define Subgroups of the scores	Gives better estimates, when compared to the total mean substitution procedure	Downward biased variance, arbitrary nature of defining subgroups in some situations	Ford (1976)
Case mean substitution / Mean of nearby point	Missing value is replaced with the mean of the valid	Particularly recommended for the construction of scale scores	Sample retention Use the valid surrounding values	Assumes equal means and standard deviations between predictors and missing variable	Nie et al. (1975), Raymond (1986)

	surrounding score values such as: condition, distress, and ride scores.			Affected by the length of the span. Less efficient at the boundary of the series.	
Median of Nearby Points	Missing value is replaced with the median of the valid surrounding score values such as: condition, distress, and ride scores.	Particularly recommended for the construction of scale scores	Reliable estimation. Use the valid surrounding values of the scores.	Affected by the length of the span. Less efficient at the boundary of the series.	Ford (1976), Raymond (1986), and Little and Rubin (1987)
Linear Interpolation	Missing value is replaced with the linear interpolation of scores such as: condition, distress, and ride scores.	When the data show linear trend of the scores within a period of time	Easiest kind of interpolation.	Assume linear trend of the data.	Little and Rubin (1987)
Moving Average	Missing value is replaced with the moving average of the scores such as: condition, distress, and ride scores.	When the data show noisy trend of the scores	Smooth out the fluctuation in data and expose the trend.	The moving average lags the underlying data.	Little and Rubin (1987)
Cubic Spline	Missing value is replaced with the cubic spline interpolation of scores such as: condition, distress, and ride scores.	When the data show oscillatory behavior of the scores	Overcome the oscillatory behavior and provide a smooth interpolation.	Cubic spline could oscillate in the neighborhood of an outlier.	Little and Rubin (1987)
Regression imputation	Estimates relationships among variables, and then uses coefficients to estimate the missing value	When more than 20% of the data are missing and variables are highly correlated	Estimated data preserve deviations from the mean and the shape of the distribution	Distorts the number of degrees of freedom and could artificially increase the relationships	Frane (1976), Cohen and Cohen (1983), Raymond and Roberts (1987), Little and Rubin (1987), Little (1988)
Linear Trend at Point	Perform linear regression, estimates relationships among variables, and then uses coefficients to estimate the missing score values	When the data show clear linear trend of the scores along the time	Use the valid surrounding values.	Assume linear trend of the data.	Frane (1976), Cohen and Cohen (1983), Raymond and Roberts (1987), Little and Rubin (1987), Little (1988)
Nonlinear Regression Imputation	Perform nonlinear regression, estimates relationships among variables, and then uses coefficients to estimate the missing score values	When the data show nonlinear trend of the scores along the time	Uses the model to substitute the missing values.	Underrates the variance Underrates the covariance.	Frane (1976), Cohen and Cohen (1983), Raymond and Roberts (1987), Little and Rubin (1987), Little (1988)
Hot-deck imputation	Replaces a missing value with the actual score from a similar case	When data are missing in certain patterns	Missing data are replaced by realistic values and not means that distort	Little theoretical or empirical work to determine its accuracy, problematic if no other case is closely related	Ford (1983), Roth et al. (1999)

	in the dataset		distributions	in all aspects of the data set	
Model-based					
Maximum likelihood	Parameters are estimated by available data and missing scores are estimated based on the parameters	When distributional assumptions are met	Increased accuracy if model is correct	The distributional assumptions required by the technique are relatively strict	Donner and Rosner (1982), DeSarbo et al. (1986), Lee and Chiu (1990)
Expected maximization	An iterative process that continues until there is convergence in the parameter estimates	When distributional assumptions are met	Increased accuracy if model is correct	The algorithm takes time to converge and is too complex	Laird (1988), Little and Rubin (1987), Malhotra (1987), Azen et al. (1989), Ruud (1991), Graham and Donaldson (1993)

TABLE 3.2 The Statistical Techniques Used in the Systematic Approach to Populate Missing Performance Data in PMS

Model	Technique	Description	When to be used	Advantages	Disadvantages	Studies
Model-Free	**Mean of Nearby Points**	Missing value is replaced with the mean of the valid surrounding score values such as: condition, distress, and ride scores.	Particularly recommended for the construction of scale scores	Reliable estimation. Use the valid surrounding values of the scores.	Affected by the length of the span. Less efficient at the boundary of the series.	Ford (1976), Raymond (1986), and Little and Rubin (1987)
	Median of Nearby Points	Missing value is replaced with the median of the valid surrounding score values such as: condition, distress, and ride scores.	Particularly recommended for the construction of scale scores	Reliable estimation. Use the valid surrounding values of the scores.	Affected by the length of the span. Less efficient at the boundary of the series.	Ford (1976), Raymond (1986), and Little and Rubin (1987)
	Moving Average	Missing value is replaced with the moving average of the scores such as: condition, distress, and ride scores.	When the data show noisy trend of the scores	Smooth out the fluctuation in data and expose the trend.	The moving average lags the underlying data.	Little and Rubin (1987)
	Subgroup mean /median/maximum	Missing value is replaced by the mean	When it is easy to define Subgroups of	Gives better estimates, when	Downward biased variance,	Ford (1976)

	/minimum substitution	/median/maximum /minimum substitution on the Subgroup of the scores such as: condition, distress, and ride scores.	the scores	compared to the total mean substitution procedure	arbitrary nature of defining subgroups in some situations	
Model -Based	**Linear Interpolation**	Missing value is replaced with the linear interpolation of scores such as: condition, distress, and ride scores.	When the data show linear trend of the scores within a period of time	Easiest kind of interpolation.	Assume linear trend of the data.	Little and Rubin (1987)
	Linear Trend at Point	Perform linear regression, estimates relationships among variables, and then uses coefficients to estimate the missing score values	When the data show clear linear trend of the scores along the time	Use the valid surrounding values.	Assume linear trend of the data.	Frane (1976), Cohen and Cohen (1983), Raymond and Roberts (1987), Little and Rubin (1987), Little (1988)
	Cubic Spline fitting	Missing value is replaced with the cubic spline interpolation of scores such as: condition, distress, and ride scores.	When the data show oscillatory behavior of the scores	Overcome the oscillatory behavior and provide a smooth interpolation.	Cubic spline could oscillate in the neighborhood of an outlier.	Little and Rubin (1987)
	Cubic Spline based on four data points	Missing value is replaced with the cubic spline interpolation of scores such as: condition, distress, and ride scores.	When the data show oscillatory behavior of the scores	Overcome the oscillatory behavior and provide a smooth interpolation.	Cubic spline could oscillate in the neighborhood of an outlier.	Little and Rubin (1987)

Chapter 4: A Systematic Statistical Approach to Populate Missing Performance Data

4.1. Introduction

This chapter includes a comprehensive description of a systematic statistical approach to populate missing performance data. In addition, several statistical techniques and methods for handling missing data in Pavement Management Systems (PMS) are discussed.

Working with pavement performance historical datasets presents a unique challenge. It is vital to understand the patterns (i.e. pavement performance models) in historical data and to predict the future of these patterns. It is also crucial to know the rate of pavement deterioration in order to predict the condition of pavement sections for upcoming years.

From a practical standpoint, there are two complications involved in the identification process: randomness (i.e. noise) in pavement performance historical data, and uncertainty as to whether the pavement performance will repeat itself in the future. The randomness in the performance data often makes it difficult to detect the underlying pavement performance patterns. The uncertainty of whether performance history will repeat itself means that even if the performance is detected, there is no guarantee that the future predictions based on these will be accurate; often they are not.

To support the decision making process, it is important to have reliable datasets on pavement conditions and accurate performance models for predicting pavement conditions. In general, the historical data on pavement conditions typically comes from annual field surveys resulting in distress, condition, and ride scores.

PMS datasets are often incomplete for some locations and some years due to several reasons. This data could be missing because it could not be rated, measured, collected, saved, and/or

managed correctly. The problem of missing data in pavement performance datasets will reduce the predictive power of the performance models.

4.2. A Systematic Statistical Approach Description

To overcome the challenges encountered when a missing data problem appears in PMS databases, specifically when the problem appears in pavement performance datasets, this study developed a systematic statistical approach to populate missing performance data in pavement management ~~is~~ as an innovative methodology.

The systematic statistical approach developed in this study aims to improve the prediction of future pavement performance. The main objective of this research is to improve the accuracy of pavement performance prediction in order to enhance the decision making process and the planning for pavement maintenance and rehabilitation.

The hypothesis of this study is that populating the missing data will improve the robustness of the performance datasets for predicting future pavement performance. It is also hypothesized that some statistical techniques will be more efficient in rebuilding and predicting the missing data depending on pavement age, condition, and rate of deterioration before or after the missing data point's period. In order to test the hypotheses, this study uses the statistical techniques in rebuilding and predicting the pavement performance missing datasets, quantifies the prediction efficiency of the used statistical techniques, and performs the nonparametric Mann-Whitney test.

The systematic approach utilizes diverse statistical tools including model-free techniques and model-based techniques. The model-free techniques include mean of nearby points, median of nearby points, moving average, and subgroup substitutions (mean/median/minimum/ /maximum). The model-based techniques include linear trend at points (i.e. global linear

regression), linear interpolation, cubic ("spline") fitting (i.e. global cubic regression), and cubic spline based on four data points.

The comprehensive structure of the systematic statistical approach is described in eleven detailed steps. The schematic diagram of the systematic statistical approach used to populate missing performance data in PMS is shown in Figure 4.1.

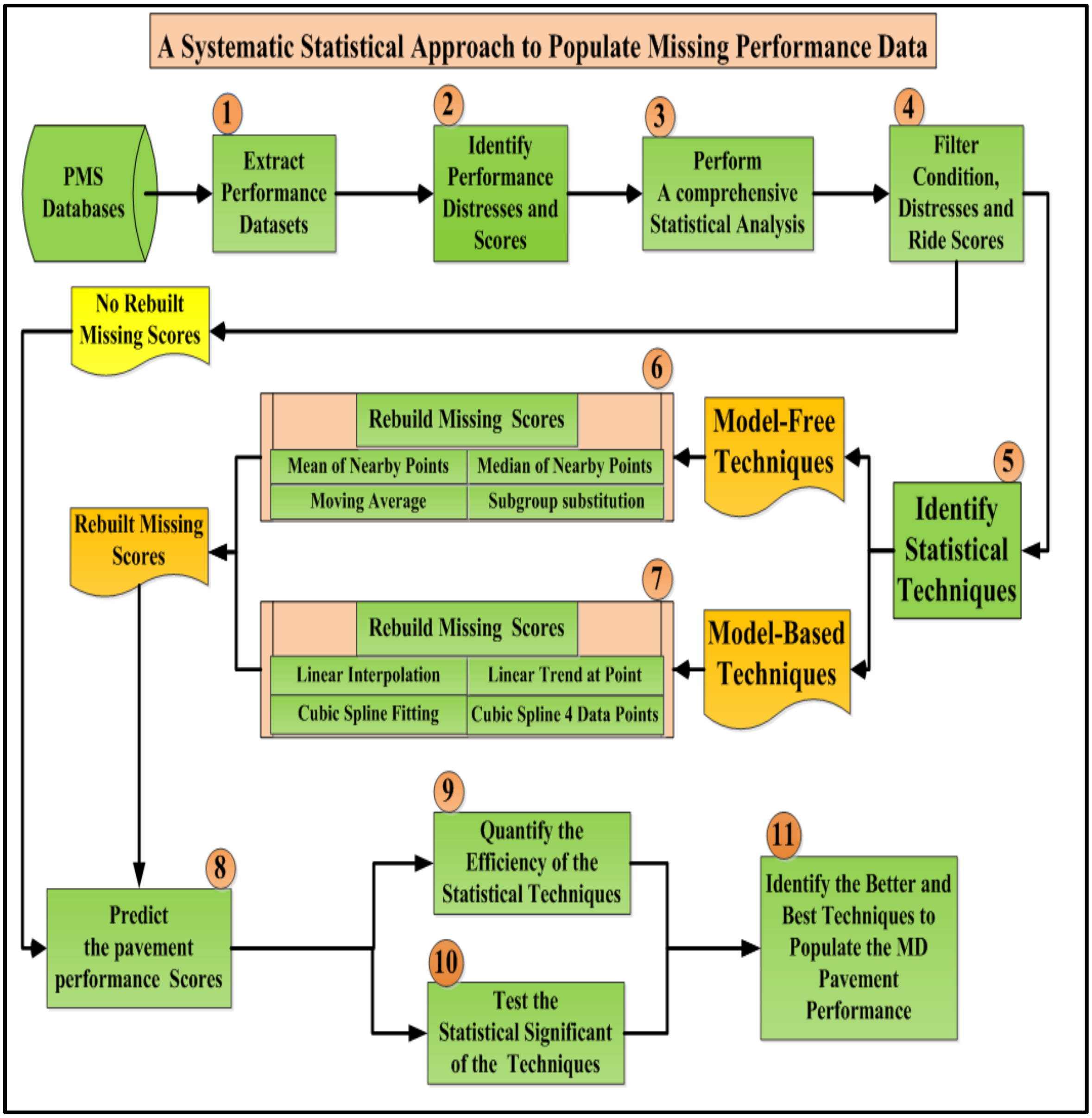

Figure 4.1. The Systematic Statistical Approach Developed to Populate PMS Missing Performance Data.

The eleven steps performed for this study are also listed below:

1. *Extract pavement performance datasets* (i.e. distresses and scores) from historical records for all pavements in the network.
2. *Identify the pavement performance distresses and scores* for all pavements in the network.
3. *Perform a comprehensive statistical analysis* of the pavement performance data (i.e. distresses and scores) in order to understand the data and condition of targeted pavements.
4. *Filter the condition, distress, and ride scores* according to a minimum number of data points and according to a minimum percentage of deterioration.
5. *Identify the statistical techniques* to be used in rebuilding and predicting the missing data points in the datasets.
6. *Rebuild the missing scores for the filtered pavement sections* using model-free techniques.
7. *Rebuild the missing scores for the filtered pavement sections* using model-based techniques.
8. *Predict future pavement performance* (i.e. conditions, distresses, and ride scores) for the pavement sections.
9. *Quantify the pavement prediction efficiency* of the statistical techniques to identify which techniques improved the prediction of future pavement performance.
10. *Perform statistical tests* such as paired sample t-test and Mann Whitney test to confirm the statistical significance of the techniques.

11. *Identify the better/best prediction techniques* to populate the missing pavement performance datasets.

Step 1: Extract Pavement Performance Datasets

TxDOT is divided into 25 geographical districts that are responsible for overseeing the construction and maintenance of state highways within their jurisdiction (TxDOT 2012). From Pavement Management Information Systems (PMIS) databases, Continuously Reinforced Concrete Pavement (CRCP) data were extracted for each of the 23 TxDOT Districts from 1993 to 2010. For this study, data was obtained for about 12,500 CRCP sections in Texas. The data collected for each section included general inventory core data, which are used to identify the section, and pavement performance data, which evaluate the condition of the pavement at the given fiscal year that the data were collected.

Step 2: Identify the pavement performance distresses and scores

The CRCP pavement performance data collected included condition score, distress score, ride score, and distresses (i.e. spalled cracks, punchouts, ACP patches and PCC patches) evaluated for all pavements in the network. Pavement performance is evaluated for each 0.5 mile pavement section through the pavement distresses and indices (i.e. distress, condition, and ride scores).

Step 3: Perform A Comprehensive Statistical Analysis of the Scores

Statistical analyses were performed on the score data collected to better understand the condition of CRCP pavements in Texas as well as to decide on the data to be used for the application of the systematic approach. Through the findings and conclusions of this comprehensive statistical analysis and the review of the available PMIS datasets, it was evident that there was a need to filter the data for further application of the approach.

Step 4: Filter the condition, distress and ride scores

To predict future pavement performance, it is necessary to know the current pavement's condition and its future deterioration rate. In order to estimate how fast the pavement deteriorates, the pavement condition history had to be known.

Ideally, each 0.50 mile pavement section should have 18 distress scores corresponding to all 18 fiscal years from 1993 to 2010. In practice, some of these data points are missing. Since accurate predictions are only possible when there are sufficient data points, this study only considers pavement sections in which at least 10 scores out of 18 possible are available. Also, this study only considers road segments that exhibit a score deterioration of at least 10% from 1993 to 2010. The CRCP pavement sections are filtered to adequate these two requirements. First the minimum data points available in the datasets and second exhibit at least a certain percentage of score deterioration for that specific pavement section. The results obtained by conducting the preceding filter are summarized in Table 1.

Table 4.1 Numbers of Filtered 0.5 Mile Pavement Sections of CRCP in Texas Districts

Minimum Data Point	Condition Score			Distress Score			Ride Score		
	Minimum Score Deterioration (%)								
	10	15	20	10	15	20	0.5	0.75	1
10	110	88	82	155	129	124	70	39	19
11	58	50	47	109	90	88	29	14	11
12	41	34	31	81	69	65	11	5	2
13	33	27	22	56	51	47	3	2	0
14	12	7	6	30	25	21	2	1	0
15	9	9	9	21	16	16	0	0	0
16	7	5	4	22	16	15	0	0	0
17	3	3	3	12	8	7	0	0	0
18	2	2	2	5	5	5	0	0	0
Total	275	225	206	491	409	388	115	61	32

Step 5: Identify the Statistical Techniques to populate Missing Data

To explain different possible ways of utilizing the systematic statistical approach, it is necessary to identify the missing data techniques. The problem of missing data is found in different

practical applications, especially when a large amount of data is involved, such as PMS databases. In many situations, the accuracy is improved by first rebuilding the missing data points and then using the rebuilt datasets for predictions. The selection of the method for populating missing data depends on the field of application. Missing data rebuilding techniques have not been applied in pavement management before this study. The following two possible approaches to the handling of missing data have been used: model-free and model-based replacement techniques.

Step 6: Rebuild the Missing Pavement Performance Data Using Model-Free Replacement Techniques

To replace the missing value, one or several available values of the same quantity are used to rebuild the one(s) that is missing. Model-free replacement techniques differ according to how the corresponding values are selected and processed to rebuild an estimate for the missing data point: *case substitution* techniques use values from the same dataset; *subgroup substitution* techniques use values from different datasets; and *total substitution* techniques use all available data.

This research uses case substitution and subgroup substitution techniques. The main limitation of total substitution is that it results in the same estimate for all the missing data points and is not very computationally efficient. To overcome these limitations, imputation methods use the experts' subjective judgment to select appropriate values.

In the case and subgroup substitution techniques, once the auxiliary data points are selected, the missing data point is rebuilt using either the mean/median of the selected values or a certain percentile of these values.

In this study, the following model-free techniques are used: case substitution techniques in which the missing value is replaced by using (1) the mean of four nearby distress score values (two before and two after); (2) the median of four nearby distress score values; (3) moving average

(replacing the missing value with the last available data point), and subgroup substitution techniques in which the missing value is replaced by (4) mean, (5) median, (6) maximum, or (7) minimum of the distress scores corresponding to the road segments of the same year. These techniques were selected because of their reliability in rebuilding the missing data points.

For some of these missing data techniques, the rebuilt value is sometimes larger than the previously available value. However, for a pavement section to which no treatment was applied, the distress score can only deteriorate (i.e. decrease) with age. Therefore, in situations when the rebuilt value estimated by a missing data technique is larger than the previous available value, the rebuilt value is instead set to be equal to this previous value.

Step7: Rebuild the Missing Pavement Performance Data Using Model-Based Replacement Techniques

In addition to model-free missing data techniques, the study also used model-based techniques. In each of these techniques, a statistical model is fixed. For example, for time series, the dependence of the observed data on time is modeled by a linear or nonlinear (e.g. cubic) dependence. The parameters of the corresponding model are estimated from available data, and then missing values are rebuilt based on the estimated parameters. The parameters are estimated based either on the whole data series or only on data from a limited time period. A model in which different values of the parameters are used to describe different time periods is known as a *spline;* the most commonly used splines are cubic splines.

To find the parameters of the corresponding models, the standard statistical techniques, such as the maximum likelihood method, are used. In missing data techniques, it is usually assumed that the observed data are a sample drawn from a multivariate normal distribution; in this case, the maximum likelihood method becomes the least squares fitting.

In this study, the following model-based replacement techniques are used: (1) linear interpolation based on two nearby distress score values (one before and one after); (2) linear regression (based on the whole history of the given road segment); (3) cubic regression (also based on the whole history); and (4) cubic spline based on four nearby distress score values (two before and two after). These techniques were also selected because of their reliability in rebuilding the missing data points.

Similar to the model-free techniques, in situations when the rebuilt value estimated by a missing data technique is larger than the previous available value, the rebuilt value is instead set.

Step 8: Predict the Future Pavement Performance Missing Data

The following procedure is used to test how efficient missing data techniques in predicting pavement performance. For each selected road segment, the actual score value A corresponding to the last year Y is deleted, and the score values in the previous years are used to predict this distress score. For example, if the last data point extends up to year 2010, the 2010 distress score value is deleted and then the data from all available previous years 1993, 1994, ..., 2009 are used to predict this distress score A (i.e. the value DS_{2010}).

To simulate the situation with missing data points, one, two, or three previous years are selected at random and the scores corresponding to these selected years are deleted. For example, if all the data corresponding to the years 1993 through 2009 are available, and year 1999 is randomly selected, then the values from 1993, 1994, …, 1998 and from years 2000, 2001, ..., 2009 are used to predict the score at year 2010.

In particular, for predicting the Distress Score (DS), the formula takes the form followed in Equation *(1)*:

$$\boldsymbol{DS = 100 - \alpha e^{-\left[\left(\frac{\rho}{Age_i}\right)^{\beta}\right]}} \qquad (1)$$

The general shape of distress score pavement performance model is illustrated in Figure 1. Since this paper concentrates on predicting the Distress Score, the direct application of the Equation *(1)* will be used as a standard against which to test the efficiency of prediction of other proposed methods.

The predicted value *(P)* for the score at year *(Y)* is then obtained using the remaining data points. In the above example, the data from years 1993, 1994, ..., 1998, 2000, 2001, ..., 2009 is used to predict the distress score at year 2010. (For some road segments, the value P predicted by using the Equation *(1)* is below 1 or above 100; such segments were excluded from the analysis). In general, this prediction is somewhat different from the actual value *(A)*; the difference |P - A| is taken as a measure of accuracy of this prediction.

After that, a missing data technique is used to rebuild the deleted distress score data points. In the above example, the distress score value at year 1999 is rebuilt. Then, either the non-linear regression (i.e. pavement performance model) or the same missing data technique is used to compute a predicted value R of the distress score at year *(Y)*. This prediction *(R)* is based both on the original data points (in previous example, data from years 1993, 1994, ..., 1998, 2000, 2001, ..., 2009) and on the rebuilt distress score value (corresponding to year 1999).

This new prediction *(R)* has accuracy |R - A|, in comparison with the prediction error |P - A| of the original PMS prediction method. The smaller the prediction error, the better the prediction method obtained.

A schematic diagram was used to clarify the main differences between the prediction by using the traditional PMS approach and the prediction by using the systematic statistical approach. Figure 2 shows a schematic diagram of predicting distress scores by using the traditional PMS

approach and by using the systematic statistical approach to populate missing pavement performance data.

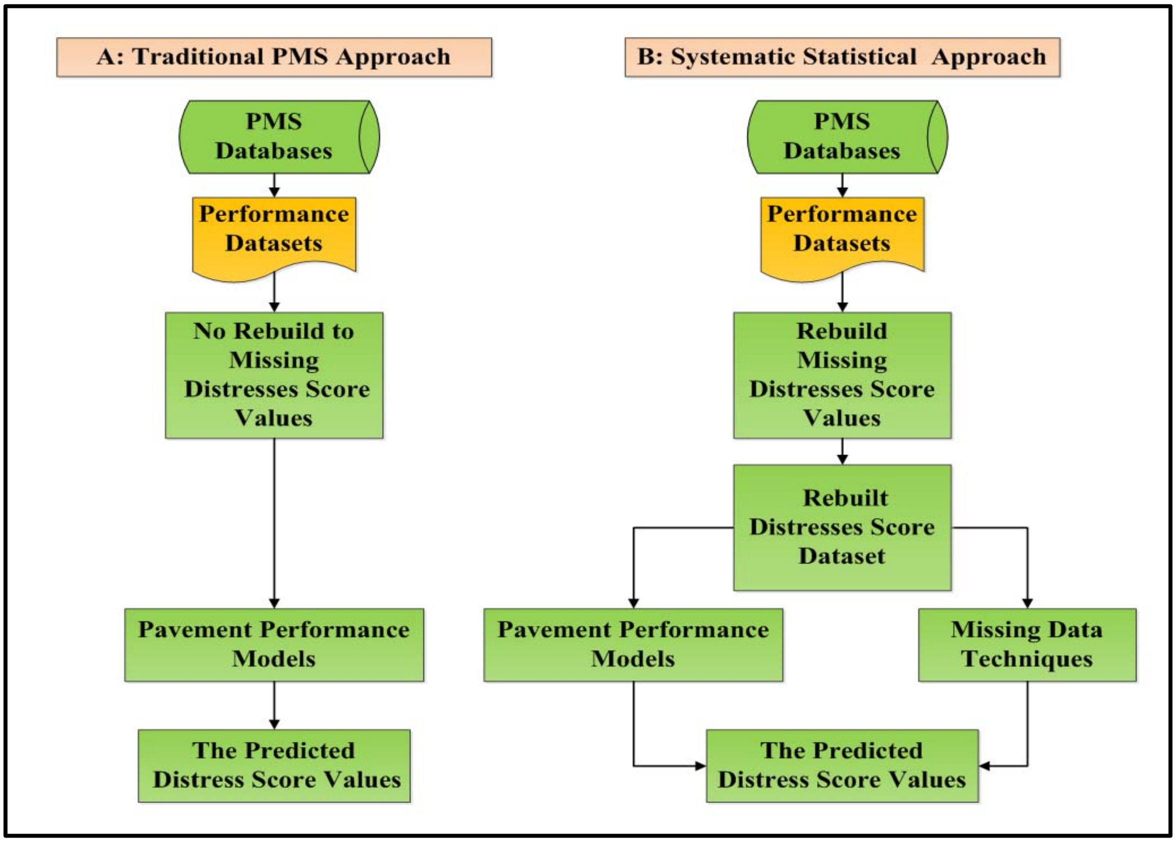

Figure 4.2 Schematic of the Traditional versus the Systematic Statistical Approach to Predict Distress Scores

Step 9: Quantify the Pavement Prediction Efficiency of the Techniques

The evaluation was performed for each *case* consisting of a road segment and a combination of one, two, or three missing data points from this pavement section. For each prediction method, and for each number of missing data points, the median value of the prediction accuracy |R – A| over all the corresponding cases was taken as a measure of the method's prediction efficiency. The outcomes corresponding to one, two, and three missing data points are documented and tabulated.

To quantify the efficiency of each data missing statistical technique utilized in this study, a percentage decrease in the median is listed as well. This percentage is computed as the ratio in Equation *(2)*.

$$Percentage\ Decrease\ in\ the\ Median\ of\ |R - A| = \frac{(M - M_{PMS})}{(M)} \times 100\% \qquad (2)$$

Where M is the median accuracy of the systematic scores prediction method and M_{PMS} is the median accuracy of the traditional scores prediction method. The study also quantifies the mean accuracy, the quartiles of the accuracy distribution, and the number of cases in which the new prediction method was more accurate, of the same accuracy, or less accurate than the current PMS prediction.

Step 10: Perform Significance Statistical Tests

This study uses a non-parametric Mann-Whitney test to check whether the prediction improvement efficiency of the distress score is statistically significant. The absolute improvement is considered to be statistically significant if the significance value of the Mann-Whitney test does not exceed 0.05 (i.e. $P <= 0.05$).

The results of the Mann-Whitney test determine whether the median value of the accuracy |R – A| of the new prediction method is statistically significantly different from the median of the accuracy |P –A| of the original PMS predictions. The null hypothesis is that the medians of the two samples of accuracy values are equal. The alternative hypothesis is that the medians are different.

The medians were used in the analysis since the distress score distributions are not normal, and for general (not normal) distributions, the median is known to be a more robust characteristic than the mean.

This test was used to compare the median prediction accuracies obtained without rebuilding data with the median prediction accuracies obtained by applying different missing data techniques to populate (rebuild) missing data sets. For each statistical technique, the Mann-Whitney test was performed for the three cases: one, two, and three years of missing data respectively.

Step 11: Identify the Better/Best Prediction Techniques

The final step of the systematic approach developed in this study is to decide which missing data techniques are more efficient in rebuilding and predicting future pavement scores. The study identified the better/best prediction techniques to populate the missing pavement performance datasets according to the obtained results of both efficiency and Mann-Whitney tests.

4.3. Finding of Developing A Systematic Statistical Approach

1. Continuous Reinforced Concrete Pavement (CRCP) sections were selected to test the statistical systematic approach from Pavement Management Information System (PMIS) maintained by the Texas Department of Transportation (TxDOT).
2. Upon applying the approach developed in this study on CRCP, the results yielded significant improvements in pavement performance predicting accuracy.
3. The pavement performance prediction results obtained by applying the developed systematic statistical approach to populate missing CRCP performance data represent an improvement when compared to the current approach since it combines the statistical techniques which allow better accuracy in predicting the pavement performance regarding distress scores.

Chapter 5: A Systematic Statistical Approach to Populate Missing Performance Data in Pavement Management Systems (PMS)

The material of this chapter, is a technical paper entitled "A Systematic Statistical Approach to Populate Missing Performance Data in Pavement Management Systems," has been submitted to the ASCE Journal of Infrastructure Systems, it has been assigned manuscript number ISENG-532 and has been forwarded to the Editor to begin the review process for publication.

A Systematic Statistical Approach to Populate Missing Performance Data in Pavement Management Systems

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Abstract

Transportation agencies use pavement management systems (PMS) for their maintenance and rehabilitation planning, programming, and budgeting. PMS is used to make decisions regarding when maintenance and rehabilitation should be applied. To support these decisions, it is important to have reliable data on pavement conditions and accurate performance models for predicting pavement condition. The data on pavement condition typically comes from regular (annual) field surveys resulting in distress, condition, and ride scores. PMS datasets are often incomplete (for some locations and some years) due to operational limitations reducing the predictive power of the performance models.

Model-free and model-based replacement techniques for estimating missing data points have been designed and successfully used in other application areas like statistics, economics, marketing, medicine, psychometrics, political science, etc. It is therefore reasonable to apply these methods to the PMS databases. Statistical techniques are assembled and used in a robust approach to systematically analyze the effect of applying these techniques to rebuild missing performance data. As a case study, Continuous Reinforced Concrete Pavement (CRCP) sections were selected to test the statistical systematic approach from Pavement Management Information System (PMIS) maintains by the Texas Department of Transportation (TxDOT). A major impact was observed in the results of predicting the distress scores due to applying the developed approach.

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5.1. Introduction

Pavement management systems (PMS) are used by transportation agencies for planning, programming, and budgeting short- and long-term treatment needs required for preserving pavement networks. Relevant data for developing these models come from field surveys regularly conducted to assess the structural and functional conditions of the pavement network.

Pavements are complex physical structures that respond to the influence of numerous environmental, subsurface, and load-related variables and their interactions. Subsequently, the task of predicting the multi-faceted responses of pavements to the series of interrelated variables is complex and must be addressed by using a number of assumptions and simplifications.

The accurate prediction of pavement performance is important at all management levels for the efficient preservation of road infrastructure. At the network level, pavement performance prediction is essential for rational budget and resource allocation. At the programming level, pavement performance prediction is needed for adequate activity planning and project prioritization. At the project level, it is required in establishing and designing the necessary corrective maintenance and rehabilitation actions.

In practice, datasets maintained in the Pavement Management Systems (PMS) are often incomplete, affecting the accuracy of pavement performance predictions. The crucial question discussed in this paper is how to improve the accuracy of pavement performance predictions with limited data. This paper presents a systematic approach, using statistical techniques, to handling missing data properly and efficiently for predicting pavement performance. The aim of this approach is to improve pavement performance predictions.

This approach is studied and validated using the Texas Department of Transportation (TxDOT) Continuous Reinforced Concrete Pavements (CRCP) database. CRCP, which is the highest-quality longest-lasting pavement, is the main type of pavement used for road segments

with high-volume traffic such as interstate highways. The maintenance of road segments with this type of pavement is of high priority.

5.2. Distress Score as a Measure of Pavement Performance

To predict the future pavement performance, it is necessary to know the current pavement condition, and the future deterioration rate. To estimate how fast the pavement deteriorates, it is desirable to know the pavement condition history.

Pavement structural and material condition is determined by exhibited distress types (i.e., cracking, faulting, spalling, etc.), the severity of these distress types, and the density of these distress types (i.e., extent of occurrence in surveyed pavement area) (Shahin, Darter, & Kohn, Pavement Condition Evaluation of Asphalt Surfaced Airfield Pavements, 1978) (Shahin, Darter, & Kohn, 1980). To evaluate the pavement condition, TxDOT has combined these characteristics into a single distress index such as the Distress Score (DS) since the late 1980s. Distress scores range from 1 to 100, with 1 representing the worst pavement and 100 representing a pavement section with no distresses (Stampley & Miller, 1995).

5.3. Current Approach for Predicting Distress Scores

TxDOT uses a "sigmoidal" expression to predict the distress deterioration characteristics (X) as a function of the age of the pavement:

$$X = X_0 - \alpha e^{-\left[\left(\frac{\rho}{Age_i}\right)^{\beta}\right]} \quad (1)$$

where X_0 is the largest value of the characteristic, α is the maximum loss factor, β is the slope factor which determines how fast the road segment deteriorates, and ρ is the prolongation factor which controls the location of the distress X curve's inflection point and the slope of the curve at that point, i.e., pavement age at which the deterioration reaches a certain level. The values of the parameters α, β, and ρ are determined based on the observed decrease of the characteristic X,

i.e., as the values for which the formula (1) provides the least-squares best fit for the observed data. In particular, for predicting the Distress Score (DS), the formula (1) takes the following form:

$$\boldsymbol{DS = 100 - \alpha e^{-\left[\left(\frac{\rho}{Age_i}\right)^{\beta}\right]}} \qquad (2)$$

The general shape of distress score pavement performance model is illustrated in Figure 1. Since this paper concentrates on predicting the Distress Score, the direct application of the Equation (2) will be used as a standard against which to test the efficiency of prediction of other proposed methods.

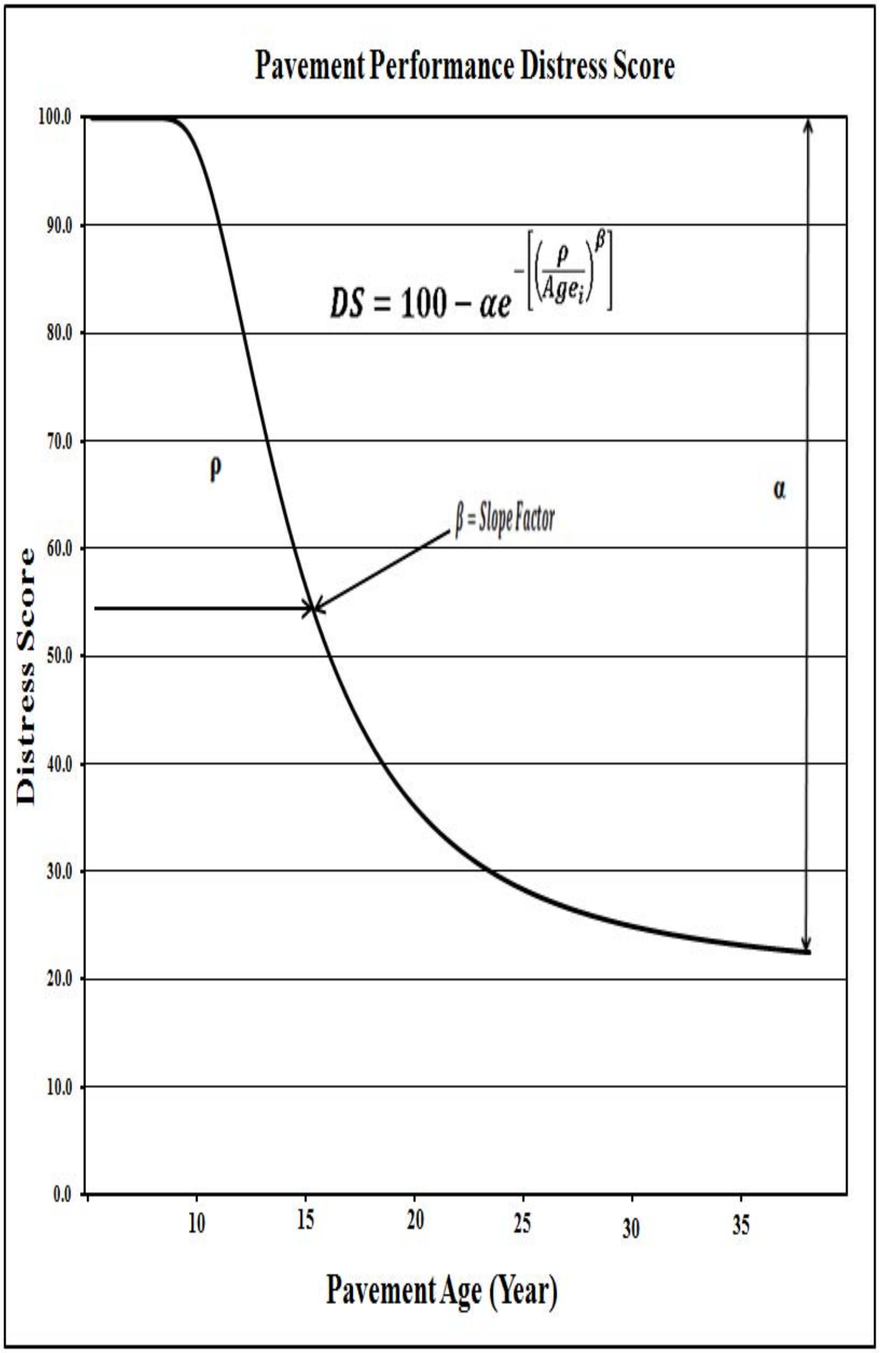

Figure 5.1 General Shape of Distress Score Pavement Performance Model

Systematic Approach to Populate Missing Pavement Performance Data

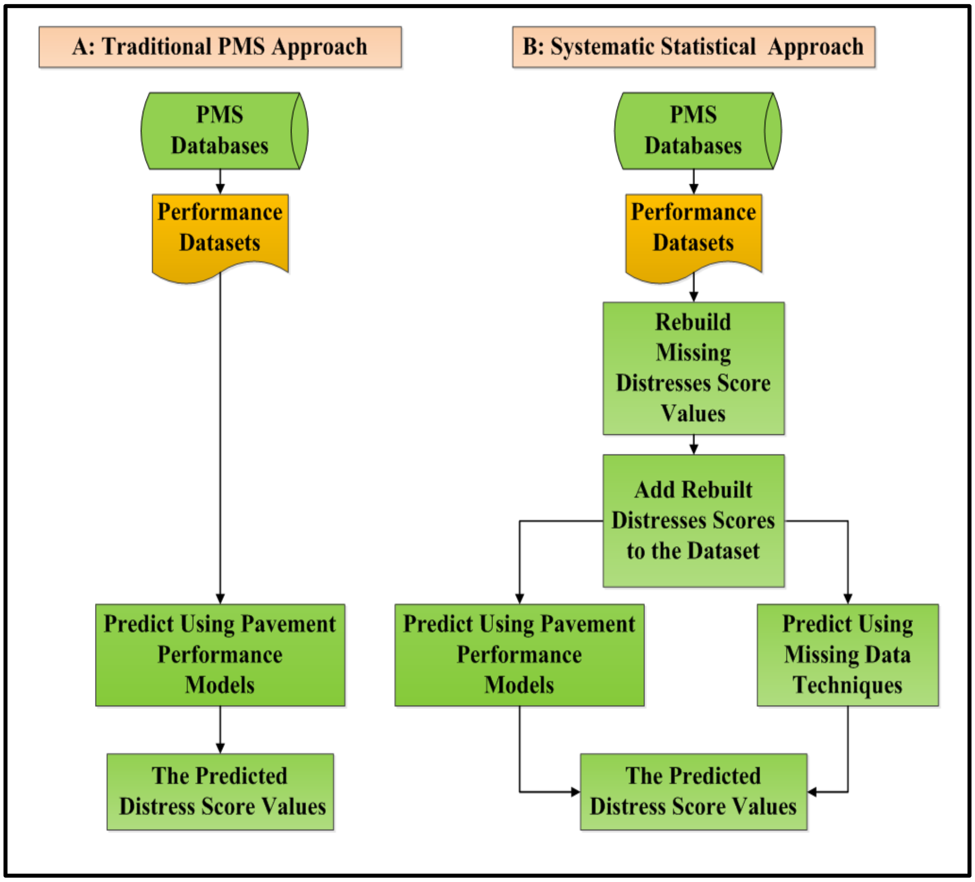

Figure 5.2 Schematic of Traditional versus Systematic Statistical Approach to Predict Distress Scores

PMS datasets are often incomplete, and pavement performance historical data are missing. The problem of missing data is found in different practical applications, especially when a large amount of data is involved. In many situations, the accuracy is improved by first rebuilding the missing data points and then using the rebuilt datasets for the predictions (Tsikriktsis, A review of techniques for treating missing data in OM survey research, 2005). Techniques for rebuilding missing data have been successfully applied in areas such as business, marketing, economics, organizational behavior, social sciences, psychometrics, medicine, nursing, biometrics, and statistics.

To improve pavement performance predictions, to attain more accurate treatment and budget needs analyses, a new systematic approach is proposed that uses statistical techniques for rebuilding missing data to predict pavement performance.

Figure 2 shows a schematic diagram of predicting Distress Score by using the traditional PMS approach and by using the systematic statistical approach to populate (rebuild) missing pavement performance data. In the traditional approach, Equation 2 is used to predict Distress Scores. Specifically, non-linear regression techniques are used to find the value of the parameters α, β, and ρ for which this model provides the best fit (i.e., the smallest mean square error) for the known Distress Scores. The resulting model is then used to predict the Distress Score at future year(s).

In the proposed systematic statistical approach, first, the missing data points are rebuilt by using known missing data techniques, and then, the prediction is performed based both on the observed data points and on the rebuilt data points. In the proposed systematic approach, two methods are applied for predicting Distress Scores: a method that uses Equation 2 and a method that uses missing data techniques. In the first prediction method, when Equation 2 is used, non-linear regression techniques are used to find the value of the parameters α, β, and ρ for which this model provides the best fit (i.e., the smallest mean square error) for the known distress scores. The resulting model is then used to predict the distress score at future year(s). In the second prediction method, a missing data technique is used both for rebuilding the missing data points and for predicting Distress Scores.

5.4. Hypotheses of Study

The hypothesis of the study is that rebuilding the missing data should improve the prediction of pavement performance. It is also hypothesized that certain statistical techniques should be more efficient than others in rebuilding the missing data, depending on pavement age, pavement condition, and rate of deterioration.

In order to test these hypotheses, statistical techniques are used to rebuild the pavement performance missing datasets. The prediction efficiency of different statistical techniques is then quantified. A non-parametric Mann-Whitney statistical test (Gharaibeh, et al., 2012) is used to check the statistical significance of the prediction improvement.

5.5. Overview of Missing Data Techniques

To explain different possible ways of utilizing the above approach, it is necessary to enumerate different known missing data techniques. The selection of the method for populating missing data depends on the field of application. The following three possible approaches to the handling of missing data have been proposed (Tsikriktsis, A review of techniques for treating missing data in OM survey research, 2005):

(a) to delete the datasets which contain the missing data; this approach is currently used when predicting pavement performance,

(b) to use model-free methods to replace the missing data with estimated values, and

(c) to model the distribution of missing data and then to fill it in with new estimates based on the resulting model(s).

5.6. Model-Free Replacement Techniques

To replace the missing value, one or several available values of the same quantity are used to rebuild the missing values. Model-free replacement techniques differ in how the corresponding values are selected and processed to rebuild an estimate for the missing data point:

case substitution techniques use values from the same dataset, *subgroup substitution* techniques use values from different datasets, while *total substitution* techniques use all available data.

This research uses case substitution and subgroup substitution techniques. The main limitation of the total substitution is that it ends up with the same estimate for all the missing data points and is not very computationally efficient. To overcome these limitations, imputation methods use the experts' subjective judgment to select appropriate values. Hot-deck imputation uses data from a given database. Cold-deck imputation uses data from different datasets and usually leads to less accurate results. Hot deck imputation has been efficiently used by: the British Census, the U.S. Bureau of the Census, the Current Population Survey, the Canadian Census of Construction, the U.S. Annual Survey of Manufactures and the U.S. National Medical Care Utilization and Expenditure Survey (Roth & Switzer, 1999) . The main limitation of the hot-deck and cold-deck imputation methods is that they are based on subjective judgments and no robust assumptions. As a consequence, the total substitution techniques are only used when other missing data replacement techniques cannot be applied.

In the case and subgroup substitution techniques, once the auxiliary data points are selected, the missing data point is rebuilt using either the mean/median of the selected values or a certain percentile of these values. In many situations, the resulting estimates using model-free replacement techniques are more accurate than the results using deletion methods (Raymond M. R., 1987).

In this study, the following model-free techniques are used: case substitution techniques in which the missing value is replaced by using (1) the mean of four nearby distress score values (two before and two after), (2) the median of four nearby distress score values, or (3) moving average (replacing the missing value with the last available data point), and subgroup

substitution techniques in which the missing value is replaced by (4) mean, (5) median, (6) maximum, or (7) minimum of the distress scores corresponding to the road segments of the same year. These techniques were selected because of their reliability in rebuilding the missing data points (Tsikriktsis, A review of techniques for treating missing data in OM survey research, 2005).

For some of these missing data techniques, the rebuilt value is sometimes larger than the previously available value. However, for a pavement section to which no treatment was applied, the Distress Score can only deteriorate (i.e., decrease) with age. So, in this study, in situations when the rebuilt value estimated by a missing data technique is larger than the previous available value, the rebuilt value is instead set to be equal to this previous value.

Out of all these techniques, only the moving average can be used for prediction, because all other model-free replacement techniques would require knowledge of distress scores from the future years. For moving average, we can use two different prediction methods: prediction based on the performance prediction Equation 2, and prediction based on using this same moving average technique. For all other model-free replacement techniques, only prediction based on performance prediction Equation 2 is possible.

5.7. Model-Based Replacement Techniques

In addition to model-free missing data techniques, researchers also use model-based techniques. In each of these techniques, a statistical model is fixed. For example, for time series, the dependence of the observed data on time is modeled by a linear or nonlinear (e.g., cubic) dependence. The parameters of the corresponding model are estimated from available data, and then missing values are rebuilt based on the estimated parameters (DeSarbo, 1986). The parameters are estimated based either on the whole data series, on only on data from a limited

time period (DeSarbo, 1986); a model in which different values of the parameters are used to describe different time periods is known as a *spline.* The most commonly used splines are cubic splines.

To find the parameters of the corresponding models, the standard statistical techniques such as the Maximum Likelihood method are used. In missing data techniques, it is usually assumed that the observed data are a sample drawn from a multivariate normal distribution; in this case, the Maximum Likelihood method becomes the Least Squares fitting.

In this study, the following model-based replacement techniques are used: (1) linear interpolation based on two nearby distress score values (one before and one after), (2) Linear Regression (based on the whole history of the given road segment), (3) cubic regression (also based on the whole history), and (4) cubic spline based on four nearby distress score values (two before and two after). These techniques were also selected because of their reliability in rebuilding the missing data points (Tsikriktsis, A review of techniques for treating missing data in OM survey research, 2005). Each of these techniques can also be used for prediction, as an alternative to using the equation (2).

Similarly to the model-free techniques, in situations when the rebuilt value estimated by a missing data technique is larger than the previous available value, the rebuilt value is instead set.

5.8. Case Study

A case study was conducted to test the efficiency of the missing data approach in predicting the distress scores. The pavement data was taken from TxDOT database. TxDOT divides Texas into 25 districts, out of which 23 have Continuous Reinforced Concrete Pavement

(CRCP). This case study used all the distress records related to CRCP pavements in the 23 districts from 1993 to 2010.

Ideally, each 0.50 mile pavement section should have 18 distress scores corresponding to all 18 fiscal years from 1993 to 2010. In practice, some of these data points are missing. Since accurate predictions are only possible when there are sufficiently many data points, this study only considers road segments in which at least 10 distress scores out of 18 possible are available. Also, this study only considers road segments that exhibit at least 10% distress score deterioration from 1993 to 2010. Overall, there are 491 pavement sections that fit these requirements.

The following procedure is used to test how efficient are missing data techniques in predicting pavement performance. For each selected road segment, the actual distress score value, A, corresponding to the last year, Y, is deleted, and the distress score values in the previous years are used to predict that distress score. For example, if the last data point extends up to year 2010, the 2010 distress score value is deleted and then the data from all available previous years 1993, 1994, ..., 2009 are used to predict this distress score, A (i.e., the value DS_{2010}).

To simulate the situation with missing data points, one, two, or three previous years are selected at random and the distress scores corresponding to these selected years are deleted. For example, if all the data corresponding to the years 1993 through 2009 are available, and we select one year 1999 at random, then we use the values from 1993, 1994, …, 1998, and from years 2000, 2001, ..., 2009 to predict the distress score at year 2010.

The predicted value P for the distress score at year Y is then obtained using the remaining data points. In the above example, the data from years 1993, 1994, ..., 1998, 2000, 2001, ..., 2009

is used to predict the distress score at year 2010. (For some road segments, the value P predicted by using the equation (2) is below 1 or above 100; such segments were excluded from the analyses.) In general, this prediction is somewhat different from the actual value A; the difference |P - A| is taken as a measure of accuracy of this prediction.

After that, a missing data technique is used to rebuild the deleted distress score data points. In the above example, the distress score value at year 1999 is rebuilt. Then, either the non-linear regression or the same missing data technique is used to compute a predicted value R of the distress score at year Y. This prediction R is based both on the original data points (in previous example, data from years 1993, 1994, ..., 1998, 2000, 2001, ..., 2009) and on the rebuilt distress score value (corresponding to year 1999).

This new prediction R has accuracy |R - A|, in comparison with the prediction error |P - A| of the original PMS prediction method. The smaller the prediction error, the better the prediction method.

5.9. Mann-Whitney Test

This study uses a non-parametric Mann-Whitney test to check whether the prediction improvement efficiency of the distress score is statistically significant. The absolute improvement is considered to be statistically significant if the significance value of the Mann-Whitney test does not exceed 0.05 (i.e. P <= 0.05).

The Mann-Whitney test checks whether the median value of the accuracy |R – A| of the new prediction method is statistically significantly different from the median of the accuracy |P – A| of the original PMS predictions. The null hypothesis is that the medians of the two samples of accuracy values are equal. The alternative hypothesis is that the medians are different.

The medians were used since the distress score distributions are not normal (Gharaibeh, et al., 2012), and for general (not normal) distributions, median is known to be a more robust characteristic than the mean.

This test was used to compare the median prediction accuracies obtained without rebuilding data with the median prediction accuracies obtained by applying different missing data techniques to populate (rebuild) missing data sets as described earlier. For each technique, the Mann-Whitney test was performed for the three cases: of one, two, and three years missing data respectively.

5.10. Results of Testing

The testing was performed for each *case* consisting of a road segment and a combination of one, two, or three missing data points from that road segment. For each prediction method, and for each number of missing data points, the median value of the prediction accuracy |R – A| over all the corresponding cases was taken as a measure of the method's prediction efficiency. The results corresponding to one, two, and three missing data points are shown in Tables 1, 2, and 3. Each table lists, for each method, the median value m of the prediction accuracy |R – A| and the p-value corresponding to the Mann-Whitney test. To quantify the efficiency of each data missing technique, a percentage decrease in the median is listed as well. This percentage is computed as the ratio in Equation (3).

$$Percentage\ Decrease\ in\ the\ Median\ of\ |R-A| = \frac{(M - M_{PMS})}{(M)} \times 100\% \qquad (3)$$

where M is the median accuracy of the systematic DS prediction method and M_{PMS} is the median accuracy of the traditional DS prediction method. The table also lists the mean accuracy, the quartiles of the accuracy distribution, and the number of cases in which the new prediction

method was more accurate, of the same accuracy, or less accurate than the current PMS prediction.

Table 5.1 Median of Prediction Accuracy and Statistical Significance of the Improvement in Predicted Distress Scores: Cases with One Missing Data Point (Number of Cases: 1232)

Prediction Method	Missing Data Technique (MDT)	Prediction Accuracy |R-A|						Number of Cases		
		Median of Prediction Accuracy |R-A|	p-value	Percentage Decrease in the Median of |R-A|	Mean of |R-A|	1st Quart	3rd Quart	More Accurate	Same Accuracy	Less Accurate
Equation (2)	**Traditional PMS Method**	6.07	-	0.00	12.00	0.94	15.72	0	1232	0
	Mean of Nearby Points	5.12	0.04	15.70	11.76	0.55	15.17	689	49	494
	Median of Nearby Points	5.32	0.03	12.33	11.77	0.56	15.15	678	54	500
	Linear Interpolation	5.32	0.03	12.33	11.77	0.56	15.15	678	54	500
	Linear Regression	5.14	0.11	15.40	11.84	0.76	15.95	683	36	513
	Moving Average	5.39	0.01	11.16	11.77	0.12	15.04	656	52	524
	Cubic Regression	5.39	0.07	11.19	11.91	0.55	16.59	692	36	504
	Cubic Spline	5.32	0.03	12.29	11.81	0.41	15.16	680	52	500
	Subgroup Substitutions Mean	5.64	0.03	7.06	11.78	0.39	15.00	667	54	511
	Subgroup Substitutions Median	5.59	0.03	7.97	11.77	0.18	15.00	662	53	517
	Subgroup Substitutions Maximum	5.75	0.03	5.23	11.79	0.20	14.97	667	53	512
	Subgroup Substitutions Minimum	5.25	0.02	13.46	11.77	0.18	15.00	656	51	525
MDT	**Linear Regression**	12.12	0.00	-99.61	17.24	4.76	25.28	164	0	1068
	Moving Average	4.00	0.00	34.10	11.75	0.00	15.00	650	6	576
	Cubic Regression	6.15	0.00	-1.28	12.46	1.93	16.52	528	0	704
	Cubic Spline	13.00	0.00	-114.16	19.14	5.50	28.71	433	0	799

Table 5.2 Median of Prediction Accuracy and Statistical Significance of the Improvement in Predicted Distress Scores: Cases with Two Missing Data Points (Number of Cases: 4144)

Prediction Method	Missing Data Technique (MDT)	Prediction Accuracy |R-A|						Number of Cases		
		Median of Prediction Accuracy |R-A|	p-value	Percentage Decrease in the Median of |R-A|	Mean of |R-A|	1st Quart	3rd Quart	More Accurate	Same Accuracy	Less Accurate
Equation (2)	**Traditional PMS Method**	4.56	-	0.00	11.44	0.52	15.34	0	4144	0
	Mean of Nearby Points	4.52	0.08	0.93	11.30	0.50	14.64	1866	120	2158
	Median of Nearby Points	4.00	0.01	12.35	11.33	0.19	14.43	1861	128	2155
	Linear Interpolation	4.00	0.01	12.35	11.33	0.19	14.43	1861	128	2155
	Linear Regression	5.00	0.49	-9.56	11.38	0.95	15.04	1839	77	2228
	Moving Average	4.00	0.00	12.35	11.33	0.05	14.95	1726	124	2294
	Cubic Regression	4.46	0.42	2.27	11.45	0.60	15.00	1953	80	2111
	Cubic Spline	4.33	0.01	5.19	11.39	0.27	14.95	1853	119	2172
	Subgroup Substitutions Mean	4.28	0.00	6.15	11.34	0.12	14.43	1771	130	2243
	Subgroup Substitutions Median	4.06	0.00	11.11	11.38	0.06	14.52	1816	127	2201
	Subgroup Substitutions Maximum	4.26	0.00	6.62	11.38	0.06	14.50	1823	127	2194
	Subgroup Substitutions Minimum	4.00	0.00	12.35	11.30	0.05	14.53	1766	121	2257
MDT	**Linear Regression**	10.76	0.00	-135.69	16.16	4.41	24.40	466	0	3678
	Moving Average	4.00	0.00	12.35	10.82	0.00	15.00	532	14	3598
	Cubic Regression	5.40	0.00	-18.32	11.45	1.91	15.19	1785	0	2359
	Cubic Spline	12.00	0.00	-162.94	18.22	5.50	25.00	1101	0	3043

Table5.3 Median of Prediction Accuracy and Statistical Significance of the Improvement in Predicted Distress Scores: Cases with Three Missing Data Points (Number of Cases: 7554)

Prediction Method	Missing Data Technique (MDT)	Prediction Accuracy |R-A|						Number of Cases		
		Median of Prediction Accuracy |R-A|	p-value	Percentage Decrease in the Median of |R-A|	Mean of |R-A|	1st Quart	3rd Quart	More Accurate	Same Accuracy	Less Accurate
Equation (2)	**Traditional PMS Method**	6.22	-	0.00	12.15	0.65	18.65	0	7554	0
	Mean of Nearby Points	6.51	0.23	-4.60	12.20	1.35	17.90	3704	86	3764
	Median of Nearby Points	6.37	0.20	-2.46	12.33	0.72	17.96	3642	101	3811
	Linear Interpolation	6.37	0..2	-2.46	12.33	0.72	17.96	3642	101	3811
	Linear Regression	6.74	0.00	-8.37	12.16	1.85	17.56	3616	60	3878
	Moving Average	6.40	0.00	-2.95	12.33	0.06	17.75	3448	100	4006
	Cubic Regression	6.39	0.03	-2.76	12.20	1.42	18.32	3840	66	3648
	Cubic Spline	6.58	0.4	-5.86	12.29	0.65	18.56	3712	94	3748
	Subgroup Substitutions Mean	6.94	0.52	-11.67	12.39	0.76	17.00	3577	103	3874
	Subgroup Substitutions Median	7.05	0.17	-13.40	12.55	0.27	18.64	3609	101	3844
	Subgroup Substitutions Maximum	6.72	0.14	-8.09	12.52	0.49	19.18	3686	106	3762
	Subgroup Substitutions Minimum	6.00	0.00	3.52	12.28	0.06	17.55	3415	88	4051
MDT	**Linear Regression**	13.23	0.00	-112.71	17.29	4.84	26.12	896	0	6658
	Moving Average	5.00	0.00	19.60	11.54	0.00	16.00	904	24	6626
	Cubic Regression	6.48	0.00	-4.18	11.87	2.17	17.12	3388	0	4166
	Cubic Spline	13.33	0.00	-114.39	19.10	7.00	26.88	2032	0	5522

For cases with one missing data point, the best method (with the best median accuracy) is when the moving average is used both to rebuild the missing values and to predict the Distress Score values; this method leads to 34% improvement in prediction accuracy. For two missing data points, this method is also one of the best, with 12% improvement; for two points, several other missing data techniques lead to similar 12% improvement, namely, methods in which median of nearby points, linear interpolation, moving average, and subgroup minimum are used to rebuild the missing values, and the model (2) is used for prediction. For three missing data points, the moving average method is again the only best one, with 20% improvement in prediction accuracy. All these improvements are statistically significant ($p < 0.05$).

In addition to the moving average, the only other rebuilding missing data technique which leads to statistically significant prediction improvements in all three situations (with one, two, and three missing data points) is the subgroup substitution minimum method; however, for this method, for one and three missing data points, the improvement is much smaller than for the moving average: 13% for one missing data point and 4% for three missing data points.

5.11. Illustrative Example

The comparison between the traditional and the proposed prediction approaches is illustrated in Figure 3. For this pavement section, the PMS contains the Distress Scores for all the years from 1993 to 2010, expect for the years 1995, 2005, and 2006. To compare different approaches, the Distress Scores for 2000 and 2010 were deleted from the records, and the remaining Distress Score values were used to predict the 2010 value.

In the traditional approach, only the remaining Distress Scores are used, from years 1993-1994, 1996-1999, 2001-2004, and 2007-2009. The resulting prediction is denoted by P. In the proposed approach, first, the 2000 value is rebuilt; then, both the available Distress Scores and

the rebuilt 2000 distress score are used to predict the 2010 value. The resulting prediction is denoted by R. One can see that the value R predicted by using the new approach is much closer to the actual value A of the 2010 Distress Score than the value P predicted by using the traditional approach.

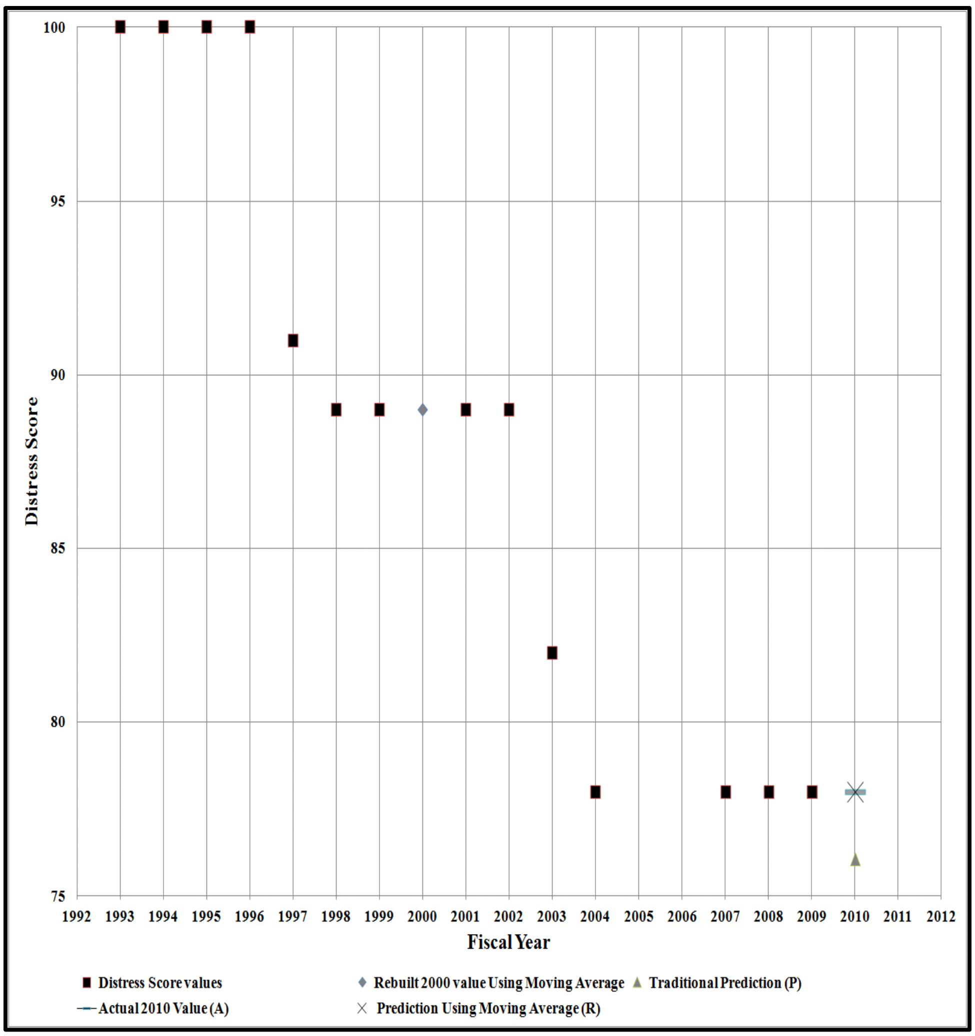

Figure 5.3 An Example of Predicting Distress Score: CRCP Pavement, Section No. 705, El Paso District

5.12. Refined Testing

Up to now, different missing data techniques were tested and compared on all CRCP road segments, and it was shown that the best technique leads to 17-19% improvement in prediction accuracy. In this testing, for each road segment, the same rebuilding missing data technique was used to rebuild all missing data points from this road segment. A natural hypothesis is that by using different missing data techniques for different missing data points, it may be possible to achieve an even better improvement in prediction accuracy.

Distress scores can be clustered in very good, good, fair, poor, and very poor condition categories; see Table 4.

Table 5.4 PMIS Distress Score Categories

Classification	Distress Score
Very Good	90–100
Good	80–89
Fair	70–79
Poor	60–69
Very Poor	1–59

To test the dependence of the efficiency on the condition of missing point, the medians of prediction accuracies corresponding to the cases with one missing data point were re-computed on five subsets of the original set of cases: the subset in which missing points are in very good condition, the subset in which missing points are in good condition, etc. The results of this re-computation are presented in Table 5.

Table 5.5 Median Prediction Accuracy and Statistical Significance of the Improvement in Predicted Distress Scores, Based on Five Distress Score Categories

Prediction Method	Missing Data Technique (MDT)	Very Good			Good			Fair			Poor			Very Poor		
		Prediction Accuracy |R-A|	p-value	Percentage Decrease in the Median of |R-A|	Prediction Accuracy |R-A|	p-value	Percentage Decrease in the Median of |R-A|	Prediction Accuracy |R-A|	p-value	Percentage Decrease in the Median of |R-A|	Prediction Accuracy |R-A|	p-value	Percentage Decrease in the Median of |R-A|	Prediction Accuracy |R-A|	p-value	Percentage Decrease in the Median of |R-A|
Equation (2)	Classical PMS Method	6.87	-	0.00	2.06	-	0.00	3.25	-	0.00	2.66	-	0.00	4.67	-	0.00
	Mean of Nearby Points	6.48	0.21	5.79	1.68	0.08	18.26	3.03	0.63	6.75	1.83	0.27	31.08	3.91	0.08	16
	Median of Nearby Points	6.95	0.20	-1.16	1.38	0.07	33.18	2.64	0.53	18.73	1.00	0.24	62.42	4.00	0.09	14
	Linear Interpolation	6.95	0.20	-1.16	1.38	0.07	33.18	2.64	0.53	18.73	1.00	0.24	62.42	4.00	0.09	14
	Linear Regression	6.80	0.42	1.06	1.48	0.07	28.40	3.74	0.66	-15.09	1.87	0.30	29.64	3.79	0.06	19
	Moving Average	6.97	0.10	-1.41	1.91	0.11	7.51	3.17	0.46	2.38	2.00	0.38	24.83	3.85	0.08	18
	Cubic Regression	6.66	0.29	3.13	1.63	0.07	21.11	2.76	0.62	15.12	2.10	0.36	21.02	3.37	0.11	28
	Cubic Spline	6.97	0.16	-1.36	1.34	0.06	34.87	2.74	0.60	15.60	1.00	0.24	62.42	4.00	0.19	14
	Subgroup Substitutions Mean	6.97	0.17	-1.41	1.50	0.09	27.10	3.35	0.64	-3.11	1.00	0.28	62.42	4.00	0.07	14
	Subgroup Substitutions Median	6.97	0.13	-1.41	1.91	0.22	7.51	3.62	0.74	-11.44	0.96	0.15	63.85	4.00	0.09	14
	Subgroup Substitutions Maximum	6.97	0.14	-1.41	1.91	0.26	7.51	3.92	0.71	-20.66	1.00	0.27	62.42	4.00	0.11	14
	Subgroup Substitutions Minimum	6.97	0.12	-1.41	1.91	0.12	7.51	3.53	0.52	-8.49	1.74	0.37	34.72	4.00	0.09	14
MDT	Linear Regression	13.50	0.00	-96.47	4.91	0.00	-138.36	7.72	0.00	-137.31	7.51	0.00	-182.38	8.39	0.02	-80
	Moving Average	5.00	0.00	27.26	0.00	0.00	100.00	2.00	0.04	38.48	2.00	0.10	24.83	2.00	0.01	57
	Cubic Regression	7.14	0.00	-3.89	1.34	0.93	34.91	3.35	0.41	-3.12	1.70	0.94	36.13	5.23	0.62	-12
	Cubic Spline	13.00	0.00	-89.13	11.00	0.00	-433.71	10.00	0.00	-207.58	7.00	0.01	-163.09	13.33	0.00	-185

For all five classes, the moving average technique improved the median accuracy. In all the classes expect for the road segments with poor distress score, this improvement is statistically significant. For pavements with poor distress scores, none of the missing data techniques lead to statistically significant improvement, since the sample of such road segments is too small. This is not a serious problem, since when one of the observed conditions is poor or very poor, the road segment clearly needs repair; the critical problem of predicting pavement performance is when the observed conditions are very good, good, or fair. For classes corresponding to very good, good, and fair DS, moving average is the only missing data technique which leads to a statistically significant prediction improvement. Based on this analysis, it is recommended to use the moving average technique.

Overall, the best pavement performance prediction method is using moving average both to rebuild the missing data points and to predict the future distress scores.

5.13. Conclusions

To achieve the best improvement of pavement prediction quality, this paper proposes that pavement engineers apply missing data techniques to populate missing data points prior to predicting the future distress scores. Such domain-based combination of different known missing data techniques constitutes a systematic approach to predict pavement performance, an approach which leads to statistically significant accuracy improvement in predicting the distress score. This study proposes to first use statistical techniques to rebuild the missing data points, and then use both original data points and the newly rebuilt points to predict future pavement performance.

After applying the non-parametric Mann-Whitney test to compare the efficiency of different missing data techniques, this study recommends using moving average both to rebuild

the missing data points and to predict the distress scores. It is observed that depending on the number of missing data points, the proposed method will have a major impact on the results, leading to statistically significant ($p < 0.05$) improvement, when compared with traditional PMS, ranging from 12% to 34%.

There are other missing data techniques that lead to statistically significant improvement in accuracy prediction. For example, the subgroup substitution minimum method improves the accuracy for cases of one, two, and three missing data points. However, the improvement using these methods is much smaller than for the moving average; for example, the improvement generated by the subgroup substitution minimum ranges only from 4% to 13%. Similar conclusions were obtained when the analysis was performed separately on cases where the missing data point corresponds to certain DS condition (very good, good, fair, etc.). These results confirm the hypotheses that the use of statistical missing data rebuilding techniques improves the accuracy of predicting pavement performance. More accurate prediction of distress scores will enable decision makers to allocate pavement management budget more efficiently.

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Chapter 6 Conclusions, Recommendations, and Future Research

Conclusions and Recommendations

1. A proper road management includes deciding whether a road section needs treatment or not, what type of treatment is needed, what is the best time for applying this treatment, and what is the best allocation of resources. The main objective of the pavement management decisions is to make sure that the road network is preserved in good condition. To make the appropriate decisions, it is important to predict future pavement conditions: if the predicted conditions are good or very good, this means that no treatment is needed at this time, but is the predicted condition is poor or very poor, this means that some treatment is needed for this pavement segment. The more accurate the predictions, the more reliable the treatment. Predictions of pavement performance are usually made based on the pavement performance history. In general, in statistics, the more observations are used for prediction, the more accurate the resulting predictions. For many road segments, some past scores are missing; as result, for such road segments, predictions may be less accurate than for other segments; this may lead to less reliable road management decisions.
2. Application of missing data techniques to predicting pavement performance faces a challenge in comparison with most known applications of the missing data techniques (including the applications to traffic prediction). In the known applications, the value of the predicted quantity can increase or decrease with time. For example, the traffic on a given road can increase with time, or it can decrease (e.g., if a new road has been built to relieve congestion). In line with these two possibilities, the values rebuilt by using missing data techniques can be smaller or larger than the previously observed values. In

contrast, the pavement performance scores (in the absence of road management and repairs) can only decrease. Because of this special feature of pavement performance data, it is necessary to adjust the existing missing data rebuilding techniques so that the rebuilt values corresponding to the missing years are always smaller than (or equal to) the values in the previous years and larger than (or equal to) the values in the following years.

3. Missing data problems are ubiquitous in many practical applications; to address these problems; special statistical missing data techniques have been designed. These techniques are used as follows: first, a missing data technique is used to rebuild the missing data points, after which both the original data points and the rebuilt ones are used for prediction. These techniques have many successful applications in different areas of science and engineering. In particular, missing data techniques have been successfully used in transportation engineering to improve traffic predictions.
4. In this work, the corresponding modifications of different missing data rebuilding techniques have been tested and compared on different pavement performance prediction problems. A non-parametric Mann-Whitney test was used for checking whether the observed improvement is statistically significant. Model-free and model-based replacement techniques were tested. The results of this comparison lead to the selection of the techniques which are the most efficient (and thus, the most promising) for pavement management. This confirms our hypothesis that missing data techniques lead to more accurate predictions of pavement performance scores. Based on the case study concluded that using the missing data techniques for predicting pavement performance make the predictions more accurate.

5. For the practically important case of Distress Score as a measure of quality of Continuous Reinforced Concrete Pavement (CRCP), the moving average technique (one of the model-free techniques) leads to the best improvement in prediction accuracy (12% to 34%) in comparison with the traditional PMS prediction techniques; see Tables 5.1-5.3. This improvement is statistically significant ($p < 0.05$). Several other missing data techniques, e.g., subgroup substitution minimum (a model-free technique) also lead to a statistically significant improvement, but with a much smaller gain in accuracy (4% to 13%).
6. Different missing data techniques were also tested according to five pavement condition categories corresponding to different quality of missing performance scores: very good, good, fair, poor, and very poor. From the practical viewpoint, situations when missing data points correspond to good or fair score are most important for decision making: indeed, if a poor or a very poor score has been already observed, this means that this road segment needs treatment. For the important classes of very good, good, and fair missing data points, the moving average also leads to statistically significant improvement in prediction accuracy. Rebuilding a good data point leads to the largest improvement (up to 100%), followed by fair (38%) and very good (27%).
7. For the same case study of Texas CRCP road segments, a similar analysis was performed for other pavement performance indices: Condition Score and Ride Score. Preliminary results of this study indicate that a similar statistically significant improvement is achieved for these scores as well, when the moving average is used for rebuilding missing data points and for predicting the performance scores.

8. In this work, the ability of missing data techniques to improve the accuracy was tested on short-term (1-year) predictions. Preliminary results of this study indicate that a similar gain in prediction accuracy is achieved for longer-term predictions as well, 2, 3, and 4 years ahead.
9. The pavement performance prediction results obtained by applying the developed systematic statistical approach to populate missing CRCP performance data represent an improvement when compared to the current approach. The proposed systematic approach combines the statistical techniques which allow 12-34% better accuracy in predicting and forecasting the pavement performance regarding distress, condition, and ride scores.

Benefits of the Research

1. The systematic statistical approach provides a robust methodology to rebuild the gaps in pavement performance history, in order to improve the pavement performance prediction.
2. Applying the approach on CRCP has shown that prediction accuracy improved in a range 12-34%.
3. The improvement is statistically significant, as confirmed by non-parametric Mann Whitney test.
4. The developed approach can be applied to any PMS database and to other pavement types.
5. More accurate prediction will lead to more accurate budget and resource allocation.

Future Research

1. Complete the analysis of applying the developed approach to other pavement performance scores such as Condition Scores (CS), Ride Score (RS).
2. Complete the analysis of applying the developed approach to longer-term predictions of pavement performance.
3. Extend the analysis of developed approach to pavement performance indices used in other states, such as Pavement Condition Index (PCI).
4. Apply the developed approach to other types of pavements, such as Asphalt Concrete Pavement (ACP), Jointed Concrete Pavement (JCP), etc.
5. The developed approach only uses the performance scores after the last repair or treatment. It may be useful to modify the developed approach so that it also takes into account pre-treatment pavement performance scores; these additional scores may provide additional information about deterioration rate of the analyzed road segment and thus, lead to even more accurate predictions of pavement performance.

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Appendix A

General Statistics of Predicted Distress Scores:

Missing Data Points of Crcp 1993-2010

Table A1. Abbreviations of Statistical Summary Used for Predicted Distress Scores.

Abbreviation	Explanation	Note
Obs.	Observation	
Valid	Valid	
Not Valid	Not Valid	
Mean	Mean	
Std. Err. Mean	Std. Error of Mean	
Med	Median	
Std. Dev.	Std. Deviation	
Var.	Variance	
Range	Range	
Min.	Minimum	
Max.	Maximum	
%	Percentiles	
Missing Data Techniques Brief	**Missing Data Techniques Explanation**	**Predicting**
Do Nothing	Do Nothing	**Pavement Performance Model**
Mean Nearby Points	Mean of Nearby Points Using	
Med. Nearby Pts.	Median of Nearby Points	
Linear Interpolation	Linear Interpolation	
Linear Trend Pts.	Linear Trend at Points	
Moving Average	Moving Average	
Cubic Spline Fitting	Cubic Spline Fitting	
Cubic Spline4 D. Pts.	Cubic Spline 4 Data Points	
Sub. Subs. Mean	Subgroup Substitutions Mean	
Sub. Subs. Med.	Subgroup Substitutions Median	
Sub. Subs. Max.	Subgroup Substitutions Maximum	
Sub. Subs. Min.	Subgroup Substitutions Minimum	
P2LinearTrendatPts	Linear Trend at Points	**Missing Data Techniques**
P2MovingAverage	Moving Average Using	
P2CubicSplineFitting	Cubic Spline Fitting Using	
P2CubicSpline4DPts	Cubic Spline 4 Data Points	
P2SubgSubsMean	Subgroup Substitutions	
P2SubgSubsMed	Subgroup Substitutions	
P2SubgSubsMax	Subgroup Substitutions Maximum	
P2SubgSubsMin	Subgroup Substitutions Minimum	

Table A2. General Statistics of Predicted Distress Scores for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1232	0	69.21	.65	75.71	22.73	516.7	98.73	.92	99.65	53.99	75.71	88.75
Mean Nearby Points	1116	116	69.57	.69	76.00	23.17	537.0	98.31	.69	99.00	53.99	76.00	88.97
Med. Nearby Pts.	1124	108	69.47	.69	75.95	23.17	536.9	98.31	.69	99.00	54.25	75.95	88.97
Linear Interpolation	1124	108	69.47	.69	75.95	23.17	536.9	98.31	.69	99.00	54.25	75.95	88.97
Linear Trend Pts.	1086	146	69.86	.70	75.97	23.09	533.2	98.00	1.00	99.00	54.71	75.97	88.98
Moving Average	1143	89	69.58	.68	75.95	23.06	531.7	98.31	.69	99.00	55.12	75.95	88.98
Cubic Spline Fitting	1122	110	69.42	.69	75.51	23.08	532.9	98.13	.87	99.00	53.99	75.51	88.98
Cubic Spline4 D. Pts.	1122	110	69.60	.69	75.98	23.10	533.6	98.31	.69	99.00	55.47	75.98	88.97
Sub. Subs. Mean	1134	98	69.40	.69	75.89	23.10	533.7	98.31	.69	99.00	54.68	75.89	88.97
Sub. Subs. Med.	1133	99	69.46	.69	75.95	23.09	533.4	98.31	.69	99.00	54.07	75.95	88.98
Sub. Subs. Max.	1142	90	69.23	.69	75.88	23.25	540.8	98.31	.69	99.00	53.99	75.88	88.97
Sub. Subs. Min.	1136	96	69.67	.68	76.09	23.02	529.8	98.31	.69	99.00	56.00	76.09	88.98
P2LinearTrendatPts	652	580	82.45	.81	90.81	20.75	430.4	91.05	8.73	99.77	75.88	90.81	95.66
P2MovingAverage	1146	86	72.83	.66	78.00	22.37	500.3	91.00	8.00	99.00	59.00	78.00	89.00
P2CubicSplineFitting	883	349	74.87	.74	81.48	21.94	481.4	95.05	4.30	99.35	64.54	81.48	90.89
P2CubicSpline4DPts	681	551	69.05	1.03	78.00	26.97	727.4	99.50	.50	100.00	52.00	78.00	92.00
P2SubgSubsMean	566	666	51.14	.78	56.10	18.62	346.7	84.00	5.00	89.00	38.40	56.10	65.62
P2SubgSubsMed	632	600	55.12	.82	59.00	20.50	420.3	84.00	5.00	89.00	41.00	59.00	72.00
P2SubgSubsMax	1032	200	71.49	.71	78.00	22.73	516.6	94.00	5.00	99.00	62.00	78.00	89.00
P2SubgSubsMin	373	859	25.19	.97	20.00	18.68	349.0	85.00	4.00	89.00	13.00	20.00	30.50

Table A3. General Statistics of Predicted Distress Scores According to Very Good (90-100) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1025	0	72.27	.67	77.75	21.55	464.5	98.73	.92	99.65	58.08	77.75	88.99
Mean Nearby Points	935	90	72.77	.72	77.99	21.95	481.7	98.31	.69	99.00	61.94	77.99	89.00
Med. Nearby Pts.	942	83	72.63	.72	77.98	21.98	483.1	98.31	.69	99.00	61.93	77.98	89.00
Linear Interpolation	942	83	72.63	.72	77.98	21.98	483.1	98.31	.69	99.00	61.93	77.98	89.00
Linear Trend Pts.	910	115	73.15	.72	77.99	21.80	475.2	98.00	1.00	99.00	61.54	77.99	89.00
Moving Average	960	65	72.64	.71	77.99	21.88	478.6	98.31	.69	99.00	61.99	77.99	89.00
Cubic Spline Fitting	940	85	72.74	.71	77.97	21.75	472.9	98.13	.87	99.00	59.63	77.97	89.00
Cubic Spline4 D. Pts.	944	81	72.71	.71	77.98	21.93	481.0	98.31	.69	99.00	61.99	77.98	89.00
Sub. Subs. Mean	953	72	72.54	.71	77.97	21.88	478.7	98.31	.69	99.00	62.00	77.97	89.00
Sub. Subs. Med.	956	69	72.51	.71	77.97	21.94	481.5	98.31	.69	99.00	61.88	77.97	89.00
Sub. Subs. Max.	957	68	72.52	.71	77.97	21.89	479.2	98.31	.69	99.00	61.99	77.97	89.00
Sub. Subs. Min.	952	73	72.80	.71	77.99	21.81	475.5	98.31	.69	99.00	62.00	77.99	89.00
P2LinearTrendatPts	560	465	86.89	.67	91.63	15.78	249.1	89.98	9.79	99.77	83.01	91.63	97.11
P2MovingAverage	952	73	76.40	.67	82.00	20.60	424.4	91.00	8.00	99.00	69.00	82.00	91.00
P2CubicSplineFitting	737	288	78.94	.72	87.01	19.60	384.1	95.05	4.30	99.35	71.18	87.01	91.58
P2CubicSpline4DPts	595	430	71.99	1.03	78.00	25.05	627.7	97.00	3.00	100.00	57.00	78.00	92.00
P2SubgSubsMean	477	548	54.58	.78	60.40	16.98	288.3	84.00	5.00	89.00	44.97	60.40	66.43
P2SubgSubsMed	537	488	58.78	.82	65.00	18.90	357.4	84.00	5.00	89.00	45.25	65.00	73.00
P2SubgSubsMax	864	161	75.10	.70	79.00	20.71	429.1	94.00	5.00	99.00	69.00	79.00	89.00
P2SubgSubsMin	303	722	26.26	1.14	20.00	19.86	394.3	85.00	4.00	89.00	13.00	20.00	32.00

Table A4. General Statistics of Predicted Distress Scores According to Good (80-89) One year Missing Data point Case (1).

Missing Data	Valid	Not	Mean	Std.	Med.	Std.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	70	0	67.79	2.43	75.92	20.30	412.0	77.20	12.39	89.59	60.98	75.92	78.89
Mean Nearby Points	63	7	67.24	2.51	75.75	19.92	396.8	77.03	11.97	89.00	62.00	75.75	78.00
Med. Nearby Pts.	64	6	66.71	2.53	74.05	20.26	410.6	76.99	12.01	89.00	59.19	74.05	78.00
Linear Interpolation	64	6	66.71	2.53	74.05	20.26	410.6	76.99	12.01	89.00	59.19	74.05	78.00
Linear Trend Pts.	61	9	66.66	2.46	72.00	19.20	368.5	76.18	12.82	89.00	57.88	72.00	78.00
Moving Average	61	9	67.77	2.54	75.54	19.86	394.6	75.78	13.22	89.00	62.00	75.54	78.00
Cubic Spline Fitting	63	7	65.81	2.53	72.00	20.11	404.5	76.86	12.14	89.00	55.48	72.00	78.00
Cubic Spline4 D. Pts.	64	6	66.20	2.52	72.00	20.17	406.7	77.09	11.91	89.00	57.60	72.00	78.00
Sub. Subs. Mean	60	10	67.00	2.54	73.91	19.69	387.7	75.78	13.22	89.00	59.44	73.91	78.00
Sub. Subs. Med.	59	11	66.98	2.59	75.81	19.86	394.4	75.78	13.22	89.00	59.00	75.81	78.00
Sub. Subs. Max.	62	8	66.56	2.60	73.91	20.45	418.0	75.78	13.22	89.00	60.18	73.91	78.00
Sub. Subs. Min.	63	7	67.76	2.50	75.52	19.82	392.9	76.49	12.51	89.00	60.59	75.52	78.00
P2LinearTrendatPts	30	40	73.87	3.07	75.45	16.82	283.0	84.32	9.05	93.37	71.55	75.45	80.77
P2MovingAverage	65	5	71.37	2.07	78.00	16.70	278.7	75.00	14.00	89.00	69.00	78.00	78.00
P2CubicSplineFitting	50	20	70.84	2.06	76.82	14.56	211.9	74.06	15.50	89.56	66.98	76.82	78.10
P2CubicSpline4DPts	30	40	67.38	4.86	78.00	26.62	708.5	96.33	3.67	100.00	54.00	78.00	87.50
P2SubgSubsMean	21	49	44.99	3.84	48.10	17.61	310.3	61.00	10.00	71.00	28.44	48.10	60.34
P2SubgSubsMed	22	48	45.14	3.94	44.50	18.49	342.0	68.00	10.00	78.00	31.00	44.50	60.63
P2SubgSubsMax	57	13	69.37	2.49	78.00	18.78	352.7	79.00	10.00	89.00	62.00	78.00	78.00
P2SubgSubsMin	12	58	25.67	4.63	22.50	16.05	257.5	48.00	9.00	57.00	9.25	22.50	35.75

Table A5. General Statistics of Predicted Distress Scores According to Fair (70-79) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	59	0	60.52	2.19	67.35	16.85	283.9	61.92	22.17	84.09	47.65	67.35	75.75
Mean Nearby Points	48	11	59.84	2.22	66.80	15.37	236.2	56.00	22.00	78.00	47.86	66.80	71.68
Med. Nearby Pts.	50	9	59.69	2.20	66.68	15.57	242.5	56.00	22.00	78.00	47.57	66.68	71.44
Linear Interpolation	50	9	59.69	2.20	66.68	15.57	242.5	56.00	22.00	78.00	47.57	66.68	71.44
Linear Trend Pts.	48	11	59.89	2.21	66.36	15.30	234.0	56.00	22.00	78.00	48.43	66.36	71.72
Moving Average	53	6	61.30	2.07	68.38	15.05	226.5	56.00	22.00	78.00	49.50	68.38	74.23
Cubic Spline Fitting	51	8	58.30	2.33	66.06	16.67	277.8	56.28	21.72	78.00	46.16	66.06	71.53
Cubic Spline4 D. Pts.	50	9	58.28	2.37	64.17	16.75	280.6	56.53	21.47	78.00	46.13	64.17	70.96
Sub. Subs. Mean	52	7	59.89	2.19	66.61	15.77	248.8	56.00	22.00	78.00	48.00	66.61	72.16
Sub. Subs. Med.	50	9	59.58	2.23	65.66	15.78	249.0	56.00	22.00	78.00	47.75	65.66	72.16
Sub. Subs. Max.	51	8	59.65	2.21	65.60	15.76	248.3	56.00	22.00	78.00	47.32	65.60	72.00
Sub. Subs. Min.	52	7	60.91	2.09	67.75	15.09	227.9	56.00	22.00	78.00	49.25	67.75	73.15
P2LinearTrendatPts	28	31	65.64	3.41	71.96	18.05	325.7	75.72	12.86	88.59	59.45	71.96	75.93
P2MovingAverage	56	3	62.46	2.01	69.00	15.04	226.1	57.00	22.00	79.00	49.25	69.00	75.00
P2CubicSplineFitting	43	16	59.79	2.37	63.76	15.56	242.1	57.19	21.80	78.99	44.35	63.76	71.23
P2CubicSpline4DPts	25	34	56.17	5.36	60.67	26.80	718.5	97.83	.50	98.33	30.50	60.67	78.00
P2SubgSubsMean	24	35	39.70	2.41	41.95	11.81	139.6	43.25	13.00	56.25	30.15	41.95	48.10
P2SubgSubsMed	26	33	41.71	2.59	44.00	13.22	174.7	59.00	13.00	72.00	33.50	44.00	50.00
P2SubgSubsMax	50	9	60.34	2.49	67.00	17.61	310.1	65.00	13.00	78.00	47.75	67.00	75.75
P2SubgSubsMin	17	42	22.29	2.21	20.00	9.12	83.2	28.00	11.00	39.00	13.00	20.00	30.00

Table A6. General Statistics of Predicted Distress Scores According to Poor (60-69) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	26	0	45.84	3.65	45.19	18.64	347.3	65.02	7.54	72.56	30.85	45.19	62.02
Mean Nearby Points	24	2	46.06	3.39	45.23	16.60	275.4	55.18	13.82	69.00	32.03	45.23	62.00
Med. Nearby Pts.	24	2	46.02	3.41	45.38	16.70	278.8	55.67	13.33	69.00	32.39	45.38	62.00
Linear Interpolation	24	2	46.02	3.41	45.38	16.70	278.8	55.67	13.33	69.00	32.39	45.38	62.00
Linear Trend Pts.	24	2	46.12	3.39	45.10	16.59	275.2	55.94	13.06	69.00	32.04	45.10	62.00
Moving Average	22	4	45.11	3.44	45.00	16.14	260.5	51.35	13.65	65.00	32.18	45.00	62.00
Cubic Spline Fitting	24	2	45.92	3.41	45.40	16.72	279.5	55.62	13.38	69.00	31.98	45.40	61.97
Cubic Spline4 D. Pts.	24	2	46.03	3.44	46.14	16.85	283.8	56.55	12.45	69.00	32.69	46.14	62.00
Sub. Subs. Mean	25	1	45.34	3.48	45.00	17.41	303.2	61.50	7.50	69.00	32.21	45.00	61.95
Sub. Subs. Med.	25	1	45.38	3.50	45.00	17.49	305.8	61.45	7.55	69.00	32.23	45.00	61.99
Sub. Subs. Max.	25	1	43.53	3.63	43.27	18.13	328.8	61.45	7.55	69.00	28.34	43.27	62.00
Sub. Subs. Min.	23	3	44.57	3.31	45.00	15.88	252.0	51.32	13.68	65.00	32.00	45.00	59.33
P2LinearTrendatPts	12	14	44.28	5.66	49.82	19.60	384.1	61.34	8.76	70.10	27.45	49.82	56.83
P2MovingAverage	24	2	46.08	3.62	48.00	17.71	313.8	61.00	8.00	69.00	33.25	48.00	62.00
P2CubicSplineFitting	18	8	45.01	3.51	46.71	14.87	221.2	47.64	18.06	65.70	33.57	46.71	57.57
P2CubicSpline4DPts	6	20	48.78	9.33	57.17	22.86	522.7	51.67	20.00	71.67	21.25	57.17	66.67
P2SubgSubsMean	8	18	32.41	5.77	28.88	16.32	266.5	49.00	13.00	62.00	20.00	28.88	45.38
P2SubgSubsMed	10	16	36.05	4.89	38.50	15.47	239.2	49.00	13.00	62.00	20.00	38.50	49.25
P2SubgSubsMax	20	6	41.70	2.88	43.00	12.88	165.9	49.00	13.00	62.00	35.00	43.00	50.00
P2SubgSubsMin	7	19	26.29	6.49	20.00	17.17	294.9	50.00	12.00	62.00	13.00	20.00	32.00

Table A7. General Statistics of Predicted Distress Scores According to Very Poor (1-59) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	53	0	32.35	1.72	31.71	12.52	156.8	45.59	11.39	56.98	21.98	31.71	42.60
Mean Nearby Points	47	6	30.02	1.90	27.00	13.03	169.9	48.72	8.28	57.00	20.00	27.00	43.10
Med. Nearby Pts.	45	8	29.61	1.89	27.00	12.70	161.4	48.28	8.72	57.00	20.00	27.00	38.83
Linear Interpolation	45	8	29.61	1.89	27.00	12.70	161.4	48.28	8.72	57.00	20.00	27.00	38.83
Linear Trend Pts.	44	9	28.88	1.89	26.50	12.54	157.2	48.22	8.78	57.00	20.00	26.50	36.39
Moving Average	48	5	29.89	1.88	26.83	13.05	170.3	45.32	11.53	56.85	20.00	26.83	41.24
Cubic Spline Fitting	45	8	29.23	1.85	27.00	12.38	153.2	49.41	7.59	57.00	20.00	27.00	37.64
Cubic Spline4 D. Pts.	41	12	29.80	1.97	27.00	12.61	159.0	46.97	9.07	56.04	20.00	27.00	39.33
Sub. Subs. Mean	45	8	29.36	1.92	27.00	12.86	165.4	49.31	7.69	57.00	19.99	27.00	38.81
Sub. Subs. Med.	44	9	30.27	2.01	27.00	13.31	177.1	49.05	7.95	57.00	19.97	27.00	42.21
Sub. Subs. Max.	48	5	29.67	1.91	27.00	13.24	175.2	52.68	4.32	57.00	19.98	27.00	42.20
Sub. Subs. Min.	47	6	29.90	1.86	27.00	12.78	163.3	45.42	11.58	57.00	20.00	27.00	41.99
P2LinearTrendatPts	23	30	22.75	2.79	19.11	13.38	179.1	48.80	8.73	57.52	13.04	19.11	29.92
P2MovingAverage	50	3	30.18	1.81	26.50	12.78	163.2	44.00	13.00	57.00	20.00	26.50	39.75
P2CubicSplineFitting	36	17	28.58	1.86	26.62	11.18	124.9	40.70	13.86	54.56	19.71	26.62	33.44
P2CubicSpline4DPts	25	28	18.73	3.23	18.00	16.13	260.1	64.00	1.00	65.00	7.00	18.00	20.75
P2SubgSubsMean	37	16	20.67	1.25	20.00	7.58	57.4	30.50	8.50	39.00	17.87	20.00	20.75
P2SubgSubsMed	38	15	22.32	1.50	20.00	9.25	85.5	40.50	8.50	49.00	18.50	20.00	22.00
P2SubgSubsMax	42	11	26.07	1.79	22.50	11.63	135.1	43.00	9.00	52.00	20.00	22.50	35.00
P2SubgSubsMin	35	18	16.57	1.25	20.00	7.42	55.0	25.00	7.00	32.00	10.00	20.00	20.00

Table A8. General Statistics of Predicted Distress Scores According Age (1993-2010) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1232	0	69.21	.65	75.71	22.73	516.7	98.73	.92	99.65	53.99	75.71	88.75
Mean Nearby Points	1116	116	69.57	.69	76.00	23.17	537.0	98.31	.69	99.00	53.99	76.00	88.97
Med. Nearby Pts.	1124	108	69.47	.69	75.95	23.17	536.9	98.31	.69	99.00	54.25	75.95	88.97
Linear Interpolation	1124	108	69.47	.69	75.95	23.17	536.9	98.31	.69	99.00	54.25	75.95	88.97
Linear Trend Pts.	1086	146	69.86	.70	75.97	23.09	533.2	98.00	1.00	99.00	54.71	75.97	88.98
Moving Average	1143	89	69.58	.68	75.95	23.06	531.7	98.31	.69	99.00	55.12	75.95	88.98
Cubic Spline Fitting	1122	110	69.42	.69	75.51	23.08	532.9	98.13	.87	99.00	53.99	75.51	88.98
Cubic Spline4 D. Pts.	1122	110	69.60	.69	75.98	23.10	533.6	98.31	.69	99.00	55.47	75.98	88.97
Sub. Subs. Mean	1134	98	69.40	.69	75.89	23.10	533.7	98.31	.69	99.00	54.68	75.89	88.97
Sub. Subs. Med.	1133	99	69.46	.69	75.95	23.09	533.4	98.31	.69	99.00	54.07	75.95	88.98
Sub. Subs. Max.	1142	90	69.23	.69	75.88	23.25	540.8	98.31	.69	99.00	53.99	75.88	88.97
Sub. Subs. Min.	1136	96	69.67	.68	76.09	23.02	529.8	98.31	.69	99.00	56.00	76.09	88.98
P2LinearTrendatPts	652	580	82.45	.81	90.81	20.75	430.4	91.05	8.73	99.77	75.88	90.81	95.66
P2MovingAverage	1146	86	72.83	.66	78.00	22.37	500.3	91.00	8.00	99.00	59.00	78.00	89.00
P2CubicSplineFitting	883	349	74.87	.74	81.48	21.94	481.4	95.05	4.30	99.35	64.54	81.48	90.89
P2CubicSpline4DPts	681	551	69.05	1.03	78.00	26.97	727.4	99.50	.50	100.00	52.00	78.00	92.00
P2SubgSubsMean	566	666	51.14	.78	56.10	18.62	346.7	84.00	5.00	89.00	38.40	56.10	65.62
P2SubgSubsMed	632	600	55.12	.82	59.00	20.50	420.3	84.00	5.00	89.00	41.00	59.00	72.00
P2SubgSubsMax	1032	200	71.49	.71	78.00	22.73	516.6	94.00	5.00	99.00	62.00	78.00	89.00
P2SubgSubsMin	373	859	25.19	.97	20.00	18.68	349.0	85.00	4.00	89.00	13.00	20.00	30.50

Table A9. General Statistics of Predicted Distress Scores According to Early Age (1993-1998) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	406	0	66.17	1.22	73.00	24.53	601.6	98.36	.92	99.28	48.60	73.00	87.36
Mean Nearby Points	393	13	66.35	1.26	72.97	24.91	620.4	98.20	.69	98.89	49.41	72.97	88.97
Med. Nearby Pts.	392	14	66.33	1.26	72.99	24.95	622.7	98.20	.69	98.89	49.41	72.99	88.98
Linear Interpolation	392	14	66.33	1.26	72.99	24.95	622.7	98.20	.69	98.89	49.41	72.99	88.98
Linear Trend Pts.	383	23	66.64	1.26	72.67	24.64	607.1	98.00	1.00	99.00	49.02	72.67	88.98
Moving Average	390	16	66.28	1.26	72.99	24.98	623.8	98.20	.69	98.89	49.23	72.99	88.98
Cubic Spline Fitting	392	14	66.59	1.25	72.82	24.67	608.5	97.91	1.09	99.00	49.76	72.82	88.98
Cubic Spline4 D. Pts.	392	14	66.50	1.25	73.00	24.83	616.7	98.20	.69	98.89	49.41	73.00	88.98
Sub. Subs. Mean	391	15	66.42	1.26	73.00	24.83	616.4	98.20	.69	98.89	49.41	73.00	88.97
Sub. Subs. Med.	389	17	66.42	1.26	73.00	24.91	620.4	98.20	.69	98.89	49.41	73.00	88.98
Sub. Subs. Max.	389	17	66.44	1.26	73.00	24.91	620.4	98.20	.69	98.89	49.41	73.00	88.98
Sub. Subs. Min.	389	17	66.38	1.26	73.00	24.90	620.2	98.20	.69	98.89	49.41	73.00	88.97
P2LinearTrendatPts	210	196	80.18	1.51	89.49	21.95	481.9	90.73	9.05	99.77	71.93	89.49	95.52
P2MovingAverage	383	23	69.28	1.24	78.00	24.24	587.5	91.00	8.00	99.00	52.00	78.00	89.00
P2CubicSplineFitting	295	111	71.88	1.37	77.62	23.52	553.1	95.05	4.30	99.35	54.81	77.62	89.81
P2CubicSpline4DPts	223	183	64.88	1.92	74.00	28.67	821.8	96.00	3.00	99.00	39.00	74.00	92.00
P2SubgSubsMean	195	211	47.52	1.39	50.33	19.40	376.4	73.80	5.00	78.80	34.44	50.33	62.55
P2SubgSubsMed	217	189	51.40	1.48	54.00	21.80	475.3	84.00	5.00	89.00	38.50	54.00	69.00
P2SubgSubsMax	352	54	67.92	1.31	78.00	24.49	599.6	94.00	5.00	99.00	49.00	78.00	89.00
P2SubgSubsMin	144	262	24.06	1.27	20.00	15.22	231.7	74.00	4.00	78.00	15.25	20.00	29.00

Table A10. General Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	687	0	70.13	.84	75.51	21.93	480.9	92.11	7.54	99.65	56.04	75.51	88.96
Mean Nearby Points	608	79	70.78	.90	76.29	22.22	493.7	90.72	8.28	99.00	56.00	76.29	88.96
Med. Nearby Pts.	616	71	70.74	.89	76.17	22.20	492.8	90.28	8.72	99.00	56.48	76.17	88.96
Linear Interpolation	616	71	70.74	.89	76.17	22.20	492.8	90.28	8.72	99.00	56.48	76.17	88.96
Linear Trend Pts.	591	96	71.07	.91	76.29	22.24	494.6	96.96	2.04	99.00	56.05	76.29	88.98
Moving Average	631	56	70.58	.88	76.09	22.14	490.1	88.14	10.86	99.00	56.65	76.09	88.98
Cubic Spline Fitting	618	69	70.58	.89	75.68	22.03	485.5	91.41	7.59	99.00	56.00	75.68	88.97
Cubic Spline4 D. Pts.	617	70	70.80	.89	76.29	22.19	492.3	89.93	9.07	99.00	56.69	76.29	88.96
Sub. Subs. Mean	628	59	70.58	.89	76.09	22.25	495.2	91.50	7.50	99.00	56.51	76.09	88.96
Sub. Subs. Med.	628	59	70.66	.89	76.09	22.20	493.0	91.45	7.55	99.00	56.88	76.09	88.98
Sub. Subs. Max.	633	54	70.23	.90	76.09	22.57	509.5	94.68	4.32	99.00	56.05	76.09	88.97
Sub. Subs. Min.	626	61	70.81	.88	76.09	22.08	487.5	88.14	10.86	99.00	57.17	76.09	88.98
P2LinearTrendatPts	367	320	83.46	1.04	91.10	19.83	393.3	91.05	8.73	99.77	76.80	91.10	96.65
P2MovingAverage	635	52	73.92	.85	78.00	21.52	463.1	91.00	8.00	99.00	62.00	78.00	90.00
P2CubicSplineFitting	492	195	76.06	.94	82.08	20.92	437.5	87.34	12.02	99.35	67.98	82.08	91.13
P2CubicSpline4DPts	389	298	69.87	1.33	78.00	26.29	691.4	99.50	.50	100.00	57.00	78.00	92.00
P2SubgSubsMean	313	374	52.91	1.02	58.58	17.97	322.9	80.50	8.50	89.00	41.64	58.58	66.14
P2SubgSubsMed	354	333	57.00	1.04	62.00	19.53	381.4	80.50	8.50	89.00	42.00	62.00	73.00
P2SubgSubsMax	567	120	72.82	.91	78.00	21.65	468.8	90.00	9.00	99.00	65.00	78.00	89.00
P2SubgSubsMin	196	491	26.46	1.50	20.00	21.03	442.1	85.00	4.00	89.00	13.00	20.00	32.00

Table A11. General Statistics of Predicted Distress Scores According to Late Age (2005-2010) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	139	0	73.55	1.70	77.98	20.06	402.6	84.48	14.94	99.43	65.65	77.98	88.97
Mean Nearby Points	115	24	74.20	1.92	78.00	20.60	424.5	82.91	16.09	99.00	64.95	78.00	89.00
Med. Nearby Pts.	116	23	73.35	1.93	77.98	20.81	433.2	84.43	14.57	99.00	64.39	77.98	88.98
Linear Interpolation	116	23	73.35	1.93	77.98	20.81	433.2	84.43	14.57	99.00	64.39	77.98	88.98
Linear Trend Pts.	112	27	74.46	1.96	78.00	20.70	428.6	82.79	16.21	99.00	65.64	78.00	89.00
Moving Average	122	17	74.94	1.79	78.00	19.80	391.9	85.50	13.50	99.00	66.46	78.00	88.99
Cubic Spline Fitting	112	27	72.99	2.09	77.98	22.15	490.7	98.13	.87	99.00	62.03	77.98	89.00
Cubic Spline4 D. Pts.	113	26	73.87	1.93	77.98	20.50	420.3	85.30	13.70	99.00	64.79	77.98	88.99
Sub. Subs. Mean	115	24	73.10	1.91	77.91	20.49	419.9	85.58	13.42	99.00	64.95	77.91	88.98
Sub. Subs. Med.	116	23	73.13	1.90	77.97	20.41	416.6	85.50	13.50	99.00	64.95	77.97	88.97
Sub. Subs. Max.	120	19	73.00	1.85	77.97	20.27	411.0	85.67	13.33	99.00	64.39	77.97	88.97
Sub. Subs. Min.	121	18	74.39	1.82	78.00	20.06	402.4	85.50	13.50	99.00	65.52	78.00	88.99
P2LinearTrendatPts	75	64	83.86	2.47	91.68	21.40	458.1	87.93	11.80	99.73	80.77	91.68	95.37
P2MovingAverage	128	11	78.07	1.68	87.00	18.98	360.3	80.00	19.00	99.00	73.00	87.00	89.00
P2CubicSplineFitting	96	43	77.89	2.17	87.41	21.26	451.8	83.66	15.65	99.31	71.43	87.41	91.08
P2CubicSpline4DPts	69	70	77.91	2.71	87.00	22.49	505.6	91.00	9.00	100.00	71.42	87.00	96.00
P2SubgSubsMean	58	81	53.75	2.34	61.14	17.85	318.5	67.83	13.00	80.83	42.92	61.14	66.79
P2SubgSubsMed	61	78	57.48	2.53	69.00	19.72	389.0	70.50	13.00	83.50	44.50	69.00	75.00
P2SubgSubsMax	113	26	75.88	1.97	87.00	20.95	439.0	86.00	13.00	99.00	73.00	87.00	89.00
P2SubgSubsMin	33	106	22.58	3.04	13.00	17.45	304.4	66.00	7.00	73.00	13.00	13.00	28.00

Table A12. General Statistics of Predicted Distress Scores for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	4144	0	71.10	.33	77.60	21.44	459.47	97.77	2.23	100.00	56.00	77.60	88.95
Mean Nearby Points	3236	908	72.22	.38	77.36	21.38	457.23	98.15	.85	99.00	56.28	77.36	88.99
Med. Nearby Pts.	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Interpolation	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Trend Pts.	3085	1059	72.11	.38	76.95	21.24	451.11	98.58	.42	99.00	55.98	76.95	88.98
Moving Average	3385	759	72.12	.37	77.96	21.43	459.24	98.15	.85	99.00	57.17	77.96	88.99
Cubic Spline Fitting	3298	846	71.73	.37	76.82	21.42	458.68	98.13	.87	99.00	55.94	76.82	88.98
Cubic Spline4 D. Pts.	3310	834	71.93	.37	76.95	21.54	464.04	98.15	.85	99.00	56.45	76.95	88.98
Sub. Subs. Mean	3383	761	71.65	.37	76.79	21.62	467.22	98.15	.85	99.00	56.30	76.79	88.99
Sub. Subs. Med.	3399	745	71.42	.37	76.71	21.76	473.57	98.15	.85	99.00	56.05	76.71	88.98
Sub. Subs. Max.	3442	702	71.45	.37	76.79	21.67	469.50	98.15	.85	99.00	56.05	76.79	88.98
Sub. Subs. Min.	3349	795	72.21	.37	77.97	21.44	459.75	98.15	.85	99.00	57.77	77.97	88.99
P2LinearTrendatPts	2124	2020	84.80	.37	90.86	17.02	289.65	99.70	.07	99.77	78.97	90.86	95.69
P2MovingAverage	2220	1924	77.51	.44	87.00	20.71	428.99	85.00	14.00	99.00	62.00	87.00	92.00
P2CubicSplineFitting	2853	1291	76.89	.37	82.18	19.65	386.19	93.17	6.18	99.35	69.30	82.18	90.98
P2CubicSpline4DPts	1895	2249	72.92	.58	83.00	25.22	635.94	99.50	.50	100.00	59.67	83.00	93.50
P2SubgSubsMean	1698	2446	54.08	.37	57.33	15.32	234.58	84.00	5.00	89.00	42.00	57.33	65.62
P2SubgSubsMed	1793	2351	58.27	.40	62.00	17.09	291.97	84.00	5.00	89.00	44.00	62.00	72.00
P2SubgSubsMax	2206	1938	73.52	.46	78.00	21.50	462.32	94.00	5.00	99.00	57.00	78.00	89.00
P2SubgSubsMin	1029	3115	24.62	.54	20.00	17.40	302.72	85.00	4.00	89.00	13.00	20.00	32.00

Table A13. General Statistics of Predicted Distress Scores According to Very Good (90-100) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	3111	1	74.61	.37	78.84	20.37	414.82	97.77	2.23	100.00	64.87	78.84	89.00
Mean Nearby Points	2562	550	75.72	.40	81.91	20.32	413.07	98.15	.85	99.00	64.73	81.91	90.79
Med. Nearby Pts.	2609	503	75.27	.40	80.46	20.67	427.41	98.15	.85	99.00	64.73	80.46	90.68
Linear Interpolation	2609	503	75.27	.40	80.46	20.67	427.41	98.15	.85	99.00	64.73	80.46	90.68
Linear Trend Pts.	2428	684	75.77	.41	82.32	20.09	403.68	98.58	.42	99.00	64.11	82.32	90.70
Moving Average	2644	468	75.50	.40	80.98	20.39	415.64	98.15	.85	99.00	64.95	80.98	90.13
Cubic Spline Fitting	2601	511	75.20	.40	80.94	20.43	417.58	98.13	.87	99.00	62.94	80.94	90.63
Cubic Spline4 D. Pts.	2634	478	75.32	.40	80.05	20.55	422.28	98.15	.85	99.00	64.95	80.05	90.29
Sub. Subs. Mean	2664	448	74.98	.40	79.09	20.66	427.04	98.15	.85	99.00	64.63	79.09	90.66
Sub. Subs. Med.	2674	438	74.83	.40	78.27	20.72	429.44	98.15	.85	99.00	64.21	78.27	90.28
Sub. Subs. Max.	2698	414	74.88	.40	78.00	20.59	423.96	98.15	.85	99.00	64.21	78.00	89.41
Sub. Subs. Min.	2619	493	75.67	.40	80.98	20.31	412.57	98.15	.85	99.00	66.34	80.98	90.66
P2LinearTrendatPts	1688	1424	89.09	.31	91.95	12.85	165.12	84.08	15.69	99.77	87.15	91.95	97.72
P2MovingAverage	1799	1313	82.42	.42	89.00	17.79	316.41	81.00	18.00	99.00	78.00	89.00	93.00
P2CubicSplineFitting	2136	976	81.89	.37	87.48	17.01	289.26	89.93	9.42	99.35	74.52	87.48	92.65
P2CubicSpline4DPts	1568	1544	76.10	.59	86.00	23.19	537.82	97.00	3.00	100.00	63.33	86.00	94.17
P2SubgSubsMean	1348	1764	57.66	.36	61.14	13.19	174.06	81.00	8.00	89.00	50.62	61.14	66.55
P2SubgSubsMed	1450	1662	62.22	.39	68.00	14.80	219.15	81.00	8.00	89.00	53.50	68.00	73.00
P2SubgSubsMax	1781	1331	78.11	.45	86.00	18.96	359.31	83.00	16.00	99.00	72.00	86.00	91.00
P2SubgSubsMin	797	2315	24.66	.67	17.00	18.79	353.22	85.00	4.00	89.00	13.00	17.00	28.00

Table A14. General Statistics of Predicted Distress Scores According to Good (80-89) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	74	0	73.93	1.49	76.89	12.79	163.57	75.52	14.21	89.72	75.40	76.89	78.58
Mean Nearby Points	46	28	71.95	1.97	76.21	13.35	178.15	74.12	14.88	89.00	71.21	76.21	76.82
Med. Nearby Pts.	47	27	71.82	2.09	76.09	14.33	205.48	71.70	17.30	89.00	71.19	76.09	76.78
Linear Interpolation	47	27	71.82	2.09	76.09	14.33	205.48	71.70	17.30	89.00	71.19	76.09	76.78
Linear Trend Pts.	50	24	72.52	1.92	76.41	13.60	185.07	69.57	19.43	89.00	71.40	76.41	77.11
Moving Average	42	32	73.40	2.07	76.09	13.38	179.10	75.78	13.22	89.00	71.32	76.09	76.76
Cubic Spline Fitting	50	24	71.73	1.88	76.08	13.29	176.63	65.90	23.10	89.00	70.82	76.08	76.99
Cubic Spline4 D. Pts.	41	33	71.05	2.28	76.19	14.58	212.67	67.07	21.93	89.00	70.89	76.19	76.69
Sub. Subs. Mean	45	29	74.10	1.88	76.38	12.64	159.79	68.23	20.77	89.00	71.19	76.38	77.23
Sub. Subs. Med.	42	32	73.71	2.03	76.09	13.13	172.32	69.17	19.83	89.00	71.19	76.09	76.61
Sub. Subs. Max.	44	30	71.94	2.28	76.02	15.10	227.95	61.17	27.83	89.00	71.19	76.02	76.61
Sub. Subs. Min.	41	33	73.53	2.13	76.09	13.65	186.20	73.06	15.94	89.00	71.28	76.09	76.31
P2LinearTrendatPts	32	42	77.74	1.01	75.62	5.70	32.50	25.42	64.01	89.43	75.31	75.62	79.42
P2MovingAverage	9	65	71.78	5.96	78.00	17.88	319.69	53.00	36.00	89.00	61.00	78.00	89.00
P2CubicSplineFitting	61	13	76.30	1.02	77.40	7.99	63.87	57.64	31.93	89.56	76.91	77.40	77.89
P2CubicSpline4DPts	13	61	73.89	6.10	79.28	22.00	484.19	76.11	12.39	88.50	72.33	79.28	87.58
P2SubgSubsMean	13	61	52.64	4.21	48.10	15.19	230.71	42.56	28.44	71.00	40.00	48.10	67.20
P2SubgSubsMed	14	60	53.75	4.80	52.00	17.95	322.03	53.00	25.00	78.00	40.00	52.00	70.00
P2SubgSubsMax	10	64	69.50	5.72	71.50	18.08	326.72	47.00	42.00	89.00	53.50	71.50	89.00
P2SubgSubsMin	5	69	27.40	5.10	32.00	11.41	130.30	30.00	9.00	39.00	17.00	32.00	35.50

Table A15. General Statistics of Predicted Distress Scores According to Fair (70-79) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	19	0	65.79	3.82	68.15	16.65	277.24	62.14	23.16	85.30	52.80	68.15	76.85
Mean Nearby Points	15	4	63.89	3.11	67.60	12.04	144.93	42.03	35.00	77.03	52.85	67.60	76.02
Med. Nearby Pts.	15	4	64.00	3.12	67.80	12.09	146.21	41.82	35.00	76.82	53.21	67.80	76.09
Linear Interpolation	15	4	64.00	3.12	67.80	12.09	146.21	41.82	35.00	76.82	53.21	67.80	76.09
Linear Trend Pts.	13	6	62.65	3.44	66.82	12.40	153.77	42.45	35.00	77.45	52.12	66.82	72.79
Moving Average	15	4	64.35	3.04	68.38	11.77	138.60	42.97	35.00	77.97	54.37	68.38	73.00
Cubic Spline Fitting	14	5	63.01	3.23	67.21	12.07	145.66	42.41	35.00	77.41	52.15	67.21	70.45
Cubic Spline4 D. Pts.	15	4	64.05	3.14	68.09	12.16	147.76	42.30	35.00	77.30	53.54	68.09	76.03
Sub. Subs. Mean	14	5	63.50	3.37	67.09	12.59	158.62	42.89	35.00	77.89	53.07	67.09	76.14
Sub. Subs. Med.	13	6	63.07	3.62	66.09	13.04	170.01	42.97	35.00	77.97	52.70	66.09	76.30
Sub. Subs. Max.	14	5	63.67	3.39	66.31	12.70	161.36	41.60	35.00	76.60	53.07	66.31	76.22
Sub. Subs. Min.	13	6	62.79	3.50	67.98	12.63	159.50	42.97	35.00	77.97	52.70	67.98	72.45
P2LinearTrendatPts	13	6	63.87	3.40	65.93	12.25	150.14	47.05	29.33	76.38	59.49	65.93	73.58
P2MovingAverage	6	13	54.50	4.08	56.00	9.99	99.90	27.00	35.00	62.00	50.75	56.00	62.00
P2CubicSplineFitting	16	3	64.96	2.83	69.24	11.30	127.73	39.97	37.20	77.17	54.72	69.24	72.82
P2CubicSpline4DPts	14	5	61.51	5.35	73.25	20.02	400.94	58.39	20.00	78.39	46.92	73.25	77.11
P2SubgSubsMean	9	10	43.91	3.04	47.00	9.11	83.06	26.50	26.50	53.00	38.40	47.00	53.00
P2SubgSubsMed	9	10	45.11	2.78	48.00	8.34	69.61	24.00	29.00	53.00	40.00	48.00	53.00
P2SubgSubsMax	6	13	49.00	4.40	45.00	10.79	116.40	27.00	35.00	62.00	42.50	45.00	62.00
P2SubgSubsMin	6	13	30.50	1.91	32.00	4.68	21.90	12.00	25.00	37.00	25.00	32.00	33.25

Table A16. General Statistics of Predicted Distress Scores According to Poor (60-69) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	8	0	53.97	4.05	51.15	11.46	131.32	29.72	43.78	73.50	43.93	51.15	62.10
Mean Nearby Points	5	3	46.62	4.61	42.52	10.30	106.07	23.90	41.10	65.00	41.33	42.52	53.97
Med. Nearby Pts.	5	3	47.43	4.40	43.09	9.83	96.59	22.54	42.46	65.00	42.76	43.09	54.27
Linear Interpolation	5	3	47.43	4.40	43.09	9.83	96.59	22.54	42.46	65.00	42.76	43.09	54.27
Linear Trend Pts.	5	3	47.13	4.48	42.99	10.02	100.33	23.04	41.96	65.00	41.98	42.99	54.35
Moving Average	7	1	51.60	4.05	44.01	10.72	114.99	23.13	41.87	65.00	42.95	44.01	62.00
Cubic Spline Fitting	5	3	47.40	4.43	43.52	9.90	97.98	23.33	41.67	65.00	42.00	43.52	54.74
Cubic Spline4 D. Pts.	6	2	50.15	4.21	43.96	10.31	106.32	22.33	42.67	65.00	43.33	43.96	62.58
Sub. Subs. Mean	6	2	49.20	4.53	42.57	11.10	123.16	23.86	41.14	65.00	41.81	42.57	62.68
Sub. Subs. Med.	6	2	49.27	4.52	42.67	11.06	122.32	23.89	41.11	65.00	41.94	42.67	62.70
Sub. Subs. Max.	5	3	46.73	4.58	42.63	10.23	104.69	23.89	41.11	65.00	41.66	42.63	53.85
Sub. Subs. Min.	7	1	51.41	4.12	43.72	10.90	118.89	23.47	41.53	65.00	42.71	43.72	62.00
P2LinearTrendatPts	2	6	57.64	1.12	57.64	1.58	2.49	2.23	56.52	58.76	56.52	57.64	
P2MovingAverage	3	5	51.67	6.67	45.00	11.55	133.33	20.00	45.00	65.00	45.00	45.00	
P2CubicSplineFitting	5	3	52.55	5.00	44.80	11.19	125.22	21.83	44.20	66.03	44.20	44.80	64.76
P2CubicSpline4DPts	2	6	61.31	3.69	61.31	5.22	27.30	7.39	57.61	65.00	57.61	61.31	
P2SubgSubsMean	0	8											
P2SubgSubsMed	0	8											
P2SubgSubsMax	1	7	50.00		50.00			.00	50.00	50.00	50.00	50.00	50.00
P2SubgSubsMin	0	8											

Table A17. General Statistics of Predicted Distress Scores According to Very Poor (1-59) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	46	0	28.54	1.65	28.88	11.21	125.62	46.88	5.12	51.99	19.98	28.88	35.59
Mean Nearby Points	29	17	24.39	1.61	27.00	8.70	75.60	45.27	5.69	50.96	19.00	27.00	27.00
Med. Nearby Pts.	30	16	23.91	1.63	27.00	8.95	80.10	45.48	5.52	51.00	19.00	27.00	27.00
Linear Interpolation	30	16	23.91	1.63	27.00	8.95	80.10	45.48	5.52	51.00	19.00	27.00	27.00
Linear Trend Pts.	28	18	24.05	1.42	27.00	7.52	56.57	38.34	12.64	50.98	19.00	27.00	27.00
Moving Average	36	10	25.06	1.73	26.50	10.38	107.83	45.20	6.80	52.00	19.00	26.50	27.00
Cubic Spline Fitting	28	18	24.95	1.57	27.00	8.29	68.79	39.28	11.72	51.00	19.00	27.00	27.00
Cubic Spline4 D. Pts.	29	17	23.20	1.55	27.00	8.32	69.23	45.47	5.53	51.00	19.00	27.00	27.00
Sub. Subs. Mean	32	14	22.60	1.48	22.99	8.37	69.98	44.90	6.10	51.00	19.00	22.99	27.00
Sub. Subs. Med.	35	11	23.13	1.63	19.99	9.65	93.04	46.72	5.27	52.00	19.00	19.99	27.00
Sub. Subs. Max.	32	14	24.89	1.81	27.00	10.26	105.28	46.01	5.98	51.99	19.00	27.00	27.00
Sub. Subs. Min.	34	12	24.49	1.66	26.50	9.69	93.89	44.50	7.50	52.00	19.00	26.50	27.00
P2LinearTrendatPts	28	18	19.06	1.84	19.14	9.72	94.50	51.96	.07	52.03	13.55	19.14	20.32
P2MovingAverage	24	22	25.58	1.43	27.00	6.98	48.78	33.00	18.00	51.00	19.00	27.00	27.00
P2CubicSplineFitting	33	13	26.03	1.44	26.86	8.28	68.49	35.28	13.50	48.78	20.15	26.86	28.29
P2CubicSpline4DPts	28	18	13.25	2.14	10.10	11.34	128.64	54.61	1.00	55.61	7.00	10.10	21.76
P2SubgSubsMean	26	20	16.93	1.20	18.40	6.13	37.52	30.20	8.00	38.20	13.00	18.40	18.40
P2SubgSubsMed	26	20	18.94	1.43	22.00	7.27	52.89	33.00	8.00	41.00	13.00	22.00	22.00
P2SubgSubsMax	26	20	22.42	1.89	25.00	9.64	92.89	39.00	8.00	47.00	13.00	25.00	25.00
P2SubgSubsMin	25	21	9.92	.97	7.00	4.85	23.49	22.00	6.00	28.00	7.00	7.00	13.00

Table A18. General Statistics of Predicted Distress Scores According Age (1993-2010) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	4144	0	71.10	.33	77.60	21.44	459.47	97.77	2.23	100.00	56.00	77.60	88.95
Mean Nearby Points	3236	908	72.22	.38	77.36	21.38	457.23	98.15	.85	99.00	56.28	77.36	88.99
Med. Nearby Pts.	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Interpolation	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Trend Pts.	3085	1059	72.11	.38	76.95	21.24	451.11	98.58	.42	99.00	55.98	76.95	88.98
Moving Average	3385	759	72.12	.37	77.96	21.43	459.24	98.15	.85	99.00	57.17	77.96	88.99
Cubic Spline Fitting	3298	846	71.73	.37	76.82	21.42	458.68	98.13	.87	99.00	55.94	76.82	88.98
Cubic Spline4 D. Pts.	3310	834	71.93	.37	76.95	21.54	464.04	98.15	.85	99.00	56.45	76.95	88.98
Sub. Subs. Mean	3383	761	71.65	.37	76.79	21.62	467.22	98.15	.85	99.00	56.30	76.79	88.99
Sub. Subs. Med.	3399	745	71.42	.37	76.71	21.76	473.57	98.15	.85	99.00	56.05	76.71	88.98
Sub. Subs. Max.	3442	702	71.45	.37	76.79	21.67	469.50	98.15	.85	99.00	56.05	76.79	88.98
Sub. Subs. Min.	3349	795	72.21	.37	77.97	21.44	459.75	98.15	.85	99.00	57.77	77.97	88.99
P2LinearTrendatPts	2124	2020	84.80	.37	90.86	17.02	289.65	99.70	.07	99.77	78.97	90.86	95.69
P2MovingAverage	2220	1924	77.51	.44	87.00	20.71	428.99	85.00	14.00	99.00	62.00	87.00	92.00
P2CubicSplineFitting	2853	1291	76.89	.37	82.18	19.65	386.19	93.17	6.18	99.35	69.30	82.18	90.98
P2CubicSpline4DPts	1895	2249	72.92	.58	83.00	25.22	635.94	99.50	.50	100.00	59.67	83.00	93.50
P2SubgSubsMean	1698	2446	54.08	.37	57.33	15.32	234.58	84.00	5.00	89.00	42.00	57.33	65.62
P2SubgSubsMed	1793	2351	58.27	.40	62.00	17.09	291.97	84.00	5.00	89.00	44.00	62.00	72.00
P2SubgSubsMax	2206	1938	73.52	.46	78.00	21.50	462.32	94.00	5.00	99.00	57.00	78.00	89.00
P2SubgSubsMin	1029	3115	24.62	.54	20.00	17.40	302.72	85.00	4.00	89.00	13.00	20.00	32.00

Table A19. General Statistics of Predicted Distress Scores According to Early Age (1993-1998) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	449	0	66.42	1.16	73.50	24.67	608.48	87.30	11.47	98.77	48.69	73.50	88.93
Mean Nearby Points	390	59	67.01	1.26	73.79	24.92	621.13	89.56	9.33	98.89	49.30	73.79	88.99
Med. Nearby Pts.	395	54	66.90	1.25	72.00	24.83	616.36	85.95	12.94	98.89	49.41	72.00	88.99
Linear Interpolation	395	54	66.90	1.25	72.00	24.83	616.36	85.95	12.94	98.89	49.41	72.00	88.99
Linear Trend Pts.	367	82	67.80	1.27	74.74	24.28	589.58	89.80	9.09	98.89	48.97	74.74	88.99
Moving Average	387	62	67.11	1.26	72.97	24.75	612.76	85.74	13.15	98.89	49.41	72.97	88.99
Cubic Spline Fitting	382	67	67.01	1.26	72.00	24.69	609.73	85.44	13.49	98.93	48.69	72.00	88.99
Cubic Spline4 D. Pts.	392	57	67.10	1.25	72.98	24.73	611.68	85.95	12.94	98.89	49.41	72.98	88.98
Sub. Subs. Mean	391	58	67.49	1.23	73.00	24.42	596.12	86.34	12.55	98.89	50.00	73.00	88.99
Sub. Subs. Med.	391	58	67.52	1.23	73.00	24.41	595.81	86.38	12.51	98.89	50.00	73.00	88.99
Sub. Subs. Max.	391	58	67.52	1.23	73.00	24.40	595.49	86.38	12.51	98.89	50.00	73.00	88.99
Sub. Subs. Min.	392	57	67.15	1.24	72.22	24.62	606.30	88.55	10.34	98.89	49.41	72.22	88.99
P2LinearTrendatPts	217	232	79.81	1.54	90.80	22.75	517.74	89.96	9.81	99.77	67.91	90.80	95.67
P2MovingAverage	248	201	72.60	1.50	79.00	23.67	560.25	85.00	14.00	99.00	51.75	79.00	92.00
P2CubicSplineFitting	314	135	72.07	1.31	77.49	23.27	541.44	89.93	9.42	99.35	52.94	77.49	89.83
P2CubicSpline4DPts	190	259	67.70	2.03	78.50	28.04	786.32	96.00	3.00	99.00	40.00	78.50	92.00
P2SubgSubsMean	177	272	50.29	1.32	54.98	17.60	309.83	70.00	8.00	78.00	38.40	54.98	64.05
P2SubgSubsMed	197	252	55.68	1.42	56.00	19.99	399.50	81.00	8.00	89.00	41.00	56.00	71.00
P2SubgSubsMax	253	196	68.62	1.49	73.00	23.67	560.29	89.00	10.00	99.00	47.00	73.00	89.00
P2SubgSubsMin	119	330	23.18	1.18	20.00	12.83	164.69	74.00	4.00	78.00	15.00	20.00	29.00

Table A20. General Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1288	0	71.78	.57	76.92	20.58	423.67	97.49	2.23	99.72	56.99	76.92	88.94
Mean Nearby Points	1014	274	73.05	.65	77.79	20.66	426.96	93.31	5.69	99.00	58.75	77.79	88.96
Med. Nearby Pts.	1039	249	72.62	.65	76.97	21.08	444.55	93.48	5.52	99.00	57.99	76.97	88.97
Linear Interpolation	1039	249	72.62	.65	76.97	21.08	444.55	93.48	5.52	99.00	57.99	76.97	88.97
Linear Trend Pts.	963	325	72.95	.66	77.50	20.53	421.45	95.59	3.41	99.00	57.17	77.50	88.98
Moving Average	1056	232	72.51	.65	77.63	21.15	447.16	92.20	6.80	99.00	58.00	77.63	88.98
Cubic Spline Fitting	1049	239	72.80	.63	76.88	20.27	411.06	96.40	2.60	99.00	57.17	76.88	88.96
Cubic Spline4 D. Pts.	1053	235	72.93	.63	76.93	20.52	421.14	94.23	4.77	99.00	59.19	76.93	88.96
Sub. Subs. Mean	1052	236	72.41	.65	76.71	21.00	440.95	92.90	6.10	99.00	57.91	76.71	88.98
Sub. Subs. Med.	1080	208	72.20	.64	76.71	21.16	447.72	93.73	5.27	99.00	57.99	76.71	88.97
Sub. Subs. Max.	1078	210	72.38	.64	76.71	20.90	436.77	93.02	5.98	99.00	58.00	76.71	88.98
Sub. Subs. Min.	1044	244	72.76	.65	77.11	20.98	440.02	91.50	7.50	99.00	59.00	77.11	88.98
P2LinearTrendatPts	694	594	85.42	.65	91.26	17.09	292.21	99.70	.07	99.77	78.99	91.26	96.82
P2MovingAverage	720	568	79.01	.75	89.00	20.20	408.04	81.00	18.00	99.00	69.00	89.00	92.00
P2CubicSplineFitting	902	386	78.28	.63	84.58	18.96	359.34	85.85	13.50	99.35	70.62	84.58	91.52
P2CubicSpline4DPts	655	633	73.46	.94	80.50	24.09	580.36	99.00	1.00	100.00	62.00	80.50	93.00
P2SubgSubsMean	560	728	55.92	.63	60.40	14.94	223.13	81.00	8.00	89.00	48.10	60.40	66.41
P2SubgSubsMed	605	683	60.35	.67	68.00	16.49	272.06	81.00	8.00	89.00	48.00	68.00	73.00
P2SubgSubsMax	725	563	75.70	.77	83.00	20.69	428.03	91.00	8.00	99.00	69.00	83.00	90.00
P2SubgSubsMin	337	951	26.31	1.12	17.00	20.61	424.81	85.00	4.00	89.00	13.00	17.00	32.00

Table A21. General Statistics of Predicted Distress Scores According to Late Age (2005-2010) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	90	0	77.86	1.62	78.00	15.38	236.60	90.59	8.84	99.43	74.49	78.00	88.81
Mean Nearby Points	60	30	79.36	2.06	81.45	15.99	255.77	86.97	12.03	99.00	74.69	81.45	88.99
Med. Nearby Pts.	63	27	79.59	1.87	80.46	14.85	220.44	81.64	17.36	99.00	76.24	80.46	88.99
Linear Interpolation	63	27	79.59	1.87	80.46	14.85	220.44	81.64	17.36	99.00	76.24	80.46	88.99
Linear Trend Pts.	54	36	80.28	2.20	83.56	16.18	261.95	88.78	10.22	99.00	74.17	83.56	89.00
Moving Average	73	17	79.55	1.61	78.00	13.78	189.83	66.00	33.00	99.00	75.00	78.00	88.99
Cubic Spline Fitting	58	32	78.07	2.20	80.98	16.77	281.38	88.71	10.29	99.00	68.66	80.98	88.80
Cubic Spline4 D. Pts.	61	29	79.88	1.90	81.56	14.85	220.45	71.21	27.79	99.00	74.87	81.56	89.00
Sub. Subs. Mean	66	24	79.09	1.73	78.00	14.09	198.39	71.96	27.04	99.00	76.02	78.00	89.00
Sub. Subs. Med.	68	22	78.50	1.71	77.98	14.06	197.74	72.83	26.17	99.00	74.99	77.98	88.99
Sub. Subs. Max.	68	22	77.83	1.90	78.00	15.69	246.09	94.57	4.43	99.00	73.67	78.00	88.99
Sub. Subs. Min.	69	21	80.01	1.63	80.13	13.51	182.46	66.00	33.00	99.00	76.17	80.13	88.99
P2LinearTrendatPts	46	44	89.20	1.24	90.57	8.43	71.08	44.57	55.10	99.68	86.38	90.57	94.70
P2MovingAverage	44	46	84.50	1.96	89.00	13.02	169.60	66.00	33.00	99.00	78.00	89.00	92.00
P2CubicSplineFitting	59	31	81.85	1.90	85.53	14.58	212.60	73.13	26.17	99.30	75.78	85.53	90.11
P2CubicSpline4DPts	42	48	82.92	2.21	87.50	14.32	205.10	59.89	39.28	99.17	76.46	87.50	94.00
P2SubgSubsMean	31	59	60.06	2.15	61.30	11.99	143.85	59.43	21.40	80.83	54.98	61.30	66.79
P2SubgSubsMed	28	62	64.59	2.69	69.00	14.25	203.11	59.50	24.00	83.50	52.75	69.00	75.50
P2SubgSubsMax	35	55	81.29	2.30	85.00	13.59	184.62	75.00	24.00	99.00	78.00	85.00	89.00
P2SubgSubsMin	14	76	19.64	4.80	13.00	17.97	322.86	52.00	10.00	62.00	13.00	13.00	13.00

Table A22. General Statistics of Predicted Distress Scores for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	7554	0	71.17	.24	77.99	21.28	453.03	99.97	.03	100.00	53.99	77.99	88.96
Mean Nearby Points	5877	1677	73.05	.27	78.34	20.64	426.08	98.15	.85	99.00	54.75	78.34	88.99
Med. Nearby Pts.	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Interpolation	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Trend Pts.	5625	1929	72.67	.28	78.00	20.64	425.89	96.06	2.94	99.00	53.99	78.00	88.99
Moving Average	6327	1227	72.47	.26	78.00	21.02	441.98	98.15	.85	99.00	54.00	78.00	88.99
Cubic Spline Fitting	6054	1500	72.29	.27	78.00	20.71	428.98	91.83	7.17	99.00	53.99	78.00	88.98
Cubic Spline4 D. Pts.	5988	1566	72.75	.27	77.99	20.83	433.75	98.15	.85	99.00	54.12	77.99	88.98
Sub. Subs. Mean	6196	1358	72.15	.27	77.99	21.11	445.52	98.15	.85	99.00	54.00	77.99	88.99
Sub. Subs. Med.	6226	1328	71.31	.28	77.99	21.72	471.78	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Max.	6451	1103	71.43	.27	77.99	21.44	459.84	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Min.	6121	1433	72.83	.27	78.00	21.02	441.82	98.15	.85	99.00	55.12	78.00	88.99
P2LinearTrendatPts	3936	3618	85.86	.25	90.93	15.45	238.63	90.98	8.77	99.76	83.32	90.93	94.43
P2MovingAverage	4351	3203	77.37	.30	87.00	19.75	390.21	85.00	14.00	99.00	59.00	87.00	92.00
P2CubicSplineFitting	5187	2367	77.32	.27	84.72	19.30	372.47	89.31	10.02	99.33	68.72	84.72	90.96
P2CubicSpline4DPts	3679	3875	73.32	.41	83.00	24.80	615.05	99.00	1.00	100.00	57.81	83.00	93.33
P2SubgSubsMean	3616	3938	53.48	.23	55.12	14.01	196.27	81.00	8.00	89.00	40.57	55.12	64.05
P2SubgSubsMed	3661	3893	57.08	.26	58.00	15.92	253.49	81.00	8.00	89.00	43.00	58.00	69.00
P2SubgSubsMax	4513	3041	73.10	.30	78.00	20.32	412.98	91.00	8.00	99.00	56.00	78.00	89.00
P2SubgSubsMin	2106	5448	23.64	.33	20.00	15.15	229.43	85.00	4.00	89.00	13.00	20.00	28.00

Table A23. General Statistics of Predicted Distress Scores According to Very Good (90-100) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	5611	0	75.47	.26	82.94	19.67	386.91	99.97	.03	100.00	62.00	82.94	89.00
Mean Nearby Points	4501	1110	77.34	.28	86.09	19.12	365.54	98.15	.85	99.00	66.08	86.09	91.00
Med. Nearby Pts.	4599	1012	76.66	.29	86.29	19.95	397.88	98.15	.85	99.00	64.95	86.29	91.00
Linear Interpolation	4599	1012	76.66	.29	86.29	19.95	397.88	98.15	.85	99.00	64.95	86.29	91.00
Linear Trend Pts.	4281	1330	77.01	.29	85.18	19.19	368.14	96.06	2.94	99.00	66.20	85.18	90.70
Moving Average	4705	906	76.55	.29	85.42	19.77	390.95	98.15	.85	99.00	64.95	85.42	90.99
Cubic Spline Fitting	4629	982	76.44	.28	85.03	19.37	375.29	91.33	7.67	99.00	62.21	85.03	91.00
Cubic Spline4 D. Pts.	4600	1011	76.80	.29	86.51	19.60	384.06	98.15	.85	99.00	65.73	86.51	90.95
Sub. Subs. Mean	4695	916	76.13	.29	85.13	20.08	403.24	98.15	.85	99.00	64.21	85.13	91.00
Sub. Subs. Med.	4694	917	75.61	.30	84.93	20.34	413.64	98.15	.85	99.00	64.20	84.93	91.00
Sub. Subs. Max.	4795	816	75.73	.29	84.23	20.10	404.10	98.15	.85	99.00	64.21	84.23	90.97
Sub. Subs. Min.	4602	1009	76.90	.29	86.62	19.69	387.63	98.15	.85	99.00	66.57	86.62	91.00
P2LinearTrendatPts	3113	2498	89.70	.20	91.81	11.01	121.32	87.40	12.36	99.76	87.94	91.81	97.03
P2MovingAverage	3261	2350	83.21	.29	90.00	16.63	276.59	79.00	20.00	99.00	78.00	90.00	92.00
P2CubicSplineFitting	3905	1706	82.83	.25	87.79	15.74	247.68	86.77	12.56	99.33	76.44	87.79	91.85
P2CubicSpline4DPts	2863	2748	76.49	.43	86.67	23.12	534.55	96.50	3.50	100.00	67.00	86.67	94.00
P2SubgSubsMean	2654	2957	57.42	.23	61.14	12.02	144.52	80.00	9.00	89.00	53.29	61.14	65.62
P2SubgSubsMed	2731	2880	61.54	.27	68.00	13.91	193.40	80.00	9.00	89.00	52.50	68.00	72.00
P2SubgSubsMax	3321	2290	78.24	.31	86.00	17.99	323.77	83.00	16.00	99.00	73.00	86.00	89.00
P2SubgSubsMin	1457	4154	22.56	.44	14.00	16.86	284.29	85.00	4.00	89.00	13.00	14.00	28.00

Table A24. General Statistics of Predicted Distress Scores According to Good (80-89) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	6	0	64.47	9.58	68.06	23.47	550.61	52.99	35.97	88.96	37.67	68.06	87.90
Mean Nearby Points	3	3	75.69	7.93	76.49	13.73	188.62	27.43	61.57	89.00	61.57	76.49	.
Med. Nearby Pts.	4	2	78.95	6.50	82.55	12.99	168.82	27.28	61.72	89.00	65.32	82.55	88.99
Linear Interpolation	4	2	78.95	6.50	82.55	12.99	168.82	27.28	61.72	89.00	65.32	82.55	88.99
Linear Trend Pts.	4	2	65.83	11.21	68.75	22.41	502.36	52.17	36.83	89.00	42.94	68.75	85.81
Moving Average	3	3	75.62	7.89	76.18	13.66	186.69	27.31	61.69	89.00	61.69	76.18	.
Cubic Spline Fitting	3	3	75.27	8.01	75.54	13.87	192.38	27.74	61.26	89.00	61.26	75.54	.
Cubic Spline4 D. Pts.	4	2	78.70	6.68	82.46	13.36	178.38	28.10	60.90	89.00	64.67	82.46	88.98
Sub. Subs. Mean	4	2	78.81	6.69	82.71	13.38	178.94	28.19	60.81	89.00	64.72	82.71	89.00
Sub. Subs. Med.	4	2	79.00	6.61	82.97	13.23	175.00	27.93	61.07	89.00	65.04	82.97	88.99
Sub. Subs. Max.	4	2	79.61	6.28	83.50	12.56	157.66	26.54	62.46	89.00	66.35	83.50	89.00
Sub. Subs. Min.	3	3	75.36	8.10	76.09	14.03	196.80	28.03	60.97	89.00	60.97	76.09	.
P2LinearTrendatPts	3	3	75.24	7.57	75.82	13.12	172.13	26.22	61.85	88.07	61.85	75.82	.
P2MovingAverage	3	3	77.33	6.94	78.00	12.01	144.33	24.00	65.00	89.00	65.00	78.00	.
P2CubicSplineFitting	3	3	77.43	7.35	78.72	12.73	162.14	25.37	64.09	89.46	64.09	78.72	.
P2CubicSpline4DPts	3	3	76.63	7.24	77.28	12.54	157.26	25.06	63.78	88.83	63.78	77.28	.
P2SubgSubsMean	4	2	56.57	7.46	57.65	14.92	222.51	31.00	40.00	71.00	42.02	57.65	70.05
P2SubgSubsMed	4	2	60.00	8.60	61.00	17.20	296.00	38.00	40.00	78.00	43.00	61.00	76.00
P2SubgSubsMax	3	3	77.33	6.94	78.00	12.01	144.33	24.00	65.00	89.00	65.00	78.00	.
P2SubgSubsMin	1	5	32.00		32.00			.00	32.00	32.00	32.00	32.00	32.00

Table A25. General Statistics of Predicted Distress Scores According to Fair (70-79) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1	0	53.35		53.35			.00	53.35	53.35	53.35	53.35	53.35
Mean Nearby Points	1	0	53.41		53.41			.00	53.41	53.41	53.41	53.41	53.41
Med. Nearby Pts.	1	0	53.73		53.73			.00	53.73	53.73	53.73	53.73	53.73
Linear Interpolation	1	0	53.73		53.73			.00	53.73	53.73	53.73	53.73	53.73
Linear Trend Pts.	1	0	52.91		52.91			.00	52.91	52.91	52.91	52.91	52.91
Moving Average	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
Cubic Spline Fitting	1	0	52.81		52.81			.00	52.81	52.81	52.81	52.81	52.81
Cubic Spline4 D. Pts.	1	0	54.73		54.73			.00	54.73	54.73	54.73	54.73	54.73
Sub. Subs. Mean	1	0	53.93		53.93			.00	53.93	53.93	53.93	53.93	53.93
Sub. Subs. Med.	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
Sub. Subs. Max.	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
Sub. Subs. Min.	1	0	55.21		55.21			.00	55.21	55.21	55.21	55.21	55.21
P2LinearTrendatPts	1	0	57.77		57.77			.00	57.77	57.77	57.77	57.77	57.77
P2MovingAverage	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
P2CubicSplineFitting	1	0	52.78		52.78			.00	52.78	52.78	52.78	52.78	52.78
P2CubicSpline4DPts	1	0	57.81		57.81			.00	57.81	57.81	57.81	57.81	57.81
P2SubgSubsMean	1	0	38.40		38.40			.00	38.40	38.40	38.40	38.40	38.40
P2SubgSubsMed	1	0	40.00		40.00			.00	40.00	40.00	40.00	40.00	40.00
P2SubgSubsMax	1	0	45.00		45.00			.00	45.00	45.00	45.00	45.00	45.00
P2SubgSubsMin	1	0	32.00		32.00			.00	32.00	32.00	32.00	32.00	32.00

Table A26. General Statistics of Predicted Distress Scores According to Poor (60-69) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	2	0	69.85	4.86	69.85	6.87	47.26	9.72	64.99	74.71	64.99	69.85	.
Mean Nearby Points	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Med. Nearby Pts.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Linear Interpolation	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Linear Trend Pts.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Moving Average	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Cubic Spline Fitting	2	0	64.41	.59	64.41	.83	.70	1.18	63.82	65.00	63.82	64.41	.
Cubic Spline4 D. Pts.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Mean	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Med.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Max.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Min.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
P2LinearTrendatPts	1	1	57.52		57.52			.00	57.52	57.52	57.52	57.52	57.52
P2MovingAverage	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
P2CubicSplineFitting	1	1	65.92		65.92			.00	65.92	65.92	65.92	65.92	65.92
P2CubicSpline4DPts	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
P2SubgSubsMean	0	2											
P2SubgSubsMed	0	2											
P2SubgSubsMax	1	1	50.00		50.00			.00	50.00	50.00	50.00	50.00	50.00
P2SubgSubsMin	0	2											

Table A27. General Statistics of Predicted Distress Scores According to Very Poor (1-59) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	38	0	29.68	1.19	31.33	7.33	53.70	42.78	7.22	50.00	26.46	31.33	34.38
Mean Nearby Points	29	9	23.79	.94	27.00	5.06	25.60	20.95	6.05	27.00	19.00	27.00	27.00
Med. Nearby Pts.	29	9	23.87	.89	27.00	4.80	23.08	18.83	8.17	27.00	19.00	27.00	27.00
Linear Interpolation	29	9	23.87	.89	27.00	4.80	23.08	18.83	8.17	27.00	19.00	27.00	27.00
Linear Trend Pts.	29	9	23.85	.91	27.00	4.88	23.80	19.47	7.53	27.00	19.00	27.00	27.00
Moving Average	35	3	24.50	.98	27.00	5.78	33.43	31.00	19.00	50.00	19.00	27.00	27.00
Cubic Spline Fitting	29	9	23.83	.91	27.00	4.92	24.23	19.83	7.17	27.00	19.00	27.00	27.00
Cubic Spline4 D. Pts.	29	9	24.27	.71	27.00	3.83	14.70	8.00	19.00	27.00	19.00	27.00	27.00
Sub. Subs. Mean	31	7	23.64	.84	27.00	4.66	21.69	18.03	8.97	27.00	19.00	27.00	27.00
Sub. Subs. Med.	32	6	23.87	.68	27.00	3.85	14.85	8.00	19.00	27.00	19.00	27.00	27.00
Sub. Subs. Max.	30	8	24.13	.70	27.00	3.84	14.76	8.00	19.00	27.00	19.00	27.00	27.00
Sub. Subs. Min.	31	7	24.00	.69	27.00	3.85	14.81	8.00	19.00	27.00	19.00	27.00	27.00
P2LinearTrendatPts	28	10	17.79	.54	19.17	2.87	8.25	8.57	12.80	21.37	14.74	19.17	20.15
P2MovingAverage	28	10	24.43	.72	27.00	3.80	14.48	8.00	19.00	27.00	19.00	27.00	27.00
P2CubicSplineFitting	30	8	25.34	.80	27.40	4.40	19.38	17.73	12.28	30.01	21.05	27.40	28.69
P2CubicSpline4DPts	28	10	11.20	1.32	10.48	6.98	48.70	22.00	1.00	23.00	7.00	10.48	15.26
P2SubgSubsMean	29	9	16.37	.56	18.40	2.99	8.95	10.40	8.00	18.40	13.00	18.40	18.40
P2SubgSubsMed	29	9	18.72	.87	22.00	4.68	21.92	14.00	8.00	22.00	13.00	22.00	22.00
P2SubgSubsMax	29	9	20.69	1.14	25.00	6.11	37.36	17.00	8.00	25.00	13.00	25.00	25.00
P2SubgSubsMin	29	9	8.90	.52	7.00	2.81	7.88	6.00	7.00	13.00	7.00	7.00	13.00

Table A28. General Statistics of Predicted Distress Scores According Age (1993-2010) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	7554	0	71.17	.24	77.99	21.28	453.03	99.97	.03	100.00	53.99	77.99	88.96
Mean Nearby Points	5877	1677	73.05	.27	78.34	20.64	426.08	98.15	.85	99.00	54.75	78.34	88.99
Med. Nearby Pts.	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Interpolation	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Trend Pts.	5625	1929	72.67	.28	78.00	20.64	425.89	96.06	2.94	99.00	53.99	78.00	88.99
Moving Average	6327	1227	72.47	.26	78.00	21.02	441.98	98.15	.85	99.00	54.00	78.00	88.99
Cubic Spline Fitting	6054	1500	72.29	.27	78.00	20.71	428.98	91.83	7.17	99.00	53.99	78.00	88.98
Cubic Spline4 D. Pts.	5988	1566	72.75	.27	77.99	20.83	433.75	98.15	.85	99.00	54.12	77.99	88.98
Sub. Subs. Mean	6196	1358	72.15	.27	77.99	21.11	445.52	98.15	.85	99.00	54.00	77.99	88.99
Sub. Subs. Med.	6226	1328	71.31	.28	77.99	21.72	471.78	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Max.	6451	1103	71.43	.27	77.99	21.44	459.84	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Min.	6121	1433	72.83	.27	78.00	21.02	441.82	98.15	.85	99.00	55.12	78.00	88.99
P2LinearTrendatPts	3936	3618	85.86	.25	90.93	15.45	238.63	90.98	8.77	99.76	83.32	90.93	94.43
P2MovingAverage	4351	3203	77.37	.30	87.00	19.75	390.21	85.00	14.00	99.00	59.00	87.00	92.00
P2CubicSplineFitting	5187	2367	77.32	.27	84.72	19.30	372.47	89.31	10.02	99.33	68.72	84.72	90.96
P2CubicSpline4DPts	3679	3875	73.32	.41	83.00	24.80	615.05	99.00	1.00	100.00	57.81	83.00	93.33
P2SubgSubsMean	3616	3938	53.48	.23	55.12	14.01	196.27	81.00	8.00	89.00	40.57	55.12	64.05
P2SubgSubsMed	3661	3893	57.08	.26	58.00	15.92	253.49	81.00	8.00	89.00	43.00	58.00	69.00
P2SubgSubsMax	4513	3041	73.10	.30	78.00	20.32	412.98	91.00	8.00	99.00	56.00	78.00	89.00
P2SubgSubsMin	2106	5448	23.64	.33	20.00	15.15	229.43	85.00	4.00	89.00	13.00	20.00	28.00

Figure A29. General Statistics of Predicted Distress Scores According to Early Age (1993-1998) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	182	0	64.43	1.99	69.94	26.85	721.12	90.54	8.35	98.89	41.98	69.94	89.00
Mean Nearby Points	162	20	66.71	2.03	70.97	25.89	670.25	89.46	9.43	98.89	45.64	70.97	90.66
Med. Nearby Pts.	166	16	65.73	2.06	69.94	26.52	703.36	87.94	10.95	98.89	45.32	69.94	90.66
Linear Interpolation	166	16	65.73	2.06	69.94	26.52	703.36	87.94	10.95	98.89	45.32	69.94	90.66
Linear Trend Pts.	158	24	66.86	2.03	69.94	25.53	651.59	89.07	9.82	98.89	45.41	69.94	90.66
Moving Average	164	18	66.43	2.03	70.30	25.96	673.80	80.79	18.10	98.89	48.05	70.30	90.66
Cubic Spline Fitting	166	16	65.36	2.05	69.74	26.46	700.27	90.45	8.44	98.89	43.59	69.74	90.66
Cubic Spline4 D. Pts.	164	18	66.72	2.01	72.00	25.79	665.29	86.24	12.65	98.89	48.69	72.00	90.66
Sub. Subs. Mean	166	16	65.70	2.06	69.94	26.50	702.18	90.23	8.66	98.89	45.32	69.94	90.66
Sub. Subs. Med.	165	17	66.04	2.04	69.94	26.25	688.93	90.09	8.80	98.89	46.63	69.94	90.66
Sub. Subs. Max.	165	17	66.06	2.04	69.94	26.21	686.75	87.17	11.72	98.89	46.63	69.94	90.66
Sub. Subs. Min.	167	15	65.64	2.05	69.94	26.46	700.05	89.89	9.00	98.89	45.43	69.94	90.66
P2LinearTrendatPts	93	89	79.48	2.67	91.87	25.76	663.59	87.40	12.36	99.76	63.79	91.87	98.98
P2MovingAverage	117	65	72.22	2.26	82.00	24.43	596.76	79.00	20.00	99.00	50.00	82.00	92.00
P2CubicSplineFitting	131	51	72.16	2.20	84.40	25.12	631.19	86.75	12.56	99.31	50.95	84.40	91.06
P2CubicSpline4DPts	86	96	69.62	2.97	86.00	27.53	757.85	88.00	11.00	99.00	40.00	86.00	94.50
P2SubgSubsMean	87	95	49.88	2.02	55.12	18.82	354.26	68.59	9.00	77.59	35.00	55.12	66.20
P2SubgSubsMed	89	93	54.61	2.29	56.00	21.59	466.08	80.00	9.00	89.00	41.00	56.00	70.50
P2SubgSubsMax	115	67	68.58	2.25	73.00	24.13	582.26	83.00	16.00	99.00	47.00	73.00	89.00
P2SubgSubsMin	51	131	21.49	1.41	20.00	10.05	101.05	58.00	4.00	62.00	15.00	20.00	25.00

Table A30. General Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1372	0	72.14	.53	77.96	19.72	388.82	99.91	.09	100.00	53.99	77.96	88.93
Mean Nearby Points	1033	339	74.07	.62	80.05	20.07	402.99	98.15	.85	99.00	57.85	80.05	89.00
Med. Nearby Pts.	1064	308	73.27	.64	78.00	20.95	438.73	98.15	.85	99.00	56.83	78.00	89.00
Linear Interpolation	1064	308	73.27	.64	78.00	20.95	438.73	98.15	.85	99.00	56.83	78.00	89.00
Linear Trend Pts.	963	409	74.39	.64	80.94	19.97	398.73	91.03	7.97	99.00	57.68	80.94	89.59
Moving Average	1116	256	72.87	.63	77.99	20.93	438.02	98.15	.85	99.00	55.99	77.99	88.99
Cubic Spline Fitting	1084	288	73.45	.60	78.00	19.80	391.96	86.05	12.95	99.00	55.71	78.00	88.96
Cubic Spline4 D. Pts.	1091	281	73.94	.60	78.00	19.75	390.19	98.15	.85	99.00	57.17	78.00	88.97
Sub. Subs. Mean	1106	266	72.87	.63	77.99	20.81	433.14	98.15	.85	99.00	55.55	77.99	88.96
Sub. Subs. Med.	1121	251	72.42	.63	77.99	21.08	444.45	98.15	.85	99.00	53.99	77.99	88.96
Sub. Subs. Max.	1154	218	72.55	.61	77.99	20.70	428.49	98.15	.85	99.00	54.02	77.99	88.96
Sub. Subs. Min.	1082	290	73.24	.63	78.00	20.85	434.66	98.15	.85	99.00	56.90	78.00	88.99
P2LinearTrendatPts	788	584	85.16	.57	90.91	16.14	260.42	90.98	8.77	99.76	79.27	90.91	95.08
P2MovingAverage	796	576	79.76	.67	89.00	18.95	359.22	80.00	19.00	99.00	69.00	89.00	92.00
P2CubicSplineFitting	954	418	78.76	.61	84.94	18.83	354.52	79.69	19.64	99.33	70.87	84.94	91.57
P2CubicSpline4DPts	748	624	73.29	.86	80.50	23.49	551.63	99.00	1.00	100.00	62.00	80.50	92.00
P2SubgSubsMean	657	715	56.26	.52	60.40	13.40	179.64	76.00	13.00	89.00	48.46	60.40	65.55
P2SubgSubsMed	690	682	60.98	.57	68.00	15.10	228.08	76.00	13.00	89.00	48.00	68.00	73.00
P2SubgSubsMax	846	526	76.30	.67	83.00	19.35	374.42	86.00	13.00	99.00	69.00	83.00	90.00
P2SubgSubsMin	367	1005	25.69	1.00	20.00	19.15	366.60	84.00	5.00	89.00	13.00	20.00	32.00

Table A31. General Statistics of Predicted Distress Scores According to Late Age (2005-2010) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	28	0	74.73	3.69	78.78	19.51	380.71	87.16	12.09	99.25	61.79	78.78	88.44
Mean Nearby Points	20	8	78.72	3.71	78.67	16.60	275.71	73.91	25.09	99.00	75.14	78.67	88.96
Med. Nearby Pts.	21	7	78.82	3.37	82.41	15.46	239.04	66.27	32.73	99.00	73.78	82.41	89.00
Linear Interpolation	21	7	78.82	3.37	82.41	15.46	239.04	66.27	32.73	99.00	73.78	82.41	89.00
Linear Trend Pts.	20	8	78.23	3.95	78.00	17.66	311.89	79.76	19.24	99.00	75.36	78.00	88.30
Moving Average	27	1	77.30	3.15	77.99	16.38	268.43	66.00	33.00	99.00	72.99	77.99	88.99
Cubic Spline Fitting	21	7	76.07	3.93	78.00	18.00	324.01	78.67	20.33	99.00	69.92	78.00	88.18
Cubic Spline4 D. Pts.	23	5	78.60	3.35	82.94	16.08	258.58	66.56	32.44	99.00	76.88	82.94	88.98
Sub. Subs. Mean	23	5	76.88	3.53	78.48	16.94	287.04	77.93	21.07	99.00	65.57	78.48	88.75
Sub. Subs. Med.	23	5	77.35	3.51	78.85	16.82	282.75	78.83	20.17	99.00	67.45	78.85	88.94
Sub. Subs. Max.	24	4	76.00	3.80	78.42	18.64	347.44	93.60	5.40	99.00	69.25	78.42	86.52
Sub. Subs. Min.	23	5	79.58	2.97	82.40	14.26	203.41	66.00	33.00	99.00	72.04	82.40	88.99
P2LinearTrendatPts	20	8	86.47	2.34	86.46	10.45	109.18	48.93	50.66	99.59	84.76	86.46	92.28
P2MovingAverage	19	9	80.21	3.46	78.00	15.09	227.62	66.00	33.00	99.00	78.00	78.00	89.00
P2CubicSplineFitting	22	6	79.78	3.40	80.59	15.93	253.79	73.04	26.24	99.28	75.22	80.59	88.86
P2CubicSpline4DPts	19	9	74.06	4.31	76.78	18.80	353.39	69.22	27.80	97.02	53.56	76.78	88.39
P2SubgSubsMean	13	15	54.76	3.53	54.98	12.72	161.78	51.27	21.40	72.67	54.54	54.98	61.11
P2SubgSubsMed	9	19	57.56	5.75	53.50	17.25	297.40	54.00	24.00	78.00	48.25	53.50	72.25
P2SubgSubsMax	15	13	76.87	4.42	83.00	17.13	293.27	65.00	24.00	89.00	78.00	83.00	89.00
P2SubgSubsMin	3	25	12.33	.67	13.00	1.15	1.33	2.00	11.00	13.00	11.00	13.00	13.00

Appendix B

Paired Samples T-Test of Predicted Distress Scores:

Missing Data Points of CRCP 1993-2010

Table B1. Abbreviations Used for Paired Samples T-Test of Predicted Distress Scores.

Abbreviation	Explanation	Note
Obs.	Observation	
Valid	Valid Observation	
Not Valid	Not Valid Observation	
Mean	Mean	
Std. Err. Mean	Std. Error of Mean	
Med.	Median	
Std. Dev.	Std. Deviation	
Var.	Variance	
Range	Range	
Min.	Minimum	
Max.	Maximum	
%	Percentiles	
Missing Data Techniques Brief	**Missing Data Techniques Explanation**	**Predicting by**
Do Nothing	Do Nothing	**Pavement Performance Model**
Mean Nearby Points	Mean of Nearby Points Using	
Med. Nearby Pts.	Median of Nearby Points	
Linear Interpolation	Linear Interpolation	
Linear Trend Pts.	Linear Trend at Points	
Moving Average	Moving Average	
Cubic Spline Fitting	Cubic Spline Fitting	
Cubic Spline4 D. Pts.	Cubic Spline 4 Data Points	
Sub. Subs. Mean	Subgroup Substitutions Mean	
Sub. Subs. Med.	Subgroup Substitutions Median	
Sub. Subs. Max.	Subgroup Substitutions Maximum	
Sub. Subs. Min.	Subgroup Substitutions Minimum	
P2LinearTrendatPts.	Linear Trend at Points	**Missing Data Techniques**
P2MovingAverage	Moving Average Using	
P2CubicSplineFitting	Cubic Spline Fitting Using	
P2CubicSpline4DPts.	Cubic Spline 4 Data Points	
P2SubgSubsMean	Subgroup Substitutions	
P2SubgSubsMed.	Subgroup Substitutions	
P2SubgSubsMax.	Subgroup Substitutions Maximum	
P2SubgSubsMin.	Subgroup Substitutions Minimum	

Table B2. Paired Samples T-Tests Statistics of Predicted Distress Scores for One year Missing Data point Case (1).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	69.76	1116	22.76	.68
	Mean Nearby Points	69.57	1116	23.17	.69
2	**Do Nothing**	69.84	1124	22.71	.68
	Med. Nearby Pts.	69.47	1124	23.17	.69
3	**Do Nothing**	69.84	1124	22.71	.68
	Linear Interpolation	69.47	1124	23.17	.69
4	**Do Nothing**	69.90	1086	22.67	.69
	Linear Trend Pts.	69.86	1086	23.09	.70
5	**Do Nothing**	69.79	1143	22.72	.67
	Moving Average	69.58	1143	23.06	.68
6	**Do Nothing**	69.75	1122	22.63	.68
	Cubic Spline Fitting	69.42	1122	23.08	.69
7	**Do Nothing**	69.90	1122	22.64	.68
	Cubic Spline4 D. Pts.	69.60	1122	23.10	.69
8	**Do Nothing**	69.80	1134	22.66	.67
	Sub. Subs. Mean	69.40	1134	23.10	.69
9	**Do Nothing**	69.85	1133	22.66	.67
	Sub. Subs. Med.	69.46	1133	23.09	.69
10	**Do Nothing**	69.68	1142	22.82	.68
	Sub. Subs. Max.	69.23	1142	23.25	.69
11	**Do Nothing**	69.93	1136	22.68	.67
	Sub. Subs. Min.	69.67	1136	23.02	.68
12	**Do Nothing**	75.93	652	21.13	.83
	P2LinearTrendatPts.	82.45	652	20.75	.81
13	**Do Nothing**	69.95	1146	22.60	.67
	P2MovingAverage	72.83	1146	22.37	.66
14	**Do Nothing**	72.10	883	21.52	.72
	P2CubicSplineFitting	74.87	883	21.94	.74
15	**Do Nothing**	72.81	681	23.24	.89
	P2CubicSpline4DPts.	69.05	681	26.97	1.03
16	**Do Nothing**	66.16	566	26.22	1.10
	P2SubgSubsMean	51.14	566	18.62	.78
17	**Do Nothing**	67.29	632	26.01	1.03
	P2SubgSubsMed.	55.12	632	20.50	.82
18	**Do Nothing**	70.63	1032	22.66	.71
	P2SubgSubsMax.	71.49	1032	22.73	.71
19	**Do Nothing**	61.02	373	28.40	1.47
	P2SubgSubsMin.	25.19	373	18.68	.97

Table B3. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Very Good (90-100) One Year Missing Data point Case (1).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	72.76	935	21.70	.71
	Mean Nearby Points	72.77	935	21.95	.72
2	**Do Nothing**	72.82	942	21.65	.71
	Med. Nearby Pts.	72.63	942	21.98	.72
3	**Do Nothing**	72.82	942	21.65	.71
	Linear Interpolation	72.63	942	21.98	.72
4	**Do Nothing**	72.99	910	21.53	.71
	Linear Trend Pts.	73.15	910	21.80	.72
5	**Do Nothing**	72.76	960	21.61	.70
	Moving Average	72.64	960	21.88	.71
6	**Do Nothing**	72.84	940	21.50	.70
	Cubic Spline Fitting	72.74	940	21.75	.71
7	**Do Nothing**	72.82	944	21.66	.70
	Cubic Spline4 D. Pts.	72.71	944	21.93	.71
8	**Do Nothing**	72.75	953	21.62	.70
	Sub. Subs. Mean	72.54	953	21.88	.71
9	**Do Nothing**	72.71	956	21.69	.70
	Sub. Subs. Med.	72.51	956	21.94	.71
10	**Do Nothing**	72.73	957	21.68	.70
	Sub. Subs. Max.	72.52	957	21.89	.71
11	**Do Nothing**	72.95	952	21.55	.70
	Sub. Subs. Min.	72.80	952	21.81	.71
12	**Do Nothing**	79.06	560	19.27	.81
	P2LinearTrendatPts.	86.89	560	15.78	.67
13	**Do Nothing**	73.00	952	21.39	.69
	P2MovingAverage	76.40	952	20.60	.67
14	**Do Nothing**	75.42	737	20.06	.74
	P2CubicSplineFitting	78.94	737	19.60	.72
15	**Do Nothing**	75.56	595	21.95	.90
	P2CubicSpline4DPts.	71.99	595	25.05	1.03
16	**Do Nothing**	70.37	477	24.70	1.13
	P2SubgSubsMean	54.58	477	16.98	.78
17	**Do Nothing**	71.35	537	24.53	1.06
	P2SubgSubsMed.	58.78	537	18.90	.82
18	**Do Nothing**	73.72	864	21.33	.73
	P2SubgSubsMax.	75.10	864	20.71	.70
19	**Do Nothing**	66.10	303	27.61	1.59
	P2SubgSubsMin.	26.26	303	19.86	1.14

Table B4. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Good (80-89) One Year Missing Data Point Case (1).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	67.51	63	20.32	2.56
	Mean Nearby Points	67.24	63	19.92	2.51
2	Do Nothing	66.98	64	20.60	2.57
	Med. Nearby Pts.	66.71	64	20.26	2.53
3	Do Nothing	66.98	64	20.60	2.57
	Linear Interpolation	66.71	64	20.26	2.53
4	Do Nothing	66.51	61	20.29	2.60
	Linear Trend Pts.	66.66	61	19.20	2.46
5	Do Nothing	67.57	61	20.53	2.63
	Moving Average	67.77	61	19.86	2.54
6	Do Nothing	66.20	63	20.62	2.60
	Cubic Spline Fitting	65.81	63	20.11	2.53
7	Do Nothing	66.38	64	20.50	2.56
	Cubic Spline4 D. Pts.	66.20	64	20.17	2.52
8	Do Nothing	67.42	60	19.76	2.55
	Sub. Subs. Mean	67.00	60	19.69	2.54
9	Do Nothing	67.38	59	19.93	2.59
	Sub. Subs. Med.	66.98	59	19.86	2.59
10	Do Nothing	67.44	62	20.57	2.61
	Sub. Subs. Max.	66.56	62	20.45	2.60
11	Do Nothing	67.64	63	20.49	2.58
	Sub. Subs. Min.	67.76	63	19.82	2.50
12	Do Nothing	72.34	30	15.78	2.88
	P2LinearTrendatPts.	73.87	30	16.82	3.07
13	Do Nothing	69.57	65	19.33	2.40
	P2MovingAverage	71.37	65	16.70	2.07
14	Do Nothing	70.43	50	14.89	2.11
	P2CubicSplineFitting	70.84	50	14.56	2.06
15	Do Nothing	66.44	30	23.79	4.34
	P2CubicSpline4DPts.	67.38	30	26.62	4.86
16	Do Nothing	58.00	21	28.15	6.14
	P2SubgSubsMean	44.99	21	17.61	3.84
17	Do Nothing	56.98	22	27.88	5.94
	P2SubgSubsMed.	45.14	22	18.49	3.94
18	Do Nothing	69.02	57	20.03	2.65
	P2SubgSubsMax.	69.37	57	18.78	2.49
19	Do Nothing	47.27	12	30.97	8.94
	P2SubgSubsMin.	25.67	12	16.05	4.63

Table B5. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Fair (70-79) One Year Missing Data Point Case (1).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	60.31	48	15.84	2.29
	Mean Nearby Points	59.84	48	15.37	2.22
2	Do Nothing	60.44	50	15.80	2.23
	Med. Nearby Pts.	59.69	50	15.57	2.20
3	Do Nothing	60.44	50	15.80	2.23
	Linear Interpolation	59.69	50	15.57	2.20
4	Do Nothing	60.37	48	15.88	2.29
	Linear Trend Pts.	59.89	48	15.30	2.21
5	Do Nothing	61.27	53	15.72	2.16
	Moving Average	61.30	53	15.05	2.07
6	Do Nothing	59.47	51	16.32	2.29
	Cubic Spline Fitting	58.30	51	16.67	2.33
7	Do Nothing	59.33	50	16.49	2.33
	Cubic Spline4 D. Pts.	58.28	50	16.75	2.37
8	Do Nothing	60.90	52	15.66	2.17
	Sub. Subs. Mean	59.89	52	15.77	2.19
9	Do Nothing	60.52	50	15.84	2.24
	Sub. Subs. Med.	59.58	50	15.78	2.23
10	Do Nothing	60.76	51	15.78	2.21
	Sub. Subs. Max.	59.65	51	15.76	2.21
11	Do Nothing	61.00	52	15.75	2.18
	Sub. Subs. Min.	60.91	52	15.09	2.09
12	Do Nothing	63.68	28	14.90	2.81
	P2LinearTrendatPts.	65.64	28	18.05	3.41
13	Do Nothing	61.66	56	15.74	2.10
	P2MovingAverage	62.46	56	15.04	2.01
14	Do Nothing	60.28	43	15.86	2.42
	P2CubicSplineFitting	59.79	43	15.56	2.37
15	Do Nothing	60.69	25	15.13	3.03
	P2CubicSpline4DPts.	56.17	25	26.80	5.36
16	Do Nothing	54.65	24	16.54	3.38
	P2SubgSubsMean	39.70	24	11.81	2.41
17	Do Nothing	55.32	26	16.14	3.16
	P2SubgSubsMed.	41.71	26	13.22	2.59
18	Do Nothing	61.62	50	16.54	2.34
	P2SubgSubsMax.	60.34	50	17.61	2.49
19	Do Nothing	52.32	17	15.85	3.84
	P2SubgSubsMin.	22.29	17	9.12	2.21

Table B6. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Poor (60-69) One Year Missing Data Point Case (1).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	47.55	24	17.62	3.60
	Mean Nearby Points	46.06	24	16.60	3.39
2	Do Nothing	47.55	24	17.62	3.60
	Med. Nearby Pts.	46.02	24	16.70	3.41
3	Do Nothing	47.55	24	17.62	3.60
	Linear Interpolation	46.02	24	16.70	3.41
4	Do Nothing	47.55	24	17.62	3.60
	Linear Trend Pts.	46.12	24	16.59	3.39
5	Do Nothing	45.92	22	17.47	3.73
	Moving Average	45.11	22	16.14	3.44
6	Do Nothing	47.55	24	17.62	3.60
	Cubic Spline Fitting	45.92	24	16.72	3.41
7	Do Nothing	47.55	24	17.62	3.60
	Cubic Spline4 D. Pts.	46.03	24	16.85	3.44
8	Do Nothing	46.87	25	18.24	3.65
	Sub. Subs. Mean	45.34	25	17.41	3.48
9	Do Nothing	46.87	25	18.24	3.65
	Sub. Subs. Med.	45.38	25	17.49	3.50
10	Do Nothing	45.19	25	18.72	3.74
	Sub. Subs. Max.	43.53	25	18.13	3.63
11	Do Nothing	45.79	23	17.08	3.56
	Sub. Subs. Min.	44.57	23	15.88	3.31
12	Do Nothing	47.59	12	20.59	5.94
	P2LinearTrendatPts.	44.28	12	19.60	5.66
13	Do Nothing	46.10	24	19.40	3.96
	P2MovingAverage	46.08	24	17.71	3.62
14	Do Nothing	46.32	18	17.14	4.04
	P2CubicSplineFitting	45.01	18	14.87	3.51
15	Do Nothing	53.09	6	20.90	8.53
	P2CubicSpline4DPts.	48.78	6	22.86	9.33
16	Do Nothing	38.03	8	19.06	6.74
	P2SubgSubsMean	32.41	8	16.32	5.77
17	Do Nothing	41.87	10	18.66	5.90
	P2SubgSubsMed.	36.05	10	15.47	4.89
18	Do Nothing	45.41	20	16.57	3.71
	P2SubgSubsMax.	41.70	20	12.88	2.88
19	Do Nothing	39.56	7	20.05	7.58
	P2SubgSubsMin.	26.29	7	17.17	6.49

Table B7. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Very Poor (1-59) One Year Missing Data Point Case (1).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	33.19	47	12.36	1.80
	Mean Nearby Points	30.02	47	13.03	1.90
2	**Do Nothing**	32.76	45	12.04	1.79
	Med. Nearby Pts.	29.61	45	12.70	1.89
3	**Do Nothing**	32.76	45	12.04	1.79
	Linear Interpolation	29.61	45	12.70	1.89
4	**Do Nothing**	32.35	44	12.30	1.85
	Linear Trend Pts.	28.88	44	12.54	1.89
5	**Do Nothing**	32.58	48	12.44	1.80
	Moving Average	29.89	48	13.05	1.88
6	**Do Nothing**	32.66	45	11.81	1.76
	Cubic Spline Fitting	29.23	45	12.38	1.85
7	**Do Nothing**	33.23	41	11.73	1.83
	Cubic Spline4 D. Pts.	29.80	41	12.61	1.97
8	**Do Nothing**	32.60	45	12.27	1.83
	Sub. Subs. Mean	29.36	45	12.86	1.92
9	**Do Nothing**	33.61	44	12.42	1.87
	Sub. Subs. Med.	30.27	44	13.31	2.01
10	**Do Nothing**	33.10	48	12.59	1.82
	Sub. Subs. Max.	29.67	48	13.24	1.91
11	**Do Nothing**	32.71	47	12.26	1.79
	Sub. Subs. Min.	29.90	47	12.78	1.86
12	**Do Nothing**	31.94	23	11.79	2.46
	P2LinearTrendatPts.	22.75	23	13.38	2.79
13	**Do Nothing**	32.19	50	12.56	1.78
	P2MovingAverage	30.18	50	12.78	1.81
14	**Do Nothing**	32.28	36	11.59	1.93
	P2CubicSplineFitting	28.58	36	11.18	1.86
15	**Do Nothing**	31.88	25	11.75	2.35
	P2CubicSpline4DPts.	18.73	25	16.13	3.23
16	**Do Nothing**	29.00	37	10.83	1.78
	P2SubgSubsMean	20.67	37	7.58	1.25
17	**Do Nothing**	29.74	38	11.60	1.88
	P2SubgSubsMed.	22.32	38	9.25	1.50
18	**Do Nothing**	31.00	42	12.09	1.87
	P2SubgSubsMax.	26.07	42	11.63	1.79
19	**Do Nothing**	29.37	35	10.98	1.86
	P2SubgSubsMin.	16.57	35	7.42	1.25

Table B8. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Age (1993-2010) for One Year Missing Data Point Case (1).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	69.76	1116	22.76	.68
	Mean Nearby Points	69.57	1116	23.17	.69
2	**Do Nothing**	69.84	1124	22.71	.68
	Med. Nearby Pts.	69.47	1124	23.17	.69
3	**Do Nothing**	69.84	1124	22.71	.68
	Linear Interpolation	69.47	1124	23.17	.69
4	**Do Nothing**	69.90	1086	22.67	.69
	Linear Trend Pts.	69.86	1086	23.09	.70
5	**Do Nothing**	69.79	1143	22.72	.67
	Moving Average	69.58	1143	23.06	.68
6	**Do Nothing**	69.75	1122	22.63	.68
	Cubic Spline Fitting	69.42	1122	23.08	.69
7	**Do Nothing**	69.90	1122	22.64	.68
	Cubic Spline4 D. Pts.	69.60	1122	23.10	.69
8	**Do Nothing**	69.80	1134	22.66	.67
	Sub. Subs. Mean	69.40	1134	23.10	.69
9	**Do Nothing**	69.85	1133	22.66	.67
	Sub. Subs. Med.	69.46	1133	23.09	.69
10	**Do Nothing**	69.68	1142	22.82	.68
	Sub. Subs. Max.	69.23	1142	23.25	.69
11	**Do Nothing**	69.93	1136	22.68	.67
	Sub. Subs. Min.	69.67	1136	23.02	.68
12	**Do Nothing**	75.93	652	21.13	.83
	P2LinearTrendatPts.	82.45	652	20.75	.81
13	**Do Nothing**	69.95	1146	22.60	.67
	P2MovingAverage	72.83	1146	22.37	.66
14	**Do Nothing**	72.10	883	21.52	.72
	P2CubicSplineFitting	74.87	883	21.94	.74
15	**Do Nothing**	72.81	681	23.24	.89
	P2CubicSpline4DPts.	69.05	681	26.97	1.03
16	**Do Nothing**	66.16	566	26.22	1.10
	P2SubgSubsMean	51.14	566	18.62	.78
17	**Do Nothing**	67.29	632	26.01	1.03
	P2SubgSubsMed.	55.12	632	20.50	.82
18	**Do Nothing**	70.63	1032	22.66	.71
	P2SubgSubsMax.	71.49	1032	22.73	.71
19	**Do Nothing**	61.02	373	28.40	1.47
	P2SubgSubsMin.	25.19	373	18.68	.97

Table B9. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Early Age (1993-1998) for One Year Missing Data Point Case (1).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	66.45	393	24.70	1.25
	Mean Nearby Points	66.35	393	24.91	1.26
2	**Do Nothing**	66.43	392	24.72	1.25
	Med. Nearby Pts.	66.33	392	24.95	1.26
3	**Do Nothing**	66.43	392	24.72	1.25
	Linear Interpolation	66.33	392	24.95	1.26
4	**Do Nothing**	66.87	383	24.35	1.24
	Linear Trend Pts.	66.64	383	24.64	1.26
5	**Do Nothing**	66.36	390	24.76	1.25
	Moving Average	66.28	390	24.98	1.26
6	**Do Nothing**	66.66	392	24.46	1.24
	Cubic Spline Fitting	66.59	392	24.67	1.25
7	**Do Nothing**	66.58	392	24.62	1.24
	Cubic Spline4 D. Pts.	66.50	392	24.83	1.25
8	**Do Nothing**	66.52	391	24.62	1.25
	Sub. Subs. Mean	66.42	391	24.83	1.26
9	**Do Nothing**	66.51	389	24.68	1.25
	Sub. Subs. Med.	66.42	389	24.91	1.26
10	**Do Nothing**	66.53	389	24.68	1.25
	Sub. Subs. Max.	66.44	389	24.91	1.26
11	**Do Nothing**	66.48	389	24.68	1.25
	Sub. Subs. Min.	66.38	389	24.90	1.26
12	**Do Nothing**	73.50	210	22.87	1.58
	P2LinearTrendatPts.	80.18	210	21.95	1.51
13	**Do Nothing**	66.59	383	24.29	1.24
	P2MovingAverage	69.28	383	24.24	1.24
14	**Do Nothing**	69.43	295	22.81	1.33
	P2CubicSplineFitting	71.88	295	23.52	1.37
15	**Do Nothing**	69.52	223	25.43	1.70
	P2CubicSpline4DPts.	64.88	223	28.67	1.92
16	**Do Nothing**	61.88	195	27.91	2.00
	P2SubgSubsMean	47.52	195	19.40	1.39
17	**Do Nothing**	63.47	217	27.96	1.90
	P2SubgSubsMed.	51.40	217	21.80	1.48
18	**Do Nothing**	67.44	352	24.25	1.29
	P2SubgSubsMax.	67.92	352	24.49	1.31
19	**Do Nothing**	56.59	144	29.73	2.48
	P2SubgSubsMin.	24.06	144	15.22	1.27

Table B10. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for One year Missing Data point Case (1).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	71.13	608	21.66	.88
	Mean Nearby Points	70.78	608	22.22	.90
2	**Do Nothing**	71.27	616	21.55	.87
	Med. Nearby Pts.	70.74	616	22.20	.89
3	**Do Nothing**	71.27	616	21.55	.87
	Linear Interpolation	70.74	616	22.20	.89
4	**Do Nothing**	71.14	591	21.76	.89
	Linear Trend Pts.	71.07	591	22.24	.91
5	**Do Nothing**	70.90	631	21.73	.87
	Moving Average	70.58	631	22.14	.88
6	**Do Nothing**	71.01	618	21.56	.87
	Cubic Spline Fitting	70.58	618	22.03	.89
7	**Do Nothing**	71.22	617	21.58	.87
	Cubic Spline4 D. Pts.	70.80	617	22.19	.89
8	**Do Nothing**	71.12	628	21.63	.86
	Sub. Subs. Mean	70.58	628	22.25	.89
9	**Do Nothing**	71.18	628	21.57	.86
	Sub. Subs. Med.	70.66	628	22.20	.89
10	**Do Nothing**	70.84	633	21.92	.87
	Sub. Subs. Max.	70.23	633	22.57	.90
11	**Do Nothing**	71.17	626	21.67	.87
	Sub. Subs. Min.	70.81	626	22.08	.88
12	**Do Nothing**	76.95	367	20.34	1.06
	P2LinearTrendatPts.	83.46	367	19.83	1.04
13	**Do Nothing**	70.87	635	21.96	.87
	P2MovingAverage	73.92	635	21.52	.85
14	**Do Nothing**	73.15	492	20.77	.94
	P2CubicSplineFitting	76.06	492	20.92	.94
15	**Do Nothing**	73.89	389	22.23	1.13
	P2CubicSpline4DPts.	69.87	389	26.29	1.33
16	**Do Nothing**	68.01	313	25.17	1.42
	P2SubgSubsMean	52.91	313	17.97	1.02
17	**Do Nothing**	69.02	354	24.83	1.32
	P2SubgSubsMed.	57.00	354	19.53	1.04
18	**Do Nothing**	71.74	567	21.84	.92
	P2SubgSubsMax.	72.82	567	21.65	.91
19	**Do Nothing**	63.33	196	27.40	1.96
	P2SubgSubsMin.	26.46	196	21.03	1.50

Table B11. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Late Age (2005-2010) for One Year Missing Data Point Case (1).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	73.82	115	20.14	1.88
	Mean Nearby Points	74.20	115	20.60	1.92
2	Do Nothing	73.73	116	20.19	1.87
	Med. Nearby Pts.	73.35	116	20.81	1.93
3	Do Nothing	73.73	116	20.19	1.87
	Linear Interpolation	73.35	116	20.81	1.93
4	Do Nothing	73.74	112	20.25	1.91
	Linear Trend Pts.	74.46	112	20.70	1.96
5	Do Nothing	74.96	122	19.23	1.74
	Moving Average	74.94	122	19.80	1.79
6	Do Nothing	73.57	112	20.65	1.95
	Cubic Spline Fitting	72.99	112	22.15	2.09
7	Do Nothing	74.23	113	19.65	1.85
	Cubic Spline4 D. Pts.	73.87	113	20.50	1.93
8	Do Nothing	73.77	115	19.82	1.85
	Sub. Subs. Mean	73.10	115	20.49	1.91
9	Do Nothing	73.85	116	19.94	1.85
	Sub. Subs. Med.	73.13	116	20.41	1.90
10	Do Nothing	73.76	120	19.99	1.83
	Sub. Subs. Max.	73.00	120	20.27	1.85
11	Do Nothing	74.61	121	19.49	1.77
	Sub. Subs. Min.	74.39	121	20.06	1.82
12	Do Nothing	77.75	75	19.46	2.25
	P2LinearTrendatPts.	83.86	75	21.40	2.47
13	Do Nothing	75.40	128	18.83	1.66
	P2MovingAverage	78.07	128	18.98	1.68
14	Do Nothing	74.95	96	20.61	2.10
	P2CubicSplineFitting	77.89	96	21.26	2.17
15	Do Nothing	77.38	69	20.15	2.43
	P2CubicSpline4DPts.	77.91	69	22.49	2.71
16	Do Nothing	73.35	55	21.71	2.93
	P2SubgSubsMean	-1.12	55	11.61	1.57
17	Do Nothing	70.81	61	24.30	3.11
	P2SubgSubsMed.	57.48	61	19.72	2.53
18	Do Nothing	74.99	113	20.35	1.91
	P2SubgSubsMax.	75.88	113	20.95	1.97
19	Do Nothing	66.63	33	26.37	4.59
	P2SubgSubsMin.	22.58	33	17.45	3.04

Table B12. Paired Samples T-Tests Statistics of Predicted Distress Scores for Two Years Missing Data Points Case (2).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	72.04	3236	21.29	.37
	Mean Nearby Points	72.22	3236	21.38	.38
2	**Do Nothing**	72.00	3315	21.25	.37
	Med. Nearby Pts.	71.88	3315	21.57	.37
3	**Do Nothing**	72.00	3315	21.25	.37
	Linear Interpolation	71.88	3315	21.57	.37
4	**Do Nothing**	71.99	3085	21.27	.38
	Linear Trend Pts.	72.11	3085	21.24	.38
5	**Do Nothing**	72.03	3385	21.29	.37
	Moving Average	72.12	3385	21.43	.37
6	**Do Nothing**	71.79	3298	21.21	.37
	Cubic Spline Fitting	71.73	3298	21.42	.37
7	**Do Nothing**	71.93	3310	21.28	.37
	Cubic Spline4 D. Pts.	71.93	3310	21.54	.37
8	**Do Nothing**	71.84	3383	21.31	.37
	Sub. Subs. Mean	71.65	3383	21.62	.37
9	**Do Nothing**	71.57	3399	21.48	.37
	Sub. Subs. Med.	71.42	3399	21.76	.37
10	**Do Nothing**	71.70	3442	21.38	.36
	Sub. Subs. Max.	71.45	3442	21.67	.37
11	**Do Nothing**	72.17	3349	21.29	.37
	Sub. Subs. Min.	72.21	3349	21.44	.37
12	**Do Nothing**	77.03	2124	19.99	.43
	P2LinearTrendatPts.	84.80	2124	17.02	.37
13	**Do Nothing**	73.37	2220	22.16	.47
	P2MovingAverage	77.51	2220	20.71	.44
14	**Do Nothing**	73.60	2853	20.26	.38
	P2CubicSplineFitting	76.89	2853	19.65	.37
15	**Do Nothing**	75.29	1895	21.98	.50
	P2CubicSpline4DPts.	72.92	1895	25.22	.58
16	**Do Nothing**	70.03	1698	22.92	.56
	P2SubgSubsMean	54.08	1698	15.32	.37
17	**Do Nothing**	71.19	1793	22.80	.54
	P2SubgSubsMed.	58.27	1793	17.09	.40
18	**Do Nothing**	71.40	2206	22.11	.47
	P2SubgSubsMax.	73.52	2206	21.50	.46
19	**Do Nothing**	66.21	1029	24.95	.78
	P2SubgSubsMin.	24.62	1029	17.40	.54

Table B13. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Very Good (90-100) Two Years Missing Data Points Case (2).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	75.40	2562	20.41	.40
	Mean Nearby Points	75.72	2562	20.32	.40
2	Do Nothing	75.35	2609	20.36	.40
	Med. Nearby Pts.	75.27	2609	20.67	.40
3	Do Nothing	75.35	2609	20.36	.40
	Linear Interpolation	75.27	2609	20.67	.40
4	Do Nothing	75.45	2428	20.38	.41
	Linear Trend Pts.	75.77	2428	20.09	.41
5	Do Nothing	75.46	2644	20.18	.39
	Moving Average	75.50	2644	20.39	.40
6	Do Nothing	75.10	2601	20.42	.40
	Cubic Spline Fitting	75.20	2601	20.43	.40
7	Do Nothing	75.23	2634	20.38	.40
	Cubic Spline4 D. Pts.	75.32	2634	20.55	.40
8	Do Nothing	75.10	2664	20.44	.40
	Sub. Subs. Mean	74.98	2664	20.66	.40
9	Do Nothing	74.92	2674	20.56	.40
	Sub. Subs. Med.	74.83	2674	20.72	.40
10	Do Nothing	74.96	2698	20.50	.39
	Sub. Subs. Max.	74.88	2698	20.59	.40
11	Do Nothing	75.66	2619	20.12	.39
	Sub. Subs. Min.	75.67	2619	20.31	.40
12	Do Nothing	79.81	1688	19.46	.47
	P2LinearTrendatPts.	89.09	1688	12.85	.31
13	Do Nothing	77.62	1799	20.69	.49
	P2MovingAverage	82.42	1799	17.79	.42
14	Do Nothing	77.32	2136	19.42	.42
	P2CubicSplineFitting	81.89	2136	17.01	.37
15	Do Nothing	78.57	1568	20.86	.53
	P2CubicSpline4DPts.	76.10	1568	23.19	.59
16	Do Nothing	74.01	1348	21.81	.59
	P2SubgSubsMean	57.66	1348	13.19	.36
17	Do Nothing	75.01	1450	21.58	.57
	P2SubgSubsMed.	62.22	1450	14.80	.39
18	Do Nothing	75.06	1781	21.16	.50
	P2SubgSubsMax.	78.11	1781	18.96	.45
19	Do Nothing	70.92	797	24.58	.87
	P2SubgSubsMin.	24.66	797.00	18.79	.67

Table B14. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Good (80-89) Two Years Missing Data Points Case (2).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	71.54	46	13.98	2.06
	Mean Nearby Points	71.95	46	13.35	1.97
2	Do Nothing	71.10	47	15.26	2.23
	Med. Nearby Pts.	71.82	47	14.33	2.09
3	Do Nothing	71.10	47	15.26	2.23
	Linear Interpolation	71.82	47	14.33	2.09
4	Do Nothing	72.07	50	14.44	2.04
	Linear Trend Pts.	72.52	50	13.60	1.92
5	Do Nothing	73.28	42	13.12	2.03
	Moving Average	73.40	42	13.38	2.07
6	Do Nothing	71.25	50	14.61	2.07
	Cubic Spline Fitting	71.73	50	13.29	1.88
7	Do Nothing	70.32	41	15.91	2.48
	Cubic Spline4 D. Pts.	71.05	41	14.58	2.28
8	Do Nothing	73.82	45	12.91	1.92
	Sub. Subs. Mean	74.10	45	12.64	1.88
9	Do Nothing	73.42	42	13.33	2.06
	Sub. Subs. Med.	73.71	42	13.13	2.03
10	Do Nothing	71.56	44	15.61	2.35
	Sub. Subs. Max.	71.94	44	15.10	2.28
11	Do Nothing	73.47	41	13.49	2.11
	Sub. Subs. Min.	73.53	41	13.65	2.13
12	Do Nothing	77.82	32	5.88	1.04
	P2LinearTrendatPts.	77.74	32	5.70	1.01
13	Do Nothing	70.24	9	18.35	6.12
	P2MovingAverage	71.78	9	17.88	5.96
14	Do Nothing	76.02	61	7.73	.99
	P2CubicSplineFitting	76.30	61	7.99	1.02
15	Do Nothing	73.82	13	20.96	5.81
	P2CubicSpline4DPts.	73.89	13	22.00	6.10
16	Do Nothing	62.54	13	24.83	6.89
	P2SubgSubsMean	52.64	13	15.19	4.21
17	Do Nothing	60.63	14	24.90	6.66
	P2SubgSubsMed.	53.75	14	17.95	4.80
18	Do Nothing	66.11	10	23.25	7.35
	P2SubgSubsMax.	69.50	10	18.08	5.72
19	Do Nothing	39.10	5	19.29	8.63
	P2SubgSubsMin.	27.40	5	11.41	5.10

Table B15. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Fair (70-79) Two Years Missing Data Points Case (2).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	66.37	15	13.84	3.57
	Mean Nearby Points	63.89	15	12.04	3.11
2	**Do Nothing**	66.37	15	13.84	3.57
	Med. Nearby Pts.	64.00	15	12.09	3.12
3	**Do Nothing**	66.37	15	13.84	3.57
	Linear Interpolation	64.00	15	12.09	3.12
4	**Do Nothing**	65.43	13	14.60	4.05
	Linear Trend Pts.	62.65	13	12.40	3.44
5	**Do Nothing**	67.66	15	14.61	3.77
	Moving Average	64.35	15	11.77	3.04
6	**Do Nothing**	65.62	14	14.05	3.75
	Cubic Spline Fitting	63.01	14	12.07	3.23
7	**Do Nothing**	66.37	15	13.84	3.57
	Cubic Spline4 D. Pts.	64.05	15	12.16	3.14
8	**Do Nothing**	65.06	14	13.37	3.57
	Sub. Subs. Mean	63.50	14	12.59	3.37
9	**Do Nothing**	64.82	13	13.88	3.85
	Sub. Subs. Med.	63.07	13	13.04	3.62
10	**Do Nothing**	65.40	14	13.52	3.61
	Sub. Subs. Max.	63.67	14	12.70	3.39
11	**Do Nothing**	65.41	13	14.59	4.05
	Sub. Subs. Min.	62.79	13	12.63	3.50
12	**Do Nothing**	66.75	13	15.61	4.33
	P2LinearTrendatPts.	63.87	13	12.25	3.40
13	**Do Nothing**	52.64	6	9.33	3.81
	P2MovingAverage	54.50	6	9.99	4.08
14	**Do Nothing**	67.31	16	14.05	3.51
	P2CubicSplineFitting	64.96	16	11.30	2.83
15	**Do Nothing**	67.47	14	15.24	4.07
	P2CubicSpline4DPts.	61.51	14	20.02	5.35
16	**Do Nothing**	63.39	9	17.74	5.91
	P2SubgSubsMean	43.91	9	9.11	3.04
17	**Do Nothing**	63.39	9	17.74	5.91
	P2SubgSubsMed.	45.11	9	8.34	2.78
18	**Do Nothing**	52.64	6	9.33	3.81
	P2SubgSubsMax.	49.00	6	10.79	4.40
19	**Do Nothing**	60.79	6	12.96	5.29
	P2SubgSubsMin.	30.50	6	4.68	1.91

Table B16. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Poor (60-69) Two Years Missing Data Points Case (2).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	49.96	5	13.16	5.89
	Mean Nearby Points	46.62	5	10.30	4.61
2	Do Nothing	49.96	5	13.16	5.89
	Med. Nearby Pts.	47.43	5	9.83	4.40
3	Do Nothing	49.96	5	13.16	5.89
	Linear Interpolation	47.43	5	9.83	4.40
4	Do Nothing	49.96	5	13.16	5.89
	Linear Trend Pts.	47.13	5	10.02	4.48
5	Do Nothing	52.80	7	11.85	4.48
	Moving Average	51.60	7	10.72	4.05
6	Do Nothing	49.96	5	13.16	5.89
	Cubic Spline Fitting	47.40	5	9.90	4.43
7	Do Nothing	51.28	6	12.21	4.98
	Cubic Spline4 D. Pts.	50.15	6	10.31	4.21
8	Do Nothing	51.99	6	12.78	5.22
	Sub. Subs. Mean	49.20	6	11.10	4.53
9	Do Nothing	51.99	6	12.78	5.22
	Sub. Subs. Med.	49.27	6	11.06	4.52
10	Do Nothing	49.96	5	13.16	5.89
	Sub. Subs. Max.	46.73	5	10.23	4.58
11	Do Nothing	52.80	7	11.85	4.48
	Sub. Subs. Min.	51.41	7	10.90	4.12
12	Do Nothing	65.68	2	11.06	7.82
	P2LinearTrendatPts.	57.64	2	1.58	1.12
13	Do Nothing	54.06	3	16.83	9.72
	P2MovingAverage	51.67	3	11.55	6.67
14	Do Nothing	52.78	5	13.02	5.82
	P2CubicSplineFitting	52.55	5	11.19	5.00
15	Do Nothing	65.68	2	11.06	7.82
	P2CubicSpline4DPts.	61.31	2	5.22	3.69
16	Do Nothing	.		.	.
	P2SubgSubsMean	.		.	.
17	Do Nothing	.		.	.
	P2SubgSubsMed.	.		.	.
18	Do Nothing	73.50	1	.	.
	P2SubgSubsMax.	-14.00	1	.	.
19	Do Nothing	.		.	.
	P2SubgSubsMin.	.		.	.

Table B17. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Very Poor (1-59) Two Years Missing Data Points Case (2).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	30.73	29	9.85	1.83
	Mean Nearby Points	24.39	29	8.70	1.61
2	Do Nothing	30.12	30	10.24	1.87
	Med. Nearby Pts.	23.91	30	8.95	1.63
3	Do Nothing	30.12	30	10.24	1.87
	Linear Interpolation	23.91	30	8.95	1.63
4	Do Nothing	30.54	28	9.09	1.72
	Linear Trend Pts.	24.05	28	7.52	1.42
5	Do Nothing	30.45	36	10.77	1.79
	Moving Average	25.06	36	10.38	1.73
6	Do Nothing	31.64	28	8.69	1.64
	Cubic Spline Fitting	24.95	28	8.29	1.57
7	Do Nothing	29.66	29	10.10	1.88
	Cubic Spline4 D. Pts.	23.20	29	8.32	1.55
8	Do Nothing	28.66	32	10.17	1.80
	Sub. Subs. Mean	22.60	32	8.37	1.48
9	Do Nothing	28.83	35	10.71	1.81
	Sub. Subs. Med.	23.13	35	9.65	1.63
10	Do Nothing	30.92	32	10.79	1.91
	Sub. Subs. Max.	24.89	32	10.26	1.81
11	Do Nothing	30.08	34	10.48	1.80
	Sub. Subs. Min.	24.49	34	9.69	1.66
12	Do Nothing	31.73	28	9.03	1.71
	P2LinearTrendatPts.	19.06	28	9.72	1.84
13	Do Nothing	33.35	24	6.24	1.27
	P2MovingAverage	25.58	24	6.98	1.43
14	Do Nothing	30.84	33	9.34	1.63
	P2CubicSplineFitting	26.03	33	8.28	1.44
15	Do Nothing	30.14	28	9.07	1.71
	P2CubicSpline4DPts.	13.25	28	11.34	2.14
16	Do Nothing	31.69	26	8.40	1.65
	P2SubgSubsMean	16.93	26	6.13	1.20
17	Do Nothing	31.69	26	8.40	1.65
	P2SubgSubsMed.	18.94	26	7.27	1.43
18	Do Nothing	32.93	26	8.24	1.62
	P2SubgSubsMax.	22.42	26	9.64	1.89
19	Do Nothing	31.54	25	8.54	1.71
	P2SubgSubsMin.	9.92	25	4.85	.97

Table B18. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Age (1993-2010) for Two Years Missing Data Points Case (1).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	72.04	3236	21.29	.37
	Mean Nearby Points	72.22	3236	21.38	.38
2	**Do Nothing**	72.00	3315	21.25	.37
	Med. Nearby Pts.	71.88	3315	21.57	.37
3	**Do Nothing**	72.00	3315	21.25	.37
	Linear Interpolation	71.88	3315	21.57	.37
4	**Do Nothing**	71.99	3085	21.27	.38
	Linear Trend Pts.	72.11	3085	21.24	.38
5	**Do Nothing**	72.03	3385	21.29	.37
	Moving Average	72.12	3385	21.43	.37
6	**Do Nothing**	71.79	3298	21.21	.37
	Cubic Spline Fitting	71.73	3298	21.42	.37
7	**Do Nothing**	71.93	3310	21.28	.37
	Cubic Spline4 D. Pts.	71.93	3310	21.54	.37
8	**Do Nothing**	71.84	3383	21.31	.37
	Sub. Subs. Mean	71.65	3383	21.62	.37
9	**Do Nothing**	71.57	3399	21.48	.37
	Sub. Subs. Med.	71.42	3399	21.76	.37
10	**Do Nothing**	71.70	3442	21.38	.36
	Sub. Subs. Max.	71.45	3442	21.67	.37
11	**Do Nothing**	72.17	3349	21.29	.37
	Sub. Subs. Min.	72.21	3349	21.44	.37
12	**Do Nothing**	77.03	2124	19.99	.43
	P2LinearTrendatPts.	84.80	2124	17.02	.37
13	**Do Nothing**	73.37	2220	22.16	.47
	P2MovingAverage	77.51	2220	20.71	.44
14	**Do Nothing**	73.60	2853	20.26	.38
	P2CubicSplineFitting	76.89	2853	19.65	.37
15	**Do Nothing**	75.29	1895	21.98	.50
	P2CubicSpline4DPts.	72.92	1895	25.22	.58
16	**Do Nothing**	70.03	1698	22.92	.56
	P2SubgSubsMean	54.08	1698	15.32	.37
17	**Do Nothing**	71.19	1793	22.80	.54
	P2SubgSubsMed.	58.27	1793	17.09	.40
18	**Do Nothing**	71.40	2206	22.11	.47
	P2SubgSubsMax.	73.52	2206	21.50	.46
19	**Do Nothing**	66.21	1029	24.95	.78
	P2SubgSubsMin.	24.62	1029	17.40	.54

Table B19. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Early Age (1993-1998) for Two Years Missing Data Points Case (2).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	66.91	390	24.86	1.26
	Mean Nearby Points	67.01	390	24.92	1.26
2	Do Nothing	66.73	395	24.85	1.25
	Med. Nearby Pts.	66.90	395	24.83	1.25
3	Do Nothing	66.73	395	24.85	1.25
	Linear Interpolation	66.90	395	24.83	1.25
4	Do Nothing	68.09	367	24.00	1.25
	Linear Trend Pts.	67.80	367	24.28	1.27
5	Do Nothing	66.93	387	24.77	1.26
	Moving Average	67.11	387	24.75	1.26
6	Do Nothing	66.92	382	24.64	1.26
	Cubic Spline Fitting	67.01	382	24.69	1.26
7	Do Nothing	66.90	392	24.80	1.25
	Cubic Spline4 D. Pts.	67.10	392	24.73	1.25
8	Do Nothing	67.31	391	24.45	1.24
	Sub. Subs. Mean	67.49	391	24.42	1.23
9	Do Nothing	67.31	391	24.45	1.24
	Sub. Subs. Med.	67.52	391	24.41	1.23
10	Do Nothing	67.32	391	24.45	1.24
	Sub. Subs. Max.	67.52	391	24.40	1.23
11	Do Nothing	66.98	392	24.64	1.24
	Sub. Subs. Min.	67.15	392	24.62	1.24
12	Do Nothing	72.81	217	23.92	1.62
	P2LinearTrendatPts.	79.81	217	22.75	1.54
13	Do Nothing	69.31	248	24.13	1.53
	P2MovingAverage	72.60	248	23.67	1.50
14	Do Nothing	69.21	314	22.74	1.28
	P2CubicSplineFitting	72.07	314	23.27	1.31
15	Do Nothing	72.12	190	24.83	1.80
	P2CubicSpline4DPts.	67.70	190	28.04	2.03
16	Do Nothing	66.78	177	25.07	1.88
	P2SubgSubsMean	50.29	177	17.60	1.32
17	Do Nothing	69.82	197	24.76	1.76
	P2SubgSubsMed.	55.68	197	19.99	1.42
18	Do Nothing	67.55	253	23.17	1.46
	P2SubgSubsMax.	68.62	253	23.67	1.49
19	Do Nothing	63.70	119	28.55	2.62
	P2SubgSubsMin.	23.18	119	12.83	1.18

Table B20. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for Two Years Missing Data points Case (2).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	72.86	1014	20.59	.65
	Mean Nearby Points	73.05	1014	20.66	.65
2	**Do Nothing**	72.78	1039	20.53	.64
	Med. Nearby Pts.	72.62	1039	21.08	.65
3	**Do Nothing**	72.78	1039	20.53	.64
	Linear Interpolation	72.62	1039	21.08	.65
4	**Do Nothing**	72.65	963	20.79	.67
	Linear Trend Pts.	72.95	963	20.53	.66
5	**Do Nothing**	72.57	1056	20.81	.64
	Moving Average	72.51	1056	21.15	.65
6	**Do Nothing**	72.66	1049	20.31	.63
	Cubic Spline Fitting	72.80	1049	20.27	.63
7	**Do Nothing**	72.79	1053	20.43	.63
	Cubic Spline4 D. Pts.	72.93	1053	20.52	.63
8	**Do Nothing**	72.63	1052	20.55	.63
	Sub. Subs. Mean	72.41	1052	21.00	.65
9	**Do Nothing**	72.36	1080	20.70	.63
	Sub. Subs. Med.	72.20	1080	21.16	.64
10	**Do Nothing**	72.69	1078	20.40	.62
	Sub. Subs. Max.	72.38	1078	20.90	.64
11	**Do Nothing**	72.84	1044	20.64	.64
	Sub. Subs. Min.	72.76	1044	20.98	.65
12	**Do Nothing**	76.94	694	20.54	.78
	P2LinearTrendatPts.	85.42	694	17.09	.65
13	**Do Nothing**	74.17	720	21.97	.82
	P2MovingAverage	79.01	720	20.20	.75
14	**Do Nothing**	74.23	902	20.09	.67
	P2CubicSplineFitting	78.28	902	18.96	.63
15	**Do Nothing**	75.86	655	21.24	.83
	P2CubicSpline4DPts.	73.46	655	24.09	.94
16	**Do Nothing**	71.05	560	22.57	.95
	P2SubgSubsMean	55.92	560	14.94	.63
17	**Do Nothing**	71.72	605	22.38	.91
	P2SubgSubsMed.	60.35	605	16.49	.67
18	**Do Nothing**	72.82	725	21.89	.81
	P2SubgSubsMax.	75.70	725	20.69	.77
19	**Do Nothing**	67.22	337	24.57	1.34
	P2SubgSubsMin.	26.31	337	20.61	1.12

Table B21. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Late Age (2005-2010) for Two Years Missing Data Points Case (2).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	78.22	60	16.64	2.15
	Mean Nearby Points	79.36	60	15.99	2.06
2	**Do Nothing**	79.19	63	15.90	2.00
	Med. Nearby Pts.	79.59	63	14.85	1.87
3	**Do Nothing**	79.19	63	15.90	2.00
	Linear Interpolation	79.59	63	14.85	1.87
4	**Do Nothing**	79.13	54	16.27	2.21
	Linear Trend Pts.	80.28	54	16.18	2.20
5	**Do Nothing**	78.24	73	15.80	1.85
	Moving Average	79.55	73	13.78	1.61
6	**Do Nothing**	78.24	58	16.94	2.22
	Cubic Spline Fitting	78.07	58	16.77	2.20
7	**Do Nothing**	79.03	61	15.96	2.04
	Cubic Spline4 D. Pts.	79.88	61	14.85	1.90
8	**Do Nothing**	78.96	66	15.58	1.92
	Sub. Subs. Mean	79.09	66	14.09	1.73
9	**Do Nothing**	78.68	68	15.72	1.91
	Sub. Subs. Med.	78.50	68	14.06	1.71
10	**Do Nothing**	78.13	68	16.11	1.95
	Sub. Subs. Max.	77.83	68	15.69	1.90
11	**Do Nothing**	78.87	69	15.80	1.90
	Sub. Subs. Min.	80.01	69	13.51	1.63
12	**Do Nothing**	81.20	46	15.66	2.31
	P2LinearTrendatPts.	89.20	46	8.43	1.24
13	**Do Nothing**	80.17	44	17.20	2.59
	P2MovingAverage	84.50	44	13.02	1.96
14	**Do Nothing**	78.67	59	16.34	2.13
	P2CubicSplineFitting	81.85	59	14.58	1.90
15	**Do Nothing**	81.18	42	16.88	2.60
	P2CubicSpline4DPts.	82.92	42	14.32	2.21
16	**Do Nothing**	80.42	31	17.37	3.12
	P2SubgSubsMean	60.06	31	11.99	2.15
17	**Do Nothing**	79.90	28	18.21	3.44
	P2SubgSubsMed.	64.59	28	14.25	2.69
18	**Do Nothing**	80.84	35	16.22	2.74
	P2SubgSubsMax.	81.29	35	13.59	2.30
19	**Do Nothing**	79.23	14	22.98	6.14
	P2SubgSubsMin.	19.64	14	17.97	4.80

Table B22. Paired Samples T-Tests Statistics of Predicted Distress Scores for Three Years Missing Data Points Case (3).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	72.80	5877	20.66	.27
1	Mean Nearby Points	73.05	5877	20.64	.27
2	Do Nothing	72.69	6029	20.70	.27
2	Med. Nearby Pts.	72.54	6029	21.10	.27
3	Do Nothing	72.69	6029	20.70	.27
3	Linear Interpolation	72.54	6029	21.10	.27
4	Do Nothing	72.58	5625	20.62	.27
4	Linear Trend Pts.	72.67	5625	20.64	.28
5	Do Nothing	72.38	6327	20.82	.26
5	Moving Average	72.47	6327	21.02	.26
6	Do Nothing	72.27	6054	20.70	.27
6	Cubic Spline Fitting	72.29	6054	20.71	.27
7	Do Nothing	72.65	5988	20.72	.27
7	Cubic Spline4 D. Pts.	72.75	5988	20.83	.27
8	Do Nothing	72.50	6196	20.63	.26
8	Sub. Subs. Mean	72.15	6196	21.11	.27
9	Do Nothing	71.66	6226	21.30	.27
9	Sub. Subs. Med.	71.31	6226	21.72	.28
10	Do Nothing	71.91	6451	21.03	.26
10	Sub. Subs. Max.	71.43	6451	21.44	.27
11	Do Nothing	72.81	6121	20.80	.27
11	Sub. Subs. Min.	72.83	6121	21.02	.27
12	Do Nothing	77.41	3936	19.38	.31
12	P2LinearTrendatPts.	85.86	3936	15.45	.25
13	Do Nothing	73.88	4351	21.02	.32
13	P2MovingAverage	77.37	4351	19.75	.30
14	Do Nothing	74.21	5187	19.83	.28
14	P2CubicSplineFitting	77.32	5187	19.30	.27
15	Do Nothing	75.47	3679	20.64	.34
15	P2CubicSpline4DPts.	73.32	3679	24.80	.41
16	Do Nothing	70.64	3616	21.65	.36
16	P2SubgSubsMean	53.48	3616	14.01	.23
17	Do Nothing	70.81	3661	21.53	.36
17	P2SubgSubsMed.	57.08	3661	15.92	.26
18	Do Nothing	71.33	4513	20.66	.31
18	P2SubgSubsMax.	73.10	4513	20.32	.30
19	Do Nothing	66.42	2106	22.84	.50
19	P2SubgSubsMin.	23.64	2106	15.15	.33

Table B23. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Very Good (90-100) Three Years Missing Data Points Case (3).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	76.95	4501	19.38	.29
	Mean Nearby Points	77.34	4501	19.12	.28
2	**Do Nothing**	76.86	4599	19.41	.29
	Med. Nearby Pts.	76.66	4599	19.95	.29
3	**Do Nothing**	76.86	4599	19.41	.29
	Linear Interpolation	76.66	4599	19.95	.29
4	**Do Nothing**	76.58	4281	19.62	.30
	Linear Trend Pts.	77.01	4281	19.19	.29
5	**Do Nothing**	76.65	4705	19.35	.28
	Moving Average	76.55	4705	19.77	.29
6	**Do Nothing**	76.22	4629	19.64	.29
	Cubic Spline Fitting	76.44	4629	19.37	.28
7	**Do Nothing**	76.64	4600	19.58	.29
	Cubic Spline4 D. Pts.	76.80	4600	19.60	.29
8	**Do Nothing**	76.47	4695	19.58	.29
	Sub. Subs. Mean	76.13	4695	20.08	.29
9	**Do Nothing**	75.99	4694	19.92	.29
	Sub. Subs. Med.	75.61	4694	20.34	.30
10	**Do Nothing**	76.07	4795	19.82	.29
	Sub. Subs. Max.	75.73	4795	20.10	.29
11	**Do Nothing**	77.01	4602	19.31	.28
	Sub. Subs. Min.	76.90	4602	19.69	.29
12	**Do Nothing**	80.37	3113	18.51	.33
	P2LinearTrendatPts.	89.70	3113	11.01	.20
13	**Do Nothing**	78.98	3261	19.47	.34
	P2MovingAverage	83.21	3261	16.63	.29
14	**Do Nothing**	78.57	3905	18.32	.29
	P2CubicSplineFitting	82.83	3905	15.74	.25
15	**Do Nothing**	79.24	2863	19.74	.37
	P2CubicSpline4DPts.	76.49	2863	23.12	.43
16	**Do Nothing**	75.07	2654	21.01	.41
	P2SubgSubsMean	57.42	2654	12.02	.23
17	**Do Nothing**	74.89	2731	20.93	.40
	P2SubgSubsMed.	61.54	2731	13.91	.27
18	**Do Nothing**	75.18	3321	20.30	.35
	P2SubgSubsMax.	78.24	3321	17.99	.31
19	**Do Nothing**	71.95	1457	23.22	.61
	P2SubgSubsMin.	22.56	1457	16.86	.44

Table B24. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Good (80-89) Three Years Missing Data Points Case (3).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	74.56	3	13.19	7.61
	Mean Nearby Points	75.69	3	13.73	7.93
2	**Do Nothing**	78.16	4	12.95	6.48
	Med. Nearby Pts.	78.95	4	12.99	6.50
3	**Do Nothing**	78.16	4	12.95	6.48
	Linear Interpolation	78.95	4	12.99	6.50
4	**Do Nothing**	64.91	4	22.10	11.05
	Linear Trend Pts.	65.83	4	22.41	11.21
5	**Do Nothing**	74.56	3	13.19	7.61
	Moving Average	75.62	3	13.66	7.89
6	**Do Nothing**	74.56	3	13.19	7.61
	Cubic Spline Fitting	75.27	3	13.87	8.01
7	**Do Nothing**	78.16	4	12.95	6.48
	Cubic Spline4 D. Pts.	78.70	4	13.36	6.68
8	**Do Nothing**	78.16	4	12.95	6.48
	Sub. Subs. Mean	78.81	4	13.38	6.69
9	**Do Nothing**	78.16	4	12.95	6.48
	Sub. Subs. Med.	79.00	4	13.23	6.61
10	**Do Nothing**	78.16	4	12.95	6.48
	Sub. Subs. Max.	79.61	4	12.56	6.28
11	**Do Nothing**	74.56	3	13.19	7.61
	Sub. Subs. Min.	75.36	3	14.03	8.10
12	**Do Nothing**	74.56	3	13.19	7.61
	P2LinearTrendatPts.	75.24	3	13.12	7.57
13	**Do Nothing**	74.56	3	13.19	7.61
	P2MovingAverage	77.33	3	12.01	6.94
14	**Do Nothing**	74.56	3	13.19	7.61
	P2CubicSplineFitting	77.43	3	12.73	7.35
15	**Do Nothing**	74.56	3	13.19	7.61
	P2CubicSpline4DPts.	76.63	3	12.54	7.24
16	**Do Nothing**	65.48	4	21.11	10.56
	P2SubgSubsMean	56.57	4	14.92	7.46
17	**Do Nothing**	65.48	4	21.11	10.56
	P2SubgSubsMed.	60.00	4	17.20	8.60
18	**Do Nothing**	74.56	3	13.19	7.61
	P2SubgSubsMax.	77.33	3	12.01	6.94
19	**Do Nothing**	38.24	1	.	.
	P2SubgSubsMin.	32.00	1	.	.

Table B25. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Fair (70-79) Three Years Missing Data Points Case (3).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing				
	Mean Nearby Points				
2	Do Nothing				
	Med. Nearby Pts.				
3	Do Nothing				
	Linear Interpolation				
4	Do Nothing				
	Linear Trend Pts.				
5	Do Nothing				
	Moving Average				
6	Do Nothing				
	Cubic Spline Fitting				
7	Do Nothing				
	Cubic Spline4 D. Pts.				
8	Do Nothing				
	Sub. Subs. Mean				
9	Do Nothing				
	Sub. Subs. Med.				
10	Do Nothing				
	Sub. Subs. Max.				
11	Do Nothing				
	Sub. Subs. Min.				
12	Do Nothing				
	P2LinearTrendatPts.				
13	Do Nothing				
	P2MovingAverage				
14	Do Nothing				
	P2CubicSplineFitting				
15	Do Nothing				
	P2CubicSpline4DPts.				
16	Do Nothing				
	P2SubgSubsMean				
17	Do Nothing				
	P2SubgSubsMed.				
18	Do Nothing				
	P2SubgSubsMax.				
19	Do Nothing				
	P2SubgSubsMin.				

Table B26. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Poor (60-69) Three Years Missing Data Points Case (3).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing				
	Mean Nearby Points				
2	Do Nothing				
	Med. Nearby Pts.				
3	Do Nothing				
	Linear Interpolation				
4	Do Nothing				
	Linear Trend Pts.				
5	Do Nothing				
	Moving Average				
6	Do Nothing				
	Cubic Spline Fitting				
7	Do Nothing				
	Cubic Spline4 D. Pts.				
8	Do Nothing				
	Sub. Subs. Mean				
9	Do Nothing				
	Sub. Subs. Med.				
10	Do Nothing				
	Sub. Subs. Max.				
11	Do Nothing				
	Sub. Subs. Min.				
12	Do Nothing				
	P2LinearTrendatPts.				
13	Do Nothing				
	P2MovingAverage				
14	Do Nothing				
	P2CubicSplineFitting				
15	Do Nothing				
	P2CubicSpline4DPts.				
16	Do Nothing				
	P2SubgSubsMean				
17	Do Nothing				
	P2SubgSubsMed.				
18	Do Nothing				
	P2SubgSubsMax.				
19	Do Nothing				
	P2SubgSubsMin.				

Table B27. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Very Poor (1-59) Three Years Missing Data Points Case (3).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	31.30	29	5.66	1.05
	Mean Nearby Points	23.79	29	5.06	.94
2	Do Nothing	31.30	29	5.66	1.05
	Med. Nearby Pts.	23.87	29	4.80	.89
3	Do Nothing	31.30	29	5.66	1.05
	Linear Interpolation	23.87	29	4.80	.89
4	Do Nothing	31.30	29	5.66	1.05
	Linear Trend Pts.	23.85	29	4.88	.91
5	Do Nothing	30.71	35	6.27	1.06
	Moving Average	24.50	35	5.78	.98
6	Do Nothing	31.30	29	5.66	1.05
	Cubic Spline Fitting	23.83	29	4.92	.91
7	Do Nothing	31.73	29	3.98	.74
	Cubic Spline4 D. Pts.	24.27	29	3.83	.71
8	Do Nothing	30.56	31	6.17	1.11
	Sub. Subs. Mean	23.64	31	4.66	.84
9	Do Nothing	30.63	32	5.14	.91
	Sub. Subs. Med.	23.87	32	3.85	.68
10	Do Nothing	31.35	30	4.45	.81
	Sub. Subs. Max.	24.13	30	3.84	.70
11	Do Nothing	30.98	31	4.83	.87
	Sub. Subs. Min.	24.00	31	3.85	.69
12	Do Nothing	32.16	28	3.32	.63
	P2LinearTrendatPts.	17.79	28	2.87	.54
13	Do Nothing	32.16	28	3.32	.63
	P2MovingAverage	24.43	28	3.80	.72
14	Do Nothing	31.12	30	5.65	1.03
	P2CubicSplineFitting	25.34	30	4.40	.80
15	Do Nothing	32.16	28	3.32	.63
	P2CubicSpline4DPts.	11.20	28	6.98	1.32
16	Do Nothing	31.30	29	5.66	1.05
	P2SubgSubsMean	16.37	29	2.99	.56
17	Do Nothing	31.30	29	5.66	1.05
	P2SubgSubsMed.	18.72	29	4.68	.87
18	Do Nothing	31.30	29	5.66	1.05
	P2SubgSubsMax.	20.69	29	6.11	1.14
19	Do Nothing	31.30	29	5.66	1.05
	P2SubgSubsMin.	8.90	29	2.81	.52

Table B28. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Age (1993-2010) for Three Years Missing Data Points Case (3).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	72.80	5877	20.66	.27
	Mean Nearby Points	73.05	5877	20.64	.27
2	**Do Nothing**	72.69	6029	20.70	.27
	Med. Nearby Pts.	72.54	6029	21.10	.27
3	**Do Nothing**	72.69	6029	20.70	.27
	Linear Interpolation	72.54	6029	21.10	.27
4	**Do Nothing**	72.58	5625	20.62	.27
	Linear Trend Pts.	72.67	5625	20.64	.28
5	**Do Nothing**	72.38	6327	20.82	.26
	Moving Average	72.47	6327	21.02	.26
6	**Do Nothing**	72.27	6054	20.70	.27
	Cubic Spline Fitting	72.29	6054	20.71	.27
7	**Do Nothing**	72.65	5988	20.72	.27
	Cubic Spline4 D. Pts.	72.75	5988	20.83	.27
8	**Do Nothing**	72.50	6196	20.63	.26
	Sub. Subs. Mean	72.15	6196	21.11	.27
9	**Do Nothing**	71.66	6226	21.30	.27
	Sub. Subs. Med.	71.31	6226	21.72	.28
10	**Do Nothing**	71.91	6451	21.03	.26
	Sub. Subs. Max.	71.43	6451	21.44	.27
11	**Do Nothing**	72.81	6121	20.80	.27
	Sub. Subs. Min.	72.83	6121	21.02	.27
12	**Do Nothing**	77.41	3936	19.38	.31
	P2LinearTrendatPts.	85.86	3936	15.45	.25
13	**Do Nothing**	73.88	4351	21.02	.32
	P2MovingAverage	77.37	4351	19.75	.30
14	**Do Nothing**	74.21	5187	19.83	.28
	P2CubicSplineFitting	77.32	5187	19.30	.27
15	**Do Nothing**	75.47	3679	20.64	.34
	P2CubicSpline4DPts.	73.32	3679	24.80	.41
16	**Do Nothing**	70.64	3616	21.65	.36
	P2SubgSubsMean	53.48	3616	14.01	.23
17	**Do Nothing**	70.81	3661	21.53	.36
	P2SubgSubsMed.	57.08	3661	15.92	.26
18	**Do Nothing**	71.33	4513	20.66	.31
	P2SubgSubsMax.	73.10	4513	20.32	.30
19	**Do Nothing**	66.42	2106	22.84	.50
	P2SubgSubsMin.	23.64	2106	15.15	.33

Table B29. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Early Age (1993-1998) for Three Years Missing Data Points Case (3).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	66.94	162	25.69	2.02
	Mean Nearby Points	66.71	162	25.89	2.03
2	**Do Nothing**	65.75	166	26.50	2.06
	Med. Nearby Pts.	65.73	166	26.52	2.06
3	**Do Nothing**	65.75	166	26.50	2.06
	Linear Interpolation	65.73	166	26.52	2.06
4	**Do Nothing**	67.79	158	24.84	1.98
	Linear Trend Pts.	66.86	158	25.53	2.03
5	**Do Nothing**	66.44	164	25.91	2.02
	Moving Average	66.43	164	25.96	2.03
6	**Do Nothing**	65.37	166	26.37	2.05
	Cubic Spline Fitting	65.36	166	26.46	2.05
7	**Do Nothing**	66.70	164	25.78	2.01
	Cubic Spline4 D. Pts.	66.72	164	25.79	2.01
8	**Do Nothing**	65.75	166	26.50	2.06
	Sub. Subs. Mean	65.70	166	26.50	2.06
9	**Do Nothing**	66.09	165	26.22	2.04
	Sub. Subs. Med.	66.04	165	26.25	2.04
10	**Do Nothing**	66.09	165	26.22	2.04
	Sub. Subs. Max.	66.06	165	26.21	2.04
11	**Do Nothing**	65.63	167	26.47	2.05
	Sub. Subs. Min.	65.64	167	26.46	2.05
12	**Do Nothing**	72.54	93	25.81	2.68
	P2LinearTrendatPts.	79.48	93	25.76	2.67
13	**Do Nothing**	69.80	117	23.87	2.21
	P2MovingAverage	72.22	117	24.43	2.26
14	**Do Nothing**	68.91	131	24.20	2.11
	P2CubicSplineFitting	72.16	131	25.12	2.20
15	**Do Nothing**	73.87	86	23.96	2.58
	P2CubicSpline4DPts.	69.62	86	27.53	2.97
16	**Do Nothing**	68.52	87	25.91	2.78
	P2SubgSubsMean	49.88	87	18.82	2.02
17	**Do Nothing**	70.22	89	25.32	2.68
	P2SubgSubsMed.	54.61	89	21.59	2.29
18	**Do Nothing**	68.25	115	22.62	2.11
	P2SubgSubsMax.	68.58	115	24.13	2.25
19	**Do Nothing**	65.47	51	28.89	4.05
	P2SubgSubsMin.	21.49	51	10.05	1.41

Table B30. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for Three Years Missing Data points Case (3).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	Do Nothing	73.81	1033	19.93	.62
	Mean Nearby Points	74.07	1033	20.07	.62
2	Do Nothing	73.70	1064	19.73	.60
	Med. Nearby Pts.	73.27	1064	20.95	.64
3	Do Nothing	73.70	1064	19.73	.60
	Linear Interpolation	73.27	1064	20.95	.64
4	Do Nothing	74.15	963	19.79	.64
	Linear Trend Pts.	74.39	963	19.97	.64
5	Do Nothing	73.22	1116	19.96	.60
	Moving Average	72.87	1116	20.93	.63
6	Do Nothing	73.40	1084	19.73	.60
	Cubic Spline Fitting	73.45	1084	19.80	.60
7	Do Nothing	73.72	1091	19.61	.59
	Cubic Spline4 D. Pts.	73.94	1091	19.75	.60
8	Do Nothing	73.48	1106	19.67	.59
	Sub. Subs. Mean	72.87	1106	20.81	.63
9	Do Nothing	72.99	1121	19.98	.60
	Sub. Subs. Med.	72.42	1121	21.08	.63
10	Do Nothing	73.24	1154	19.60	.58
	Sub. Subs. Max.	72.55	1154	20.70	.61
11	Do Nothing	73.72	1082	19.77	.60
	Sub. Subs. Min.	73.24	1082	20.85	.63
12	Do Nothing	76.75	788	19.78	.70
	P2LinearTrendatPts.	85.16	788	16.14	.57
13	Do Nothing	75.18	796	20.69	.73
	P2MovingAverage	79.76	796	18.95	.67
14	Do Nothing	74.89	954	19.64	.64
	P2CubicSplineFitting	78.76	954	18.83	.61
15	Do Nothing	76.02	748	19.98	.73
	P2CubicSpline4DPts.	73.29	748	23.49	.86
16	Do Nothing	72.44	657	20.64	.81
	P2SubgSubsMean	56.26	657	13.40	.52
17	Do Nothing	72.67	690	20.57	.78
	P2SubgSubsMed.	60.98	690	15.10	.57
18	Do Nothing	73.81	846	19.94	.69
	P2SubgSubsMax.	76.30	846	19.35	.67
19	Do Nothing	68.38	367	22.54	1.18
	P2SubgSubsMin.	25.69	367	19.15	1.00

Table B31. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Late Age (2005-2010) for Three Years Missing Data Points Case (3).

Pair	Missing Data Techniques Brief	Mean	Valid	Std. Deviation	Std. Error Mean
1	**Do Nothing**	75.40	20	19.86	4.44
	Mean Nearby Points	78.72	20	16.60	3.71
2	**Do Nothing**	76.18	21	19.68	4.29
	Med. Nearby Pts.	78.82	21	15.46	3.37
3	**Do Nothing**	76.18	21	19.68	4.29
	Linear Interpolation	78.82	21	15.46	3.37
4	**Do Nothing**	75.40	20	19.86	4.44
	Linear Trend Pts.	78.23	20	17.66	3.95
5	**Do Nothing**	74.55	27	19.86	3.82
	Moving Average	77.30	27	16.38	3.15
6	**Do Nothing**	74.95	21	19.47	4.25
	Cubic Spline Fitting	76.07	21	18.00	3.93
7	**Do Nothing**	77.08	23	18.99	3.96
	Cubic Spline4 D. Pts.	78.60	23	16.08	3.35
8	**Do Nothing**	76.20	23	19.03	3.97
	Sub. Subs. Mean	76.88	23	16.94	3.53
9	**Do Nothing**	77.20	23	19.07	3.98
	Sub. Subs. Med.	77.35	23	16.82	3.51
10	**Do Nothing**	76.73	24	18.79	3.84
	Sub. Subs. Max.	76.00	24	18.64	3.80
11	**Do Nothing**	77.20	23	19.07	3.98
	Sub. Subs. Min.	79.58	23	14.26	2.97
12	**Do Nothing**	77.16	20	19.64	4.39
	P2LinearTrendatPts.	86.47	20	10.45	2.34
13	**Do Nothing**	75.18	19	20.38	4.67
	P2MovingAverage	80.21	19	15.09	3.46
14	**Do Nothing**	75.71	22	19.33	4.12
	P2CubicSplineFitting	79.78	22	15.93	3.40
15	**Do Nothing**	74.98	19	20.33	4.66
	P2CubicSpline4DPts.	74.06	19	18.80	4.31
16	**Do Nothing**	76.10	13	21.52	5.97
	P2SubgSubsMean	54.76	13	12.72	3.53
17	**Do Nothing**	72.74	9	25.55	8.52
	P2SubgSubsMed.	57.56	9	17.25	5.75
18	**Do Nothing**	75.65	15	20.13	5.20
	P2SubgSubsMax.	76.87	15	17.13	4.42
19	**Do Nothing**	63.10	3	45.44	26.23
	P2SubgSubsMin.	12.33	3	1.15	.67

Table B32. Paired Samples T-Tests Correlations of Predicted Distress Scores for One year Missing Data point Case (1).

Pair	Do Nothing	Valid	Correlation	Significance
1	**Mean Nearby Points**	1116	.988	.000
2	**Med. Nearby Pts.**	1124	.988	.000
3	**Linear Interpolation**	1124	.988	.000
4	**Linear Trend Pts.**	1086	.981	.000
5	**Moving Average**	1143	.987	.000
6	**Cubic Spline Fitting**	1122	.991	.000
7	**Cubic Spline4 D. Pts.**	1122	.989	.000
8	**Sub. Subs. Mean**	1134	.988	.000
9	**Sub. Subs. Med.**	1133	.988	.000
10	**Sub. Subs. Max.**	1142	.987	.000
11	**Sub. Subs. Min.**	1136	.987	.000
12	**P2LinearTrendatPts.**	652	.792	.000
13	**P2MovingAverage**	1146	.926	.000
14	**P2CubicSplineFitting**	883	.877	.000
15	**P2CubicSpline4DPts.**	681	.907	.000
16	**P2SubgSubsMean**	566	.848	.000
17	**P2SubgSubsMed.**	632	.857	.000
18	**P2SubgSubsMax.**	1032	.908	.000
19	**P2SubgSubsMin.**	373	.251	.000

Table B33. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Very Good (90-100) One Year Missing Data point Case (1).

Pair	Do Nothing	Valid	Correlation	Significance
1	**Mean Nearby Points**	935	.986	.000
2	**Med. Nearby Pts.**	942	.986	.000
3	**Linear Interpolation**	942	.986	.000
4	**Linear Trend Pts.**	910	.978	.000
5	**Moving Average**	960	.986	.000
6	**Cubic Spline Fitting**	940	.990	.000
7	**Cubic Spline4 D. Pts.**	944	.988	.000
8	**Sub. Subs. Mean**	953	.987	.000
9	**Sub. Subs. Med.**	956	.986	.000
10	**Sub. Subs. Max.**	957	.985	.000
11	**Sub. Subs. Min.**	952	.986	.000
12	**P2LinearTrendatPts.**	560	.712	.000
13	**P2MovingAverage**	952	.907	.000
14	**P2CubicSplineFitting**	737	.833	.000
15	**P2CubicSpline4DPts.**	595	.899	.000
16	**P2SubgSubsMean**	477	.807	.000
17	**P2SubgSubsMed.**	537	.824	.000
18	**P2SubgSubsMax.**	864	.884	.000
19	**P2SubgSubsMin.**	303	.191	.001

Table B34. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Good (80-89) One Year Missing Data point Case (1).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	63	.991	.000
2	Med. Nearby Pts.	64	.992	.000
3	Linear Interpolation	64	.992	.000
4	Linear Trend Pts.	61	.989	.000
5	Moving Average	61	.988	.000
6	Cubic Spline Fitting	63	.993	.000
7	Cubic Spline4 D. Pts.	64	.993	.000
8	Sub. Subs. Mean	60	.992	.000
9	Sub. Subs. Med.	59	.993	.000
10	Sub. Subs. Max.	62	.987	.000
11	Sub. Subs. Min.	63	.990	.000
12	P2LinearTrendatPts.	30	.928	.000
13	P2MovingAverage	65	.946	.000
14	P2CubicSplineFitting	50	.978	.000
15	P2CubicSpline4DPts.	30	.953	.000
16	P2SubgSubsMean	21	.913	.000
17	P2SubgSubsMed.	22	.866	.000
18	P2SubgSubsMax.	57	.936	.000
19	P2SubgSubsMin.	12	.885	.000

Table B35. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Fair (70-79) One Year Missing Data Point Case (1).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	48	.975	.000
2	Med. Nearby Pts.	50	.985	.000
3	Linear Interpolation	50	.985	.000
4	Linear Trend Pts.	48	.972	.000
5	Moving Average	53	.968	.000
6	Cubic Spline Fitting	51	.987	.000
7	Cubic Spline4 D. Pts.	50	.987	.000
8	Sub. Subs. Mean	52	.987	.000
9	Sub. Subs. Med.	50	.988	.000
10	Sub. Subs. Max.	51	.986	.000
11	Sub. Subs. Min.	52	.968	.000
12	P2LinearTrendatPts.	28	.897	.000
13	P2MovingAverage	56	.962	.000
14	P2CubicSplineFitting	43	.935	.000
15	P2CubicSpline4DPts.	25	.762	.000
16	P2SubgSubsMean	24	.883	.000
17	P2SubgSubsMed.	26	.832	.000
18	P2SubgSubsMax.	50	.947	.000
19	P2SubgSubsMin.	17	.119	.648

Table B36. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Poor (60-69) One Year Missing Data Point Case (1).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	24	.990	.000
2	Med. Nearby Pts.	24	.990	.000
3	Linear Interpolation	24	.990	.000
4	Linear Trend Pts.	24	.989	.000
5	Moving Average	22	.983	.000
6	Cubic Spline Fitting	24	.991	.000
7	Cubic Spline4 D. Pts.	24	.989	.000
8	Sub. Subs. Mean	25	.991	.000
9	Sub. Subs. Med.	25	.989	.000
10	Sub. Subs. Max.	25	.990	.000
11	Sub. Subs. Min.	23	.988	.000
12	P2LinearTrendatPts.	12	.871	.000
13	P2MovingAverage	24	.980	.000
14	P2CubicSplineFitting	18	.972	.000
15	P2CubicSpline4DPts.	6	.902	.014
16	P2SubgSubsMean	8	.893	.003
17	P2SubgSubsMed.	10	.895	.000
18	P2SubgSubsMax.	20	.870	.000
19	P2SubgSubsMin.	7	.579	.174

Table B37. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Very Poor (1-59) One Year Missing Data Point Case (1).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	47	.955	.000
2	Med. Nearby Pts.	45	.953	.000
3	Linear Interpolation	45	.953	.000
4	Linear Trend Pts.	44	.950	.000
5	Moving Average	48	.953	.000
6	Cubic Spline Fitting	45	.949	.000
7	Cubic Spline4 D. Pts.	41	.951	.000
8	Sub. Subs. Mean	45	.953	.000
9	Sub. Subs. Med.	44	.955	.000
10	Sub. Subs. Max.	48	.952	.000
11	Sub. Subs. Min.	47	.951	.000
12	P2LinearTrendatPts.	23	.842	.000
13	P2MovingAverage	50	.935	.000
14	P2CubicSplineFitting	36	.897	.000
15	P2CubicSpline4DPts.	25	.611	.001
16	P2SubgSubsMean	37	.673	.000
17	P2SubgSubsMed.	38	.784	.000
18	P2SubgSubsMax.	42	.857	.000
19	P2SubgSubsMin.	35	.209	.228

Table B38. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Age (1993-2010) for One Year Missing Data Point Case (1).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	1116	.988	.000
2	Med. Nearby Pts.	1124	.988	.000
3	Linear Interpolation	1124	.988	.000
4	Linear Trend Pts.	1086	.981	.000
5	Moving Average	1143	.987	.000
6	Cubic Spline Fitting	1122	.991	.000
7	Cubic Spline4 D. Pts.	1122	.989	.000
8	Sub. Subs. Mean	1134	.988	.000
9	Sub. Subs. Med.	1133	.988	.000
10	Sub. Subs. Max.	1142	.987	.000
11	Sub. Subs. Min.	1136	.987	.000
12	P2LinearTrendatPts.	652	.792	.000
13	P2MovingAverage	1146	.926	.000
14	P2CubicSplineFitting	883	.877	.000
15	P2CubicSpline4DPts.	681	.907	.000
16	P2SubgSubsMean	566	.848	.000
17	P2SubgSubsMed.	632	.857	.000
18	P2SubgSubsMax.	1032	.908	.000
19	P2SubgSubsMin.	373	.251	.000

Table B39. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Early Age (1993-1998) for One Year Missing Data Point Case (1).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	393	.996	.000
2	Med. Nearby Pts.	392	.996	.000
3	Linear Interpolation	392	.996	.000
4	Linear Trend Pts.	383	.994	.000
5	Moving Average	390	.996	.000
6	Cubic Spline Fitting	392	.996	.000
7	Cubic Spline4 D. Pts.	392	.996	.000
8	Sub. Subs. Mean	391	.996	.000
9	Sub. Subs. Med.	389	.996	.000
10	Sub. Subs. Max.	389	.996	.000
11	Sub. Subs. Min.	389	.996	.000
12	P2LinearTrendatPts.	210	.811	.000
13	P2MovingAverage	383	.938	.000
14	P2CubicSplineFitting	295	.887	.000
15	P2CubicSpline4DPts.	223	.920	.000
16	P2SubgSubsMean	195	.874	.000
17	P2SubgSubsMed.	217	.883	.000
18	P2SubgSubsMax.	352	.920	.000
19	P2SubgSubsMin.	144	.238	.004

Table B40. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Middle Age (1999-2004) for One year Missing Data point Case (1).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	608	.982	.000
2	Med. Nearby Pts.	616	.983	.000
3	Linear Interpolation	616	.983	.000
4	Linear Trend Pts.	591	.976	.000
5	Moving Average	631	.981	.000
6	Cubic Spline Fitting	618	.990	.000
7	Cubic Spline4 D. Pts.	617	.985	.000
8	Sub. Subs. Mean	628	.983	.000
9	Sub. Subs. Med.	628	.983	.000
10	Sub. Subs. Max.	633	.982	.000
11	Sub. Subs. Min.	626	.981	.000
12	P2LinearTrendatPts.	367	.774	.000
13	P2MovingAverage	635	.918	.000
14	P2CubicSplineFitting	492	.866	.000
15	P2CubicSpline4DPts.	389	.899	.000
16	P2SubgSubsMean	313	.828	.000
17	P2SubgSubsMed.	354	.838	.000
18	P2SubgSubsMax.	567	.896	.000
19	P2SubgSubsMin.	196	.298	.000

Table B41. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Late Age (2005-2010) for One Year Missing Data Point Case (1).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	115	.980	.000
2	Med. Nearby Pts.	116	.980	.000
3	Linear Interpolation	116	.980	.000
4	Linear Trend Pts.	112	.949	.000
5	Moving Average	122	.979	.000
6	Cubic Spline Fitting	112	.977	.000
7	Cubic Spline4 D. Pts.	113	.988	.000
8	Sub. Subs. Mean	115	.983	.000
9	Sub. Subs. Med.	116	.977	.000
10	Sub. Subs. Max.	120	.975	.000
11	Sub. Subs. Min.	121	.980	.000
12	P2LinearTrendatPts.	75	.812	.000
13	P2MovingAverage	128	.907	.000
14	P2CubicSplineFitting	96	.886	.000
15	P2CubicSpline4DPts.	69	.895	.000
16	P2SubgSubsMean	55	.272	.044
17	P2SubgSubsMed.	61	.839	.000
18	P2SubgSubsMax.	113	.911	.000
19	P2SubgSubsMin.	33	-.009	.959

Table B42. Paired Samples T-Tests Correlations of Predicted Distress Scores for Two Years Missing Data Points Case (2).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	3236	.975	.000
2	Med. Nearby Pts.	3315	.979	.000
3	Linear Interpolation	3315	.979	.000
4	Linear Trend Pts.	3085	.964	.000
5	Moving Average	3385	.978	.000
6	Cubic Spline Fitting	3298	.982	.000
7	Cubic Spline4 D. Pts.	3310	.977	.000
8	Sub. Subs. Mean	3383	.980	.000
9	Sub. Subs. Med.	3399	.979	.000
10	Sub. Subs. Max.	3442	.978	.000
11	Sub. Subs. Min.	3349	.978	.000
12	P2LinearTrendatPts.	2124	.673	.000
13	P2MovingAverage	2220	.853	.000
14	P2CubicSplineFitting	2853	.801	.000
15	P2CubicSpline4DPts.	1895	.858	.000
16	P2SubgSubsMean	1698	.738	.000
17	P2SubgSubsMed.	1793	.734	.000
18	P2SubgSubsMax.	2206	.822	.000
19	P2SubgSubsMin.	1029	.159	.000

Table B43. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Very Good (90-100) Two Years Missing Data Points Case (2).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	2562	.969	.000
2	Med. Nearby Pts.	2609	.973	.000
3	Linear Interpolation	2609	.973	.000
4	Linear Trend Pts.	2428	.954	.000
5	Moving Average	2644	.972	.000
6	Cubic Spline Fitting	2601	.978	.000
7	Cubic Spline4 D. Pts.	2634	.971	.000
8	Sub. Subs. Mean	2664	.974	.000
9	Sub. Subs. Med.	2674	.973	.000
10	Sub. Subs. Max.	2698	.972	.000
11	Sub. Subs. Min.	2619	.972	.000
12	P2LinearTrendatPts.	1688	.556	.000
13	P2MovingAverage	1799	.792	.000
14	P2CubicSplineFitting	2136	.708	.000
15	P2CubicSpline4DPts.	1568	.841	.000
16	P2SubgSubsMean	1348	.637	.000
17	P2SubgSubsMed.	1450	.642	.000
18	P2SubgSubsMax.	1781	.762	.000
19	P2SubgSubsMin.	797	.130	.000

Table B44. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Good (80-89) Two Years Missing Data Points Case (2).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	46	.996	.000
2	Med. Nearby Pts.	47	.995	.000
3	Linear Interpolation	47	.995	.000
4	Linear Trend Pts.	50	.997	.000
5	Moving Average	42	.995	.000
6	Cubic Spline Fitting	50	.996	.000
7	Cubic Spline4 D. Pts.	41	.995	.000
8	Sub. Subs. Mean	45	.993	.000
9	Sub. Subs. Med.	42	.994	.000
10	Sub. Subs. Max.	44	.985	.000
11	Sub. Subs. Min.	41	.996	.000
12	P2LinearTrendatPts.	32	.882	.000
13	P2MovingAverage	9	.996	.000
14	P2CubicSplineFitting	61	.977	.000
15	P2CubicSpline4DPts.	13	.968	.000
16	P2SubgSubsMean	13	.902	.000
17	P2SubgSubsMed.	14	.895	.000
18	P2SubgSubsMax.	10	.922	.000
19	P2SubgSubsMin.	5	.568	.318

Table B45. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Fair (70-79) Two Years Missing Data Points Case (2).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	15	.910	.000
2	Med. Nearby Pts.	15	.911	.000
3	Linear Interpolation	15	.911	.000
4	Linear Trend Pts.	13	.910	.000
5	Moving Average	15	.888	.000
6	Cubic Spline Fitting	14	.904	.000
7	Cubic Spline4 D. Pts.	15	.911	.000
8	Sub. Subs. Mean	14	.936	.000
9	Sub. Subs. Med.	13	.933	.000
10	Sub. Subs. Max.	14	.936	.000
11	Sub. Subs. Min.	13	.906	.000
12	P2LinearTrendatPts.	13	.744	.004
13	P2MovingAverage	6	.968	.002
14	P2CubicSplineFitting	16	.900	.000
15	P2CubicSpline4DPts.	14	.879	.000
16	P2SubgSubsMean	9	.955	.000
17	P2SubgSubsMed.	9	.936	.000
18	P2SubgSubsMax.	6	.943	.005
19	P2SubgSubsMin.	6	.356	.488

Table B46. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Poor (60-69) Two Years Missing Data Points Case (2).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	5	.998	.000
2	Med. Nearby Pts.	5	.999	.000
3	Linear Interpolation	5	.999	.000
4	Linear Trend Pts.	5	.997	.000
5	Moving Average	7	.948	.001
6	Cubic Spline Fitting	5	.994	.001
7	Cubic Spline4 D. Pts.	6	.949	.004
8	Sub. Subs. Mean	6	.979	.001
9	Sub. Subs. Med.	6	.979	.001
10	Sub. Subs. Max.	5	.998	.000
11	Sub. Subs. Min.	7	.948	.001
12	P2LinearTrendatPts.	2	-1.000	.000
13	P2MovingAverage	3	1.000	.004
14	P2CubicSplineFitting	5	.936	.019
15	P2CubicSpline4DPts.	2	1.000	.000
16	P2SubgSubsMean			
17	P2SubgSubsMed.			
18	P2SubgSubsMax.			
19	P2SubgSubsMin.			

Table B47. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Very Poor (1-59) Two Years Missing Data Points Case (2).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	29	.883	.000
2	Med. Nearby Pts.	30	.896	.000
3	Linear Interpolation	30	.896	.000
4	Linear Trend Pts.	28	.858	.000
5	Moving Average	36	.906	.000
6	Cubic Spline Fitting	28	.871	.000
7	Cubic Spline4 D. Pts.	29	.902	.000
8	Sub. Subs. Mean	32	.908	.000
9	Sub. Subs. Med.	35	.914	.000
10	Sub. Subs. Max.	32	.915	.000
11	Sub. Subs. Min.	34	.896	.000
12	P2LinearTrendatPts.	28	.832	.000
13	P2MovingAverage	24	.852	.000
14	P2CubicSplineFitting	33	.834	.000
15	P2CubicSpline4DPts.	28	.229	.241
16	P2SubgSubsMean	26	.868	.000
17	P2SubgSubsMed.	26	.890	.000
18	P2SubgSubsMax.	26	.881	.000
19	P2SubgSubsMin.	25	.309	.133

Table B48. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Age (1993-2010) for Two Years Missing Data Points Case (1).

Pair	Do Nothing	Valid	Correlation	Significance
1	**Mean Nearby Points**	3236	.975	.000
2	**Med. Nearby Pts.**	3315	.979	.000
3	**Linear Interpolation**	3315	.979	.000
4	**Linear Trend Pts.**	3085	.964	.000
5	**Moving Average**	3385	.978	.000
6	**Cubic Spline Fitting**	3298	.982	.000
7	**Cubic Spline4 D. Pts.**	3310	.977	.000
8	**Sub. Subs. Mean**	3383	.980	.000
9	**Sub. Subs. Med.**	3399	.979	.000
10	**Sub. Subs. Max.**	3442	.978	.000
11	**Sub. Subs. Min.**	3349	.978	.000
12	**P2LinearTrendatPts.**	2124	.673	.000
13	**P2MovingAverage**	2220	.853	.000
14	**P2CubicSplineFitting**	2853	.801	.000
15	**P2CubicSpline4DPts.**	1895	.858	.000
16	**P2SubgSubsMean**	1698	.738	.000
17	**P2SubgSubsMed.**	1793	.734	.000
18	**P2SubgSubsMax.**	2206	.822	.000
19	**P2SubgSubsMin.**	1029	.159	.000

Table B49. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Early Age (1993-1998) for Two Years Missing Data Points Case (2).

Pair	Do Nothing	Valid	Correlation	Significance
1	**Mean Nearby Points**	390	.997	.000
2	**Med. Nearby Pts.**	395	.998	.000
3	**Linear Interpolation**	395	.998	.000
4	**Linear Trend Pts.**	367	.995	.000
5	**Moving Average**	387	.998	.000
6	**Cubic Spline Fitting**	382	.998	.000
7	**Cubic Spline4 D. Pts.**	392	.998	.000
8	**Sub. Subs. Mean**	391	.998	.000
9	**Sub. Subs. Med.**	391	.998	.000
10	**Sub. Subs. Max.**	391	.998	.000
11	**Sub. Subs. Min.**	392	.998	.000
12	**P2LinearTrendatPts.**	217	.798	.000
13	**P2MovingAverage**	248	.916	.000
14	**P2CubicSplineFitting**	314	.871	.000
15	**P2CubicSpline4DPts.**	190	.918	.000
16	**P2SubgSubsMean**	177	.843	.000
17	**P2SubgSubsMed.**	197	.848	.000
18	**P2SubgSubsMax.**	253	.854	.000
19	**P2SubgSubsMin.**	119	.183	.046

Table B50. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Middle Age (1999-2004) for Two Years Missing Data points Case (2).

Pair	Do Nothing	Valid	Correlation	Significance
1	**Mean Nearby Points**	1014	.964	.000
2	**Med. Nearby Pts.**	1039	.966	.000
3	**Linear Interpolation**	1039	.966	.000
4	**Linear Trend Pts.**	963	.941	.000
5	**Moving Average**	1056	.966	.000
6	**Cubic Spline Fitting**	1049	.969	.000
7	**Cubic Spline4 D. Pts.**	1053	.963	.000
8	**Sub. Subs. Mean**	1052	.967	.000
9	**Sub. Subs. Med.**	1080	.968	.000
10	**Sub. Subs. Max.**	1078	.965	.000
11	**Sub. Subs. Min.**	1044	.966	.000
12	**P2LinearTrendatPts.**	694	.635	.000
13	**P2MovingAverage**	720	.801	.000
14	**P2CubicSplineFitting**	902	.744	.000
15	**P2CubicSpline4DPts.**	655	.817	.000
16	**P2SubgSubsMean**	560	.666	.000
17	**P2SubgSubsMed.**	605	.663	.000
18	**P2SubgSubsMax.**	725	.779	.000
19	**P2SubgSubsMin.**	337	.250	.000

Table B51. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Late Age (2005-2010) for Two Years Missing Data Points Case (2).

Pair	Do Nothing	Valid	Correlation	Significance
1	**Mean Nearby Points**	60	.980	.000
2	**Med. Nearby Pts.**	63	.986	.000
3	**Linear Interpolation**	63	.986	.000
4	**Linear Trend Pts.**	54	.922	.000
5	**Moving Average**	73	.971	.000
6	**Cubic Spline Fitting**	58	.992	.000
7	**Cubic Spline4 D. Pts.**	61	.980	.000
8	**Sub. Subs. Mean**	66	.978	.000
9	**Sub. Subs. Med.**	68	.961	.000
10	**Sub. Subs. Max.**	68	.962	.000
11	**Sub. Subs. Min.**	69	.971	.000
12	**P2LinearTrendatPts.**	46	.772	.000
13	**P2MovingAverage**	44	.902	.000
14	**P2CubicSplineFitting**	59	.882	.000
15	**P2CubicSpline4DPts.**	42	.914	.000
16	**P2SubgSubsMean**	31	.672	.000
17	**P2SubgSubsMed.**	28	.709	.000
18	**P2SubgSubsMax.**	35	.958	.000
19	**P2SubgSubsMin.**	14	-.187	.521

Table B52. Paired Samples T-Tests Correlations of Predicted Distress Scores for Three Years Missing Data Points Case (3).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	5877	.969	.000
2	Med. Nearby Pts.	6029	.979	.000
3	Linear Interpolation	6029	.979	.000
4	Linear Trend Pts.	5625	.949	.000
5	Moving Average	6327	.977	.000
6	Cubic Spline Fitting	6054	.971	.000
7	Cubic Spline4 D. Pts.	5988	.975	.000
8	Sub. Subs. Mean	6196	.980	.000
9	Sub. Subs. Med.	6226	.980	.000
10	Sub. Subs. Max.	6451	.979	.000
11	Sub. Subs. Min.	6121	.977	.000
12	P2LinearTrendatPts.	3936	.668	.000
13	P2MovingAverage	4351	.860	.000
14	P2CubicSplineFitting	5187	.793	.000
15	P2CubicSpline4DPts.	3679	.845	.000
16	P2SubgSubsMean	3616	.749	.000
17	P2SubgSubsMed.	3661	.735	.000
18	P2SubgSubsMax.	4513	.819	.000
19	P2SubgSubsMin.	2106	.018	.398

Table B53. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Very Good (90-100) Three Years Missing Data Points Case (3).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	4501	.958	.000
2	Med. Nearby Pts.	4599	.971	.000
3	Linear Interpolation	4599	.971	.000
4	Linear Trend Pts.	4281	.933	.000
5	Moving Average	4705	.970	.000
6	Cubic Spline Fitting	4629	.961	.000
7	Cubic Spline4 D. Pts.	4600	.967	.000
8	Sub. Subs. Mean	4695	.974	.000
9	Sub. Subs. Med.	4694	.972	.000
10	Sub. Subs. Max.	4795	.971	.000
11	Sub. Subs. Min.	4602	.969	.000
12	P2LinearTrendatPts.	3113	.510	.000
13	P2MovingAverage	3261	.781	.000
14	P2CubicSplineFitting	3905	.671	.000
15	P2CubicSpline4DPts.	2863	.826	.000
16	P2SubgSubsMean	2654	.637	.000
17	P2SubgSubsMed.	2731	.635	.000
18	P2SubgSubsMax.	3321	.747	.000
19	P2SubgSubsMin.	1457	.040	.124

Table B54. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Good (80-89) Three Years Missing Data Points Case (3).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	3	1.000	.016
2	Med. Nearby Pts.	4	.999	.001
3	Linear Interpolation	4	.999	.001
4	Linear Trend Pts.	4	1.000	.000
5	Moving Average	3	1.000	.006
6	Cubic Spline Fitting	3	1.000	.005
7	Cubic Spline4 D. Pts.	4	.998	.002
8	Sub. Subs. Mean	4	.998	.002
9	Sub. Subs. Med.	4	.997	.003
10	Sub. Subs. Max.	4	.996	.004
11	Sub. Subs. Min.	3	1.000	.013
12	P2LinearTrendatPts.	3	1.000	.008
13	P2MovingAverage	3	1.000	.015
14	P2CubicSplineFitting	3	.998	.040
15	P2CubicSpline4DPts.	3	1.000	.012
16	P2SubgSubsMean	4	.909	.091
17	P2SubgSubsMed.	4	.890	.110
18	P2SubgSubsMax.	3	1.000	.015
19	P2SubgSubsMin.			

Table B55. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Fair (70-79) Three Years Missing Data Points Case (3).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points			
2	Med. Nearby Pts.			
3	Linear Interpolation			
4	Linear Trend Pts.			
5	Moving Average			
6	Cubic Spline Fitting			
7	Cubic Spline4 D. Pts.			
8	Sub. Subs. Mean			
9	Sub. Subs. Med.			
10	Sub. Subs. Max.			
11	Sub. Subs. Min.			
12	P2LinearTrendatPts.			
13	P2MovingAverage			
14	P2CubicSplineFitting			
15	P2CubicSpline4DPts.			
16	P2SubgSubsMean			
17	P2SubgSubsMed.			
18	P2SubgSubsMax.			
19	P2SubgSubsMin.			

Table B56. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Poor (60-69) Three Years Missing Data Points Case (3).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points			
2	Med. Nearby Pts.			
3	Linear Interpolation			
4	Linear Trend Pts.			
5	Moving Average			
6	Cubic Spline Fitting			
7	Cubic Spline4 D. Pts.			
8	Sub. Subs. Mean			
9	Sub. Subs. Med.			
10	Sub. Subs. Max.			
11	Sub. Subs. Min.			
12	P2LinearTrendatPts.			
13	P2MovingAverage			
14	P2CubicSplineFitting			
15	P2CubicSpline4DPts.			
16	P2SubgSubsMean			
17	P2SubgSubsMed.			
18	P2SubgSubsMax.			
19	P2SubgSubsMin.			

Table B57. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Very Poor (1-59) Three Years Missing Data Points Case (3).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	29	.928	.000
2	Med. Nearby Pts.	29	.910	.000
3	Linear Interpolation	29	.910	.000
4	Linear Trend Pts.	29	.916	.000
5	Moving Average	35	.836	.000
6	Cubic Spline Fitting	29	.919	.000
7	Cubic Spline4 D. Pts.	29	.835	.000
8	Sub. Subs. Mean	31	.880	.000
9	Sub. Subs. Med.	32	.801	.000
10	Sub. Subs. Max.	30	.814	.000
11	Sub. Subs. Min.	31	.805	.000
12	P2LinearTrendatPts.	28	.900	.000
13	P2MovingAverage	28	.886	.000
14	P2CubicSplineFitting	30	.824	.000
15	P2CubicSpline4DPts.	28	.717	.000
16	P2SubgSubsMean	29	.869	.000
17	P2SubgSubsMed.	29	.818	.000
18	P2SubgSubsMax.	29	.794	.000
19	P2SubgSubsMin.	29	-.458	.012

Table B58. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Age (1993-2010) for Three Years Missing Data Points Case (3).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	5877	.969	.000
2	Med. Nearby Pts.	6029	.979	.000
3	Linear Interpolation	6029	.979	.000
4	Linear Trend Pts.	5625	.949	.000
5	Moving Average	6327	.977	.000
6	Cubic Spline Fitting	6054	.971	.000
7	Cubic Spline4 D. Pts.	5988	.975	.000
8	Sub. Subs. Mean	6196	.980	.000
9	Sub. Subs. Med.	6226	.980	.000
10	Sub. Subs. Max.	6451	.979	.000
11	Sub. Subs. Min.	6121	.977	.000
12	P2LinearTrendatPts.	3936	.668	.000
13	P2MovingAverage	4351	.860	.000
14	P2CubicSplineFitting	5187	.793	.000
15	P2CubicSpline4DPts.	3679	.845	.000
16	P2SubgSubsMean	3616	.749	.000
17	P2SubgSubsMed.	3661	.735	.000
18	P2SubgSubsMax.	4513	.819	.000
19	P2SubgSubsMin.	2106	.018	.398

Table B59. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Early Age (1993-1998) for Three Years Missing Data Points Case (3).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	162	.998	.000
2	Med. Nearby Pts.	166	.999	.000
3	Linear Interpolation	166	.999	.000
4	Linear Trend Pts.	158	.993	.000
5	Moving Average	164	.999	.000
6	Cubic Spline Fitting	166	.999	.000
7	Cubic Spline4 D. Pts.	164	.999	.000
8	Sub. Subs. Mean	166	.999	.000
9	Sub. Subs. Med.	165	.999	.000
10	Sub. Subs. Max.	165	.999	.000
11	Sub. Subs. Min.	167	.999	.000
12	P2LinearTrendatPts.	93	.875	.000
13	P2MovingAverage	117	.977	.000
14	P2CubicSplineFitting	131	.920	.000
15	P2CubicSpline4DPts.	86	.955	.000
16	P2SubgSubsMean	87	.900	.000
17	P2SubgSubsMed.	89	.876	.000
18	P2SubgSubsMax.	115	.900	.000
19	P2SubgSubsMin.	51	.130	.364

Table B60. Paired Samples T-Tests Correlations of Predicted Distress Scores According to Middle Age (1999-2004) for Three Years Missing Data points Case (3).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	1033	.951	.000
2	Med. Nearby Pts.	1064	.969	.000
3	Linear Interpolation	1064	.969	.000
4	Linear Trend Pts.	963	.928	.000
5	Moving Average	1116	.969	.000
6	Cubic Spline Fitting	1084	.949	.000
7	Cubic Spline4 D. Pts.	1091	.952	.000
8	Sub. Subs. Mean	1106	.970	.000
9	Sub. Subs. Med.	1121	.970	.000
10	Sub. Subs. Max.	1154	.970	.000
11	Sub. Subs. Min.	1082	.968	.000
12	P2LinearTrendatPts.	788	.659	.000
13	P2MovingAverage	796	.794	.000
14	P2CubicSplineFitting	954	.744	.000
15	P2CubicSpline4DPts.	748	.819	.000
16	P2SubgSubsMean	657	.648	.000
17	P2SubgSubsMed.	690	.646	.000
18	P2SubgSubsMax.	846	.750	.000
19	P2SubgSubsMin.	367	.142	.006

Table B61. Paired Samples T-Tests Statistics of Predicted Distress Scores According to Late Age (2005-2010) for Three Years Missing Data Points Case (3).

Pair	Do Nothing	Valid	Correlation	Significance
1	Mean Nearby Points	20	.962	.000
2	Med. Nearby Pts.	21	.975	.000
3	Linear Interpolation	21	.975	.000
4	Linear Trend Pts.	20	.932	.000
5	Moving Average	27	.965	.000
6	Cubic Spline Fitting	21	.984	.000
7	Cubic Spline4 D. Pts.	23	.974	.000
8	Sub. Subs. Mean	23	.988	.000
9	Sub. Subs. Med.	23	.972	.000
10	Sub. Subs. Max.	24	.955	.000
11	Sub. Subs. Min.	23	.980	.000
12	P2LinearTrendatPts.	20	.888	.000
13	P2MovingAverage	19	.937	.000
14	P2CubicSplineFitting	22	.899	.000
15	P2CubicSpline4DPts.	19	.959	.000
16	P2SubgSubsMean	13	.883	.000
17	P2SubgSubsMed.	9	.860	.003
18	P2SubgSubsMax.	15	.979	.000
19	P2SubgSubsMin.	3	.972	.151

Table B62. Paired Samples T-Tests of Predicted Distress Scores for One Year Missing Data point Case (1).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	.19	3.65	.11	-.02	.40	1.74	1115	.081
2	Med. Nearby Pts.	.37	3.57	.11	.16	.58	3.43	1123	.001
3	Linear Interpolation	.37	3.57	.11	.16	.58	3.43	1123	.001
4	Linear Trend Pts.	.04	4.45	.13	-.22	.31	.31	1085	.760
5	Moving Average	.21	3.70	.11	.00	.43	1.92	1142	.055
6	Cubic Spline Fitting	.32	3.06	.09	.14	.50	3.52	1121	.000
7	Cubic Spline4 D. Pts.	.30	3.35	.10	.10	.49	2.99	1121	.003
8	Sub. Subs. Mean	.40	3.53	.10	.20	.61	3.83	1133	.000
9	Sub. Subs. Med.	.39	3.64	.11	.18	.60	3.60	1132	.000
10	Sub. Subs. Max.	.45	3.73	.11	.23	.67	4.06	1141	.000
11	Sub. Subs. Min.	.26	3.67	.11	.04	.47	2.36	1135	.018
12	P2LinearTrendatPts.	-6.52	13.50	.53	-7.56	-5.48	-12.33	651	.000
13	P2MovingAverage	-2.88	8.64	.26	-3.38	-2.38	-11.29	1145	.000
14	P2CubicSplineFitting	-2.77	10.78	.36	-3.48	-2.05	-7.62	882	.000
15	P2CubicSpline4DPts.	3.76	11.44	.44	2.90	4.62	8.59	680	.000
16	P2SubgSubsMean	15.02	14.36	.60	13.84	16.21	24.89	565	.000
17	P2SubgSubsMed.	12.17	13.51	.54	11.11	13.22	22.65	631	.000
18	P2SubgSubsMax.	-.85	9.74	.30	-1.45	-.26	-2.82	1031	.005
19	P2SubgSubsMin.	35.83	29.82	1.54	32.80	38.87	23.21	372	.000

Table B63. Paired Samples T-Tests of Predicted Distress Scores According to Very Good (90-100) One Year Missing Data point Case (1).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	-.01	3.66	.12	-.24	.23	-.05	934	.962
2	Med. Nearby Pts.	.20	3.62	.12	-.04	.43	1.66	941	.098
3	Linear Interpolation	.20	3.62	.12	-.04	.43	1.66	941	.098
4	Linear Trend Pts.	-.16	4.55	.15	-.46	.13	-1.09	909	.275
5	Moving Average	.12	3.68	.12	-.11	.35	1.00	959	.319
6	Cubic Spline Fitting	.10	3.00	.10	-.10	.29	.98	939	.327
7	Cubic Spline4 D. Pts.	.11	3.35	.11	-.11	.32	.97	943	.331
8	Sub. Subs. Mean	.21	3.58	.12	-.02	.44	1.81	952	.071
9	Sub. Subs. Med.	.20	3.70	.12	-.03	.44	1.69	955	.092
10	Sub. Subs. Max.	.21	3.75	.12	-.03	.45	1.73	956	.083
11	Sub. Subs. Min.	.15	3.66	.12	-.08	.38	1.25	951	.211
12	P2LinearTrendatPts.	-7.83	13.69	.58	-8.97	-6.69	-13.54	559	.000
13	P2MovingAverage	-3.40	9.09	.29	-3.98	-2.82	-11.54	951	.000
14	P2CubicSplineFitting	-3.52	11.46	.42	-4.35	-2.69	-8.34	736	.000
15	P2CubicSpline4DPts.	3.57	10.99	.45	2.68	4.45	7.92	594	.000
16	P2SubgSubsMean	15.79	14.88	.68	14.45	17.13	23.18	476	.000
17	P2SubgSubsMed.	12.57	13.96	.60	11.39	13.75	20.87	536	.000
18	P2SubgSubsMax.	-1.38	10.12	.34	-2.05	-.70	-4.00	863	.000
19	P2SubgSubsMin.	39.84	30.77	1.77	36.36	43.31	22.53	302	.000

Table B64. Paired Samples T-Tests of Predicted Distress Scores According to Good (80-89) One Year Missing Data point Case (1).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	.27	2.69	.34	-.41	.94	.78	62	.437
2	Med. Nearby Pts.	.27	2.61	.33	-.38	.93	.84	63	.405
3	Linear Interpolation	.27	2.61	.33	-.38	.93	.84	63	.405
4	Linear Trend Pts.	-.15	3.11	.40	-.95	.65	-.38	60	.707
5	Moving Average	-.20	3.13	.40	-1.01	.60	-.51	60	.614
6	Cubic Spline Fitting	.39	2.39	.30	-.21	.99	1.29	62	.200
7	Cubic Spline4 D. Pts.	.18	2.39	.30	-.42	.78	.60	63	.550
8	Sub. Subs. Mean	.42	2.56	.33	-.24	1.08	1.26	59	.212
9	Sub. Subs. Med.	.39	2.36	.31	-.22	1.01	1.28	58	.204
10	Sub. Subs. Max.	.88	3.27	.42	.05	1.71	2.12	61	.038
11	Sub. Subs. Min.	-.12	2.90	.37	-.85	.61	-.32	62	.749
12	P2LinearTrendatPts.	-1.54	6.29	1.15	-3.89	.81	-1.34	29	.191
13	P2MovingAverage	-1.80	6.48	.80	-3.40	-.19	-2.24	64	.029
14	P2CubicSplineFitting	-.41	3.12	.44	-1.29	.48	-.93	49	.359
15	P2CubicSpline4DPts.	-.95	8.19	1.49	-4.00	2.11	-.63	29	.531
16	P2SubgSubsMean	13.01	14.06	3.07	6.61	19.40	4.24	20	.000
17	P2SubgSubsMed.	11.85	15.04	3.21	5.18	18.51	3.70	21	.001
18	P2SubgSubsMax.	-.35	7.05	.93	-2.22	1.52	-.37	56	.711
19	P2SubgSubsMin.	21.60	18.34	5.30	9.95	33.26	4.08	11	.002

Table B65. Paired Samples T-Tests of Predicted Distress Scores According to Fair (70-79) One Year Missing Data point Case (1).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	**Mean Nearby Points**	.47	3.50	.50	-.55	1.48	.93	47	.359
2	**Med. Nearby Pts.**	.75	2.76	.39	-.03	1.53	1.92	49	.060
3	**Linear Interpolation**	.75	2.76	.39	-.03	1.53	1.92	49	.060
4	**Linear Trend Pts.**	.48	3.73	.54	-.61	1.56	.88	47	.382
5	**Moving Average**	-.03	3.97	.54	-1.12	1.07	-.05	52	.960
6	**Cubic Spline Fitting**	1.17	2.72	.38	.41	1.94	3.08	50	.003
7	**Cubic Spline4 D. Pts.**	1.05	2.68	.38	.29	1.81	2.77	49	.008
8	**Sub. Subs. Mean**	1.02	2.53	.35	.31	1.72	2.90	51	.006
9	**Sub. Subs. Med.**	.94	2.44	.35	.24	1.63	2.71	49	.009
10	**Sub. Subs. Max.**	1.11	2.59	.36	.38	1.84	3.07	50	.003
11	**Sub. Subs. Min.**	.09	3.94	.55	-1.01	1.18	.16	51	.874
12	**P2LinearTrendatPts.**	-1.95	8.08	1.53	-5.09	1.18	-1.28	27	.212
13	**P2MovingAverage**	-.80	4.30	.57	-1.95	.35	-1.40	55	.168
14	**P2CubicSplineFitting**	.49	5.67	.87	-1.25	2.24	.57	42	.572
15	**P2CubicSpline4DPts.**	4.53	18.14	3.63	-2.96	12.01	1.25	24	.224
16	**P2SubgSubsMean**	14.94	8.24	1.68	11.46	18.42	8.89	23	.000
17	**P2SubgSubsMed.**	13.61	8.95	1.75	10.00	17.22	7.76	25	.000
18	**P2SubgSubsMax.**	1.28	5.64	.80	-.32	2.88	1.60	49	.116
19	**P2SubgSubsMin.**	30.02	17.32	4.20	21.12	38.93	7.15	16	.000

Table B66. Paired Samples T-Tests of Predicted Distress Scores According to Poor (60-69) One Year Missing Data point Case (1).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	1.49	2.63	.54	.37	2.60	2.77	23	.011
2	Med. Nearby Pts.	1.53	2.54	.52	.46	2.60	2.95	23	.007
3	Linear Interpolation	1.53	2.54	.52	.46	2.60	2.95	23	.007
4	Linear Trend Pts.	1.43	2.78	.57	.25	2.60	2.51	23	.019
5	Moving Average	.81	3.40	.73	-.70	2.32	1.11	21	.279
6	Cubic Spline Fitting	1.63	2.52	.52	.56	2.69	3.16	23	.004
7	Cubic Spline4 D. Pts.	1.51	2.63	.54	.40	2.63	2.82	23	.010
8	Sub. Subs. Mean	1.53	2.50	.50	.50	2.56	3.06	24	.005
9	Sub. Subs. Med.	1.49	2.73	.55	.36	2.62	2.73	24	.012
10	Sub. Subs. Max.	1.66	2.64	.53	.57	2.75	3.13	24	.004
11	Sub. Subs. Min.	1.22	2.82	.59	.01	2.44	2.09	22	.049
12	P2LinearTrendatPts.	3.31	10.25	2.96	-3.20	9.82	1.12	11	.287
13	P2MovingAverage	.02	4.05	.83	-1.69	1.73	.03	23	.980
14	P2CubicSplineFitting	1.31	4.40	1.04	-.87	3.50	1.27	17	.222
15	P2CubicSpline4DPts.	4.31	9.87	4.03	-6.04	14.67	1.07	5	.333
16	P2SubgSubsMean	5.62	8.60	3.04	-1.57	12.81	1.85	7	.107
17	P2SubgSubsMed.	5.82	8.40	2.66	-.19	11.83	2.19	9	.056
18	P2SubgSubsMax.	3.71	8.31	1.86	-.18	7.60	2.00	19	.060
19	P2SubgSubsMin.	13.27	17.28	6.53	-2.71	29.25	2.03	6	.088

Table B67. Paired Samples T-Tests of Predicted Distress Scores According to Very Poor (1-59) One Year Missing Data point Case (1).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	3.18	3.87	.56	2.04	4.31	5.63	46	.000
2	Med. Nearby Pts.	3.15	3.87	.58	1.99	4.31	5.46	44	.000
3	Linear Interpolation	3.15	3.87	.58	1.99	4.31	5.46	44	.000
4	Linear Trend Pts.	3.47	3.93	.59	2.28	4.67	5.85	43	.000
5	Moving Average	2.69	3.95	.57	1.54	3.84	4.71	47	.000
6	Cubic Spline Fitting	3.43	3.89	.58	2.26	4.60	5.90	44	.000
7	Cubic Spline4 D. Pts.	3.43	3.90	.61	2.20	4.66	5.63	40	.000
8	Sub. Subs. Mean	3.23	3.90	.58	2.06	4.41	5.56	44	.000
9	Sub. Subs. Med.	3.34	3.95	.59	2.14	4.54	5.62	43	.000
10	Sub. Subs. Max.	3.43	4.04	.58	2.25	4.60	5.87	47	.000
11	Sub. Subs. Min.	2.80	3.97	.58	1.64	3.97	4.84	46	.000
12	P2LinearTrendatPts.	9.19	7.23	1.51	6.06	12.32	6.10	22	.000
13	P2MovingAverage	2.01	4.58	.65	.71	3.31	3.10	49	.003
14	P2CubicSplineFitting	3.70	5.18	.86	1.95	5.45	4.29	35	.000
15	P2CubicSpline4DPts.	13.15	12.90	2.58	7.83	18.48	5.10	24	.000
16	P2SubgSubsMean	8.33	8.01	1.32	5.66	11.00	6.32	36	.000
17	P2SubgSubsMed.	7.42	7.20	1.17	5.06	9.79	6.36	37	.000
18	P2SubgSubsMax.	4.93	6.35	.98	2.95	6.91	5.03	41	.000
19	P2SubgSubsMin.	12.80	11.90	2.01	8.71	16.88	6.36	34	.000

Table B68. Paired Samples T-Tests of Predicted Distress Scores According Age (1993-2010) for One Year Missing Data point Case (1).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	.19	3.65	.11	-.02	.40	1.74	1115	.081
2	Med. Nearby Pts.	.37	3.57	.11	.16	.58	3.43	1123	.001
3	Linear Interpolation	.37	3.57	.11	.16	.58	3.43	1123	.001
4	Linear Trend Pts.	.04	4.45	.13	-.22	.31	.31	1085	.760
5	Moving Average	.21	3.70	.11	.00	.43	1.92	1142	.055
6	Cubic Spline Fitting	.32	3.06	.09	.14	.50	3.52	1121	.000
7	Cubic Spline4 D. Pts.	.30	3.35	.10	.10	.49	2.99	1121	.003
8	Sub. Subs. Mean	.40	3.53	.10	.20	.61	3.83	1133	.000
9	Sub. Subs. Med.	.39	3.64	.11	.18	.60	3.60	1132	.000
10	Sub. Subs. Max.	.45	3.73	.11	.23	.67	4.06	1141	.000
11	Sub. Subs. Min.	.26	3.67	.11	.04	.47	2.36	1135	.018
12	P2LinearTrendatPts.	-6.52	13.50	.53	-7.56	-5.48	-12.33	651	.000
13	P2MovingAverage	-2.88	8.64	.26	-3.38	-2.38	-11.29	1145	.000
14	P2CubicSplineFitting	-2.77	10.78	.36	-3.48	-2.05	-7.62	882	.000
15	P2CubicSpline4DPts.	3.76	11.44	.44	2.90	4.62	8.59	680	.000
16	P2SubgSubsMean	15.02	14.36	.60	13.84	16.21	24.89	565	.000
17	P2SubgSubsMed.	12.17	13.51	.54	11.11	13.22	22.65	631	.000
18	P2SubgSubsMax.	-.85	9.74	.30	-1.45	-.26	-2.82	1031	.005
19	P2SubgSubsMin.	35.83	29.82	1.54	32.80	38.87	23.21	372	.000

Table B69. Paired Samples T-Tests of Predicted Distress Scores According to Early Age (1993-1998) for One Year Missing Data point Case (1).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	.10	2.27	.11	-.12	.33	.89	392	.373
2	Med. Nearby Pts.	.10	2.27	.11	-.13	.32	.86	391	.392
3	Linear Interpolation	.10	2.27	.11	-.13	.32	.86	391	.392
4	Linear Trend Pts.	.23	2.64	.13	-.04	.49	1.70	382	.089
5	Moving Average	.09	2.28	.12	-.14	.32	.76	389	.447
6	Cubic Spline Fitting	.08	2.23	.11	-.15	.30	.67	391	.502
7	Cubic Spline4 D. Pts.	.08	2.28	.11	-.15	.31	.69	391	.490
8	Sub. Subs. Mean	.10	2.28	.12	-.13	.33	.87	390	.384
9	Sub. Subs. Med.	.09	2.28	.12	-.14	.31	.75	388	.453
10	Sub. Subs. Max.	.09	2.28	.12	-.14	.32	.77	388	.440
11	Sub. Subs. Min.	.10	2.28	.12	-.12	.33	.89	388	.375
12	P2LinearTrendatPts.	-6.68	13.79	.95	-8.55	-4.80	-7.02	209	.000
13	P2MovingAverage	-2.69	8.58	.44	-3.55	-1.83	-6.13	382	.000
14	P2CubicSplineFitting	-2.46	11.02	.64	-3.72	-1.20	-3.83	294	.000
15	P2CubicSpline4DPts.	4.65	11.31	.76	3.16	6.14	6.14	222	.000
16	P2SubgSubsMean	14.35	14.44	1.03	12.31	16.39	13.88	194	.000
17	P2SubgSubsMed.	12.07	13.44	.91	10.28	13.87	13.23	216	.000
18	P2SubgSubsMax.	-.48	9.77	.52	-1.50	.55	-.91	351	.361
19	P2SubgSubsMin.	32.53	30.00	2.50	27.59	37.48	13.01	143	.000

Table B70. Paired Samples T-Tests of Predicted Distress Scores According to Middle Age (1999-2004) for One Year Missing Data point Case (1).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	.35	4.23	.17	.02	.69	2.07	607	.039
2	Med. Nearby Pts.	.53	4.10	.17	.21	.86	3.24	615	.001
3	Linear Interpolation	.53	4.10	.17	.21	.86	3.24	615	.001
4	Linear Trend Pts.	.06	4.86	.20	-.33	.46	.32	590	.749
5	Moving Average	.32	4.29	.17	-.01	.66	1.88	630	.061
6	Cubic Spline Fitting	.43	3.11	.13	.19	.68	3.45	617	.001
7	Cubic Spline4 D. Pts.	.43	3.90	.16	.12	.73	2.71	616	.007
8	Sub. Subs. Mean	.54	4.07	.16	.22	.86	3.32	627	.001
9	Sub. Subs. Med.	.52	4.13	.16	.19	.84	3.13	627	.002
10	Sub. Subs. Max.	.61	4.24	.17	.28	.94	3.62	632	.000
11	Sub. Subs. Min.	.36	4.26	.17	.03	.69	2.11	625	.035
12	P2LinearTrendatPts.	-6.51	13.52	.71	-7.90	-5.12	-9.22	366	.000
13	P2MovingAverage	-3.04	8.79	.35	-3.73	-2.36	-8.73	634	.000
14	P2CubicSplineFitting	-2.92	10.80	.49	-3.88	-1.96	-5.99	491	.000
15	P2CubicSpline4DPts.	4.02	11.60	.59	2.86	5.17	6.83	388	.000
16	P2SubgSubsMean	15.11	14.39	.81	13.50	16.71	18.57	312	.000
17	P2SubgSubsMed.	12.02	13.62	.72	10.60	13.45	16.61	353	.000
18	P2SubgSubsMax.	-1.08	9.91	.42	-1.90	-.26	-2.60	566	.010
19	P2SubgSubsMin.	36.87	29.15	2.08	32.76	40.98	17.71	195	.000

Table B71. Paired Samples T-Tests of Predicted Distress Scores According to Late Age (2005-2010) for One Year Missing Data point Case (1).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	-.37	4.08	.38	-1.13	.38	-.98	114	.329
2	Med. Nearby Pts.	.37	4.10	.38	-.38	1.13	.98	115	.328
3	Linear Interpolation	.37	4.10	.38	-.38	1.13	.98	115	.328
4	Linear Trend Pts.	-.72	6.55	.62	-1.95	.50	-1.17	111	.245
5	Moving Average	.03	4.05	.37	-.70	.75	.07	121	.943
6	Cubic Spline Fitting	.58	4.80	.45	-.32	1.48	1.27	111	.206
7	Cubic Spline4 D. Pts.	.36	3.18	.30	-.23	.95	1.21	112	.231
8	Sub. Subs. Mean	.67	3.80	.35	-.03	1.37	1.89	114	.062
9	Sub. Subs. Med.	.72	4.37	.41	-.09	1.52	1.76	115	.081
10	Sub. Subs. Max.	.76	4.49	.41	-.06	1.57	1.84	119	.068
11	Sub. Subs. Min.	.22	3.97	.36	-.49	.94	.62	120	.540
12	P2LinearTrendatPts.	-6.10	12.67	1.46	-9.02	-3.19	-4.17	74	.000
13	P2MovingAverage	-2.67	8.14	.72	-4.09	-1.24	-3.71	127	.000
14	P2CubicSplineFitting	-2.93	10.01	1.02	-4.96	-.91	-2.87	95	.005
15	P2CubicSpline4DPts.	-.53	10.05	1.21	-2.94	1.89	-.43	68	.665
16	P2SubgSubsMean	74.47	21.66	2.92	68.62	80.32	25.50	54	.000
17	P2SubgSubsMed.	13.33	13.24	1.70	9.94	16.72	7.86	60	.000
18	P2SubgSubsMax.	-.89	8.74	.82	-2.52	.74	-1.08	112	.281
19	P2SubgSubsMin.	44.06	31.76	5.53	32.80	55.32	7.97	32	.000

Table B72. Paired Samples T-Tests of Predicted Distress Scores for Two Years Missing Data points Case (2).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	-.18	4.73	.08	-.34	-.02	-2.15	3235	.032
2	Med. Nearby Pts.	.12	4.41	.08	-.03	.27	1.58	3314	.115
3	Linear Interpolation	.12	4.41	.08	-.03	.27	1.58	3314	.115
4	Linear Trend Pts.	-.12	5.70	.10	-.32	.08	-1.18	3084	.239
5	Moving Average	-.08	4.53	.08	-.24	.07	-1.09	3384	.276
6	Cubic Spline Fitting	.06	4.06	.07	-.08	.20	.86	3297	.391
7	Cubic Spline4 D. Pts.	.00	4.60	.08	-.16	.16	.01	3309	.994
8	Sub. Subs. Mean	.18	4.34	.07	.04	.33	2.46	3382	.014
9	Sub. Subs. Med.	.15	4.44	.08	.00	.30	1.96	3398	.050
10	Sub. Subs. Max.	.26	4.55	.08	.10	.41	3.30	3441	.001
11	Sub. Subs. Min.	-.03	4.53	.08	-.19	.12	-.44	3348	.660
12	P2LinearTrendatPts.	-7.76	15.20	.33	-8.41	-7.12	-23.55	2123	.000
13	P2MovingAverage	-4.13	11.71	.25	-4.62	-3.65	-16.63	2219	.000
14	P2CubicSplineFitting	-3.30	12.60	.24	-3.76	-2.84	-13.98	2852	.000
15	P2CubicSpline4DPts.	2.37	12.95	.30	1.79	2.95	7.97	1894	.000
16	P2SubgSubsMean	15.95	15.54	.38	15.21	16.69	42.28	1697	.000
17	P2SubgSubsMed.	12.92	15.48	.37	12.21	13.64	35.35	1792	.000
18	P2SubgSubsMax.	-2.12	13.04	.28	-2.67	-1.58	-7.65	2205	.000
19	P2SubgSubsMin.	41.59	28.06	.87	39.87	43.30	47.55	1028	.000

Table B73. Paired Samples T-Tests of Predicted Distress Scores According to Very Good (90-100) Two Years Missing Data points Case (2).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	-.32	5.05	.10	-.52	-.13	-3.26	2561	.00
2	Med. Nearby Pts.	.08	4.77	.09	-.10	.26	.87	2608	.38
3	Linear Interpolation	.08	4.77	.09	-.10	.26	.87	2608	.38
4	Linear Trend Pts.	-.32	6.13	.12	-.56	-.08	-2.58	2427	.01
5	Moving Average	-.04	4.80	.09	-.23	.14	-.46	2643	.64
6	Cubic Spline Fitting	-.11	4.30	.08	-.27	.06	-1.27	2600	.21
7	Cubic Spline4 D. Pts.	-.09	4.97	.10	-.28	.10	-.89	2633	.37
8	Sub. Subs. Mean	.12	4.68	.09	-.06	.30	1.34	2663	.18
9	Sub. Subs. Med.	.10	4.81	.09	-.09	.28	1.04	2673	.30
10	Sub. Subs. Max.	.08	4.83	.09	-.10	.27	.90	2697	.37
11	Sub. Subs. Min.	-.01	4.80	.09	-.20	.17	-.13	2618	.90
12	P2LinearTrendatPts.	-9.28	16.29	.40	-10.06	-8.50	-23.40	1687	.00
13	P2MovingAverage	-4.80	12.72	.30	-5.39	-4.21	-16.00	1798	.00
14	P2CubicSplineFitting	-4.57	14.10	.31	-5.17	-3.97	-14.97	2135	.00
15	P2CubicSpline4DPts.	2.46	12.63	.32	1.84	3.09	7.72	1567	.00
16	P2SubgSubsMean	16.35	16.83	.46	15.45	17.25	35.67	1347	.00
17	P2SubgSubsMed.	12.79	16.57	.44	11.94	13.65	29.39	1449	.00
18	P2SubgSubsMax.	-3.05	14.00	.33	-3.70	-2.40	-9.21	1780	.00
19	P2SubgSubsMin.	46.27	28.93	1.02	44.26	48.28	45.14	796	.00

Table B74. Paired Samples T-Tests of Predicted Distress Scores According to Good (80-89) Two Years Missing Data points Case (2).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	-.41	1.41	.21	-.83	.01	-1.97	45	.05
2	Med. Nearby Pts.	-.72	1.73	.25	-1.23	-.21	-2.85	46	.01
3	Linear Interpolation	-.72	1.73	.25	-1.23	-.21	-2.85	46	.01
4	Linear Trend Pts.	-.45	1.36	.19	-.83	-.06	-2.33	49	.02
5	Moving Average	-.12	1.37	.21	-.55	.31	-.57	41	.57
6	Cubic Spline Fitting	-.48	1.86	.26	-1.01	.05	-1.83	49	.07
7	Cubic Spline4 D. Pts.	-.72	1.98	.31	-1.35	-.10	-2.34	40	.02
8	Sub. Subs. Mean	-.28	1.57	.23	-.75	.19	-1.20	44	.24
9	Sub. Subs. Med.	-.29	1.48	.23	-.75	.17	-1.26	41	.21
10	Sub. Subs. Max.	-.38	2.68	.40	-1.19	.44	-.94	43	.35
11	Sub. Subs. Min.	-.06	1.24	.19	-.45	.33	-.30	40	.76
12	P2LinearTrendatPts.	.08	2.82	.50	-.94	1.09	.16	31	.87
13	P2MovingAverage	-1.54	1.66	.55	-2.81	-.26	-2.77	8	.02
14	P2CubicSplineFitting	-.27	1.69	.22	-.71	.16	-1.27	60	.21
15	P2CubicSpline4DPts.	-.07	5.53	1.53	-3.41	3.27	-.05	12	.96
16	P2SubgSubsMean	9.90	12.92	3.58	2.09	17.71	2.76	12	.02
17	P2SubgSubsMed.	6.88	11.91	3.18	.00	13.76	2.16	13	.05
18	P2SubgSubsMax.	-3.39	9.59	3.03	-10.25	3.47	-1.12	9	.29
19	P2SubgSubsMin.	11.70	15.88	7.10	-8.02	31.42	1.65	4	.17

Table B75. Paired Samples T-Tests of Predicted Distress Scores According to Fair (70-79) Two Years Missing Data points Case (2).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	2.48	5.77	1.49	-.71	5.67	1.67	14	.12
2	Med. Nearby Pts.	2.37	5.73	1.48	-.81	5.54	1.60	14	.13
3	Linear Interpolation	2.37	5.73	1.48	-.81	5.54	1.60	14	.13
4	Linear Trend Pts.	2.78	6.10	1.69	-.91	6.47	1.64	12	.13
5	Moving Average	3.31	6.83	1.76	-.47	7.09	1.88	14	.08
6	Cubic Spline Fitting	2.61	6.05	1.62	-.88	6.10	1.61	13	.13
7	Cubic Spline4 D. Pts.	2.32	5.74	1.48	-.86	5.50	1.57	14	.14
8	Sub. Subs. Mean	1.56	4.72	1.26	-1.16	4.29	1.24	13	.24
9	Sub. Subs. Med.	1.75	4.98	1.38	-1.26	4.76	1.27	12	.23
10	Sub. Subs. Max.	1.73	4.77	1.27	-1.02	4.48	1.36	13	.20
11	Sub. Subs. Min.	2.62	6.22	1.72	-1.13	6.38	1.52	12	.15
12	P2LinearTrendatPts.	2.88	10.45	2.90	-3.43	9.20	.99	12	.34
13	P2MovingAverage	-1.86	2.53	1.03	-4.52	.80	-1.80	5	.13
14	P2CubicSplineFitting	2.35	6.28	1.57	-.99	5.70	1.50	15	.15
15	P2CubicSpline4DPts.	5.96	9.83	2.63	.28	11.64	2.27	13	.04
16	P2SubgSubsMean	19.48	9.42	3.14	12.24	26.72	6.20	8	.00
17	P2SubgSubsMed.	18.28	10.36	3.45	10.32	26.24	5.29	8	.00
18	P2SubgSubsMax.	3.64	3.68	1.50	-.23	7.50	2.42	5	.06
19	P2SubgSubsMin.	30.29	12.11	4.94	17.58	43.00	6.13	5	.00

Table B76. Paired Samples T-Tests of Predicted Distress Scores According to Poor (60-69) Two Years Missing Data points Case (2).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	3.34	2.98	1.33	-.36	7.03	2.51	4	.07
2	Med. Nearby Pts.	2.53	3.37	1.51	-1.66	6.71	1.68	4	.17
3	Linear Interpolation	2.53	3.37	1.51	-1.66	6.71	1.68	4	.17
4	Linear Trend Pts.	2.83	3.27	1.46	-1.23	6.89	1.93	4	.13
5	Moving Average	1.20	3.80	1.44	-2.32	4.72	.83	6	.44
6	Cubic Spline Fitting	2.56	3.48	1.56	-1.76	6.89	1.64	4	.18
7	Cubic Spline4 D. Pts.	1.12	4.06	1.66	-3.14	5.38	.68	5	.53
8	Sub. Subs. Mean	2.79	2.94	1.20	-.30	5.88	2.32	5	.07
9	Sub. Subs. Med.	2.72	2.98	1.22	-.40	5.85	2.24	5	.08
10	Sub. Subs. Max.	3.23	3.04	1.36	-.55	7.00	2.37	4	.08
11	Sub. Subs. Min.	1.39	3.78	1.43	-2.10	4.89	.97	6	.37
12	P2LinearTrendatPts.	8.04	12.63	8.93	-105.47	121.56	.90	1	.53
13	P2MovingAverage	2.40	5.29	3.05	-10.73	15.53	.79	2	.51
14	P2CubicSplineFitting	.23	4.68	2.09	-5.58	6.03	.11	4	.92
15	P2CubicSpline4DPts.	4.38	5.83	4.12	-48.02	56.77	1.06	1	.48
16	P2SubgSubsMean								
17	P2SubgSubsMed.								
18	P2SubgSubsMax.								
19	P2SubgSubsMin.								

Table B77. Paired Samples T-Tests of Predicted Distress Scores According to Very Poor (1-59) Two Years Missing Data points Case (2).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	6.33	4.63	.86	4.57	8.09	7.37	28	.00
2	Med. Nearby Pts.	6.21	4.56	.83	4.51	7.91	7.46	29	.00
3	Linear Interpolation	6.21	4.56	.83	4.51	7.91	7.46	29	.00
4	Linear Trend Pts.	6.48	4.68	.88	4.67	8.30	7.33	27	.00
5	Moving Average	5.40	4.59	.76	3.84	6.95	7.05	35	.00
6	Cubic Spline Fitting	6.69	4.33	.82	5.01	8.37	8.18	27	.00
7	Cubic Spline4 D. Pts.	6.46	4.44	.82	4.77	8.15	7.83	28	.00
8	Sub. Subs. Mean	6.06	4.35	.77	4.49	7.63	7.89	31	.00
9	Sub. Subs. Med.	5.71	4.34	.73	4.22	7.20	7.78	34	.00
10	Sub. Subs. Max.	6.04	4.37	.77	4.46	7.61	7.82	31	.00
11	Sub. Subs. Min.	5.60	4.66	.80	3.97	7.22	7.00	33	.00
12	P2LinearTrendatPts.	12.67	5.48	1.04	10.55	14.80	12.24	27	.00
13	P2MovingAverage	7.77	3.67	.75	6.22	9.32	10.36	23	.00
14	P2CubicSplineFitting	4.81	5.17	.90	2.98	6.65	5.34	32	.00
15	P2CubicSpline4DPts.	16.88	12.79	2.42	11.92	21.85	6.98	27	.00
16	P2SubgSubsMean	14.76	4.33	.85	13.01	16.51	17.39	25	.00
17	P2SubgSubsMed.	12.74	3.83	.75	11.20	14.29	16.97	25	.00
18	P2SubgSubsMax.	10.51	4.57	.90	8.66	12.35	11.72	25	.00
19	P2SubgSubsMin.	21.62	8.42	1.68	18.14	25.09	12.84	24	.00

Table B78. Paired Samples T-Tests of Predicted Distress Scores According Age (1993-2010) for Two Years Missing Data points Case (2).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	-.18	4.73	.08	-.34	-.02	-2.15	3235	.032
2	Med. Nearby Pts.	.12	4.41	.08	-.03	.27	1.58	3314	.115
3	Linear Interpolation	.12	4.41	.08	-.03	.27	1.58	3314	.115
4	Linear Trend Pts.	-.12	5.70	.10	-.32	.08	-1.18	3084	.239
5	Moving Average	-.08	4.53	.08	-.24	.07	-1.09	3384	.276
6	Cubic Spline Fitting	.06	4.06	.07	-.08	.20	.86	3297	.391
7	Cubic Spline4 D. Pts.	.00	4.60	.08	-.16	.16	.01	3309	.994
8	Sub. Subs. Mean	.18	4.34	.07	.04	.33	2.46	3382	.014
9	Sub. Subs. Med.	.15	4.44	.08	.00	.30	1.96	3398	.050
10	Sub. Subs. Max.	.26	4.55	.08	.10	.41	3.30	3441	.001
11	Sub. Subs. Min.	-.03	4.53	.08	-.19	.12	-.44	3348	.660
12	P2LinearTrendatPts.	-7.76	15.20	.33	-8.41	-7.12	-23.55	2123	.000
13	P2MovingAverage	-4.13	11.71	.25	-4.62	-3.65	-16.63	2219	.000
14	P2CubicSplineFitting	-3.30	12.60	.24	-3.76	-2.84	-13.98	2852	.000
15	P2CubicSpline4DPts.	2.37	12.95	.30	1.79	2.95	7.97	1894	.000
16	P2SubgSubsMean	15.95	15.54	.38	15.21	16.69	42.28	1697	.000
17	P2SubgSubsMed.	12.92	15.48	.37	12.21	13.64	35.35	1792	.000
18	P2SubgSubsMax.	-2.12	13.04	.28	-2.67	-1.58	-7.65	2205	.000
19	P2SubgSubsMin.	41.59	28.06	.87	39.87	43.30	47.55	1028	.000

Table B79. Paired Samples T-Tests of Predicted Distress Scores According to Early Age (1993-1998) for Two Years Missing Data points Case (2).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	-.10	1.88	.10	-.29	.09	-1.05	389	.30
2	Med. Nearby Pts.	-.17	1.62	.08	-.33	-.01	-2.05	394	.04
3	Linear Interpolation	-.17	1.62	.08	-.33	-.01	-2.05	394	.04
4	Linear Trend Pts.	.29	2.37	.12	.05	.53	2.34	366	.02
5	Moving Average	-.19	1.63	.08	-.35	-.02	-2.25	386	.02
6	Cubic Spline Fitting	-.09	1.54	.08	-.25	.06	-1.15	381	.25
7	Cubic Spline4 D. Pts.	-.20	1.62	.08	-.36	-.04	-2.41	391	.02
8	Sub. Subs. Mean	-.18	1.64	.08	-.34	-.02	-2.17	390	.03
9	Sub. Subs. Med.	-.21	1.59	.08	-.37	-.05	-2.62	390	.01
10	Sub. Subs. Max.	-.20	1.57	.08	-.36	-.05	-2.53	390	.01
11	Sub. Subs. Min.	-.18	1.61	.08	-.34	-.02	-2.17	391	.03
12	P2LinearTrendatPts.	-7.00	14.89	1.01	-8.99	-5.01	-6.93	216	.00
13	P2MovingAverage	-3.30	9.78	.62	-4.52	-2.07	-5.31	247	.00
14	P2CubicSplineFitting	-2.86	11.68	.66	-4.15	-1.56	-4.33	313	.00
15	P2CubicSpline4DPts.	4.42	11.14	.81	2.83	6.02	5.47	189	.00
16	P2SubgSubsMean	16.49	13.94	1.05	14.42	18.56	15.74	176	.00
17	P2SubgSubsMed.	14.14	13.16	.94	12.29	15.99	15.08	196	.00
18	P2SubgSubsMax.	-1.07	12.69	.80	-2.64	.50	-1.34	252	.18
19	P2SubgSubsMin.	40.52	29.08	2.67	35.24	45.80	15.20	118	.00

Table B80. Paired Samples T-Tests of Predicted Distress Scores According to Middle Age (1999-2004) for Two Years Missing Data points Case (2).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	**Mean Nearby Points**	-.19	5.55	.17	-.53	.15	-1.10	1013	.27
2	**Med. Nearby Pts.**	.16	5.44	.17	-.17	.49	.95	1038	.34
3	**Linear Interpolation**	.16	5.44	.17	-.17	.49	.95	1038	.34
4	**Linear Trend Pts.**	-.30	7.12	.23	-.75	.15	-1.31	962	.19
5	**Moving Average**	.06	5.46	.17	-.27	.39	.35	1055	.72
6	**Cubic Spline Fitting**	-.14	5.04	.16	-.45	.16	-.92	1048	.36
7	**Cubic Spline4 D. Pts.**	-.14	5.60	.17	-.48	.20	-.83	1052	.41
8	**Sub. Subs. Mean**	.22	5.35	.16	-.10	.54	1.33	1051	.18
9	**Sub. Subs. Med.**	.16	5.33	.16	-.16	.48	.99	1079	.32
10	**Sub. Subs. Max.**	.30	5.45	.17	-.02	.63	1.82	1077	.07
11	**Sub. Subs. Min.**	.08	5.45	.17	-.25	.41	.47	1043	.64
12	**P2LinearTrendatPts.**	-8.47	16.37	.62	-9.69	-7.25	-13.64	693	.00
13	**P2MovingAverage**	-4.84	13.40	.50	-5.82	-3.86	-9.70	719	.00
14	**P2CubicSplineFitting**	-4.05	14.01	.47	-4.96	-3.13	-8.68	901	.00
15	**P2CubicSpline4DPts.**	2.40	13.96	.55	1.33	3.47	4.40	654	.00
16	**P2SubgSubsMean**	15.13	16.83	.71	13.73	16.52	21.27	559	.00
17	**P2SubgSubsMed.**	11.37	16.83	.68	10.02	12.71	16.61	604	.00
18	**P2SubgSubsMax.**	-2.88	14.20	.53	-3.91	-1.84	-5.46	724	.00
19	**P2SubgSubsMin.**	40.91	27.84	1.52	37.93	43.90	26.97	336	.00

Table B81. Paired Samples T-Tests of Predicted Distress Scores According to Late Age (2005-2010) for Two Years Missing Data points Case (2).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	**Mean Nearby Points**	-1.14	3.36	.43	-2.01	-.27	-2.62	59	.01
2	**Med. Nearby Pts.**	-.41	2.79	.35	-1.11	.30	-1.16	62	.25
3	**Linear Interpolation**	-.41	2.79	.35	-1.11	.30	-1.16	62	.25
4	**Linear Trend Pts.**	-1.14	6.40	.87	-2.89	.61	-1.31	53	.20
5	**Moving Average**	-1.32	4.11	.48	-2.28	-.36	-2.74	72	.01
6	**Cubic Spline Fitting**	.17	2.11	.28	-.39	.72	.61	57	.54
7	**Cubic Spline4 D. Pts.**	-.85	3.26	.42	-1.69	-.01	-2.03	60	.05
8	**Sub. Subs. Mean**	-.13	3.47	.43	-.98	.73	-.30	65	.77
9	**Sub. Subs. Med.**	.18	4.49	.54	-.91	1.27	.33	67	.74
10	**Sub. Subs. Max.**	.30	4.41	.54	-.77	1.37	.56	67	.58
11	**Sub. Subs. Min.**	-1.14	4.22	.51	-2.15	-.13	-2.24	68	.03
12	**P2LinearTrendatPts.**	-7.99	10.61	1.56	-11.14	-4.84	-5.11	45	.00
13	**P2MovingAverage**	-4.33	7.83	1.18	-6.71	-1.95	-3.66	43	.00
14	**P2CubicSplineFitting**	-3.18	7.71	1.00	-5.19	-1.17	-3.17	58	.00
15	**P2CubicSpline4DPts.**	-1.74	6.95	1.07	-3.91	.42	-1.63	41	.11
16	**P2SubgSubsMean**	20.36	12.87	2.31	15.64	25.08	8.81	30	.00
17	**P2SubgSubsMed.**	15.31	12.91	2.44	10.30	20.31	6.27	27	.00
18	**P2SubgSubsMax.**	-.45	5.06	.86	-2.19	1.29	-.52	34	.60
19	**P2SubgSubsMin.**	59.58	31.71	8.48	41.27	77.89	7.03	13	.00

Table B82. Paired Samples T-Tests of Predicted Distress Scores for Three Years Missing Data points Case (3).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	-.25	5.15	.07	-.38	-.12	-3.70	5876	.000
2	Med. Nearby Pts.	.15	4.35	.06	.04	.26	2.72	6028	.007
3	Linear Interpolation	.15	4.35	.06	.04	.26	2.72	6028	.007
4	Linear Trend Pts.	-.08	6.62	.09	-.26	.09	-.95	5624	.340
5	Moving Average	-.09	4.45	.06	-.20	.02	-1.58	6326	.114
6	Cubic Spline Fitting	-.02	4.98	.06	-.15	.10	-.37	6053	.712
7	Cubic Spline4 D. Pts.	-.11	4.60	.06	-.22	.01	-1.77	5987	.078
8	Sub. Subs. Mean	.34	4.16	.05	.24	.45	6.51	6195	.000
9	Sub. Subs. Med.	.34	4.32	.05	.23	.45	6.24	6225	.000
10	Sub. Subs. Max.	.48	4.42	.06	.38	.59	8.78	6450	.000
11	Sub. Subs. Min.	-.02	4.54	.06	-.13	.10	-.27	6120	.785
12	P2LinearTrendatPts.	-8.45	14.63	.23	-8.91	-7.99	-36.24	3935	.000
13	P2MovingAverage	-3.50	10.84	.16	-3.82	-3.18	-21.29	4350	.000
14	P2CubicSplineFitting	-3.11	12.59	.17	-3.45	-2.77	-17.78	5186	.000
15	P2CubicSpline4DPts.	2.14	13.27	.22	1.71	2.57	9.79	3678	.000
16	P2SubgSubsMean	17.15	14.51	.24	16.68	17.63	71.09	3615	.000
17	P2SubgSubsMed.	13.73	14.59	.24	13.25	14.20	56.92	3660	.000
18	P2SubgSubsMax.	-1.77	12.34	.18	-2.13	-1.41	-9.65	4512	.000
19	P2SubgSubsMin.	42.78	27.18	.59	41.62	43.94	72.24	2105	.000

Table B83. Paired Samples T-Tests of Predicted Distress Scores According to Very Good (90-100) Three Years Missing Data points Case (3).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	-.39	5.55	.08	-.55	-.23	-4.72	4500	.00
2	Med. Nearby Pts.	.20	4.74	.07	.06	.34	2.88	4598	.00
3	Linear Interpolation	.20	4.74	.07	.06	.34	2.88	4598	.00
4	Linear Trend Pts.	-.43	7.13	.11	-.64	-.21	-3.92	4280	.00
5	Moving Average	.10	4.80	.07	-.04	.24	1.44	4704	.15
6	Cubic Spline Fitting	-.22	5.43	.08	-.37	-.06	-2.72	4628	.01
7	Cubic Spline4 D. Pts.	-.15	5.06	.07	-.30	-.01	-2.06	4599	.04
8	Sub. Subs. Mean	.34	4.55	.07	.21	.47	5.08	4694	.00
9	Sub. Subs. Med.	.38	4.76	.07	.24	.51	5.42	4693	.00
10	Sub. Subs. Max.	.34	4.79	.07	.20	.47	4.90	4794	.00
11	Sub. Subs. Min.	.11	4.86	.07	-.03	.25	1.59	4601	.11
12	P2LinearTrendatPts.	-9.33	16.00	.29	-9.89	-8.77	-32.53	3112	.00
13	P2MovingAverage	-4.23	12.26	.21	-4.65	-3.80	-19.69	3260	.00
14	P2CubicSplineFitting	-4.26	14.02	.22	-4.70	-3.82	-19.00	3904	.00
15	P2CubicSpline4DPts.	2.75	13.05	.24	2.27	3.23	11.29	2862	.00
16	P2SubgSubsMean	17.65	16.25	.32	17.03	18.27	55.96	2653	.00
17	P2SubgSubsMed.	13.35	16.18	.31	12.74	13.96	43.11	2730	.00
18	P2SubgSubsMax.	-3.06	13.80	.24	-3.53	-2.59	-12.80	3320	.00
19	P2SubgSubsMin.	49.39	28.14	.74	47.94	50.83	66.98	1456	.00

Table B84. Paired Samples T-Tests of Predicted Distress Scores According to Good (80-89) Three Years Missing Data points Case (3).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	-1.130	.645	.372	-2.732	.473	-3.034	2	.094
2	Med. Nearby Pts.	-.797	.645	.322	-1.824	.229	-2.473	3	.090
3	Linear Interpolation	-.797	.645	.322	-1.824	.229	-2.473	3	.090
4	Linear Trend Pts.	-.921	.610	.305	-1.891	.049	-3.021	3	.057
5	Moving Average	-1.067	.494	.285	-2.295	.162	-3.737	2	.065
6	Cubic Spline Fitting	-.710	.692	.400	-2.429	1.009	-1.777	2	.218
7	Cubic Spline4 D. Pts.	-.546	.833	.417	-1.872	.780	-1.310	3	.282
8	Sub. Subs. Mean	-.652	.963	.482	-2.185	.881	-1.354	3	.269
9	Sub. Subs. Med.	-.843	1.063	.531	-2.534	.848	-1.586	3	.211
10	Sub. Subs. Max.	-1.457	1.239	.620	-3.429	.514	-2.352	3	.100
11	Sub. Subs. Min.	-.799	.885	.511	-2.996	1.399	-1.563	2	.258
12	P2LinearTrendatPts.	-.686	.179	.103	-1.130	-.242	-6.651	2	.022
13	P2MovingAverage	-2.777	1.208	.698	-5.778	.225	-3.981	2	.058
14	P2CubicSplineFitting	-2.869	.936	.540	-5.194	-.545	-5.311	2	.034
15	P2CubicSpline4DPts.	-2.073	.694	.401	-3.797	-.349	-5.173	2	.035
16	P2SubgSubsMean	8.902	9.777	4.888	-6.655	24.459	1.821	3	.166
17	P2SubgSubsMed.	5.477	9.741	4.870	-10.023	20.977	1.125	3	.343
18	P2SubgSubsMax.	-2.777	1.208	.698	-5.778	.225	-3.981	2	.058
19	P2SubgSubsMin.								

Table B85. Paired Samples T-Tests of Predicted Distress Scores According to Fair (70-79) Three Years Missing Data points Case (3).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points								
2	Med. Nearby Pts.								
3	Linear Interpolation								
4	Linear Trend Pts.								
5	Moving Average								
6	Cubic Spline Fitting								
7	Cubic Spline4 D. Pts.								
8	Sub. Subs. Mean								
9	Sub. Subs. Med.								
10	Sub. Subs. Max.								
11	Sub. Subs. Min.								
12	P2LinearTrendatPts.								
13	P2MovingAverage								
14	P2CubicSplineFitting								
15	P2CubicSpline4DPts.								
16	P2SubgSubsMean								
17	P2SubgSubsMed.								
18	P2SubgSubsMax.								
19	P2SubgSubsMin.								

Table B86. Paired Samples T-Tests of Predicted Distress Scores According to Poor (60-69) Three Years Missing Data points Case (3).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points								
2	Med. Nearby Pts.								
3	Linear Interpolation								
4	Linear Trend Pts.								
5	Moving Average								
6	Cubic Spline Fitting								
7	Cubic Spline4 D. Pts.								
8	Sub. Subs. Mean								
9	Sub. Subs. Med.								
10	Sub. Subs. Max.								
11	Sub. Subs. Min.								
12	P2LinearTrendatPts.								
13	P2MovingAverage								
14	P2CubicSplineFitting								
15	P2CubicSpline4DPts.								
16	P2SubgSubsMean								
17	P2SubgSubsMed.								
18	P2SubgSubsMax.								
19	P2SubgSubsMin.								

Table B87. Paired Samples T-Tests of Predicted Distress Scores According to Very Poor (1-59) Three Years Missing Data points Case (3).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	**Mean Nearby Points**	7.50	2.12	.39	6.70	8.31	19.05	28	.00
2	**Med. Nearby Pts.**	7.43	2.37	.44	6.53	8.33	16.89	28	.00
3	**Linear Interpolation**	7.43	2.37	.44	6.53	8.33	16.89	28	.00
4	**Linear Trend Pts.**	7.45	2.29	.43	6.58	8.32	17.52	28	.00
5	**Moving Average**	6.20	3.48	.59	5.01	7.40	10.55	34	.00
6	**Cubic Spline Fitting**	7.47	2.25	.42	6.61	8.32	17.89	28	.00
7	**Cubic Spline4 D. Pts.**	7.47	2.25	.42	6.61	8.32	17.88	28	.00
8	**Sub. Subs. Mean**	6.92	3.03	.54	5.81	8.03	12.74	30	.00
9	**Sub. Subs. Med.**	6.76	3.09	.55	5.65	7.87	12.38	31	.00
10	**Sub. Subs. Max.**	7.22	2.60	.47	6.25	8.19	15.21	29	.00
11	**Sub. Subs. Min.**	6.98	2.87	.52	5.93	8.03	13.55	30	.00
12	**P2LinearTrendatPts.**	14.36	1.45	.27	13.80	14.93	52.43	27	.00
13	**P2MovingAverage**	7.73	1.77	.33	7.05	8.42	23.14	27	.00
14	**P2CubicSplineFitting**	5.78	3.21	.59	4.58	6.98	9.86	29	.00
15	**P2CubicSpline4DPts.**	20.95	5.15	.97	18.96	22.95	21.54	27	.00
16	**P2SubgSubsMean**	14.93	3.40	.63	13.64	16.23	23.66	28	.00
17	**P2SubgSubsMed.**	12.58	3.26	.61	11.34	13.81	20.78	28	.00
18	**P2SubgSubsMax.**	10.61	3.81	.71	9.16	12.06	15.01	28	.00
19	**P2SubgSubsMin.**	22.40	7.38	1.37	19.59	25.21	16.34	28	.00

Table B88. Paired Samples T-Tests of Predicted Distress Scores According Age (1993-2010) for Three Years Missing Data points Case (3).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	-.25	5.15	.07	-.38	-.12	-3.70	5876	.000
2	Med. Nearby Pts.	.15	4.35	.06	.04	.26	2.72	6028	.007
3	Linear Interpolation	.15	4.35	.06	.04	.26	2.72	6028	.007
4	Linear Trend Pts.	-.08	6.62	.09	-.26	.09	-.95	5624	.340
5	Moving Average	-.09	4.45	.06	-.20	.02	-1.58	6326	.114
6	Cubic Spline Fitting	-.02	4.98	.06	-.15	.10	-.37	6053	.712
7	Cubic Spline4 D. Pts.	-.11	4.60	.06	-.22	.01	-1.77	5987	.078
8	Sub. Subs. Mean	.34	4.16	.05	.24	.45	6.51	6195	.000
9	Sub. Subs. Med.	.34	4.32	.05	.23	.45	6.24	6225	.000
10	Sub. Subs. Max.	.48	4.42	.06	.38	.59	8.78	6450	.000
11	Sub. Subs. Min.	-.02	4.54	.06	-.13	.10	-.27	6120	.785
12	P2LinearTrendatPts.	-8.45	14.63	.23	-8.91	-7.99	-36.24	3935	.000
13	P2MovingAverage	-3.50	10.84	.16	-3.82	-3.18	-21.29	4350	.000
14	P2CubicSplineFitting	-3.11	12.59	.17	-3.45	-2.77	-17.78	5186	.000
15	P2CubicSpline4DPts.	2.14	13.27	.22	1.71	2.57	9.79	3678	.000
16	P2SubgSubsMean	17.15	14.51	.24	16.68	17.63	71.09	3615	.000
17	P2SubgSubsMed.	13.73	14.59	.24	13.25	14.20	56.92	3660	.000
18	P2SubgSubsMax.	-1.77	12.34	.18	-2.13	-1.41	-9.65	4512	.000
19	P2SubgSubsMin.	42.78	27.18	.59	41.62	43.94	72.24	2105	.000

Figure A89. Paired Samples T-Tests of Predicted Distress Scores According to Early Age (1993-1998) for Three Years Missing Data points Case (3).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	Mean Nearby Points	.23	1.77	.14	-.05	.50	1.63	161	.11
2	Med. Nearby Pts.	.02	1.35	.10	-.19	.23	.20	165	.84
3	Linear Interpolation	.02	1.35	.10	-.19	.23	.20	165	.84
4	Linear Trend Pts.	.93	2.98	.24	.46	1.40	3.93	157	.00
5	Moving Average	.01	1.34	.10	-.20	.21	.05	163	.96
6	Cubic Spline Fitting	.01	1.42	.11	-.20	.23	.12	165	.90
7	Cubic Spline4 D. Pts.	-.02	1.35	.11	-.23	.19	-.21	163	.83
8	Sub. Subs. Mean	.05	1.31	.10	-.15	.25	.49	165	.63
9	Sub. Subs. Med.	.04	1.25	.10	-.15	.23	.43	164	.67
10	Sub. Subs. Max.	.03	1.29	.10	-.17	.23	.28	164	.78
11	Sub. Subs. Min.	-.01	1.29	.10	-.21	.18	-.14	166	.89
12	P2LinearTrendatPts.	-6.95	12.90	1.34	-9.60	-4.29	-5.19	92	.00
13	P2MovingAverage	-2.42	5.17	.48	-3.37	-1.48	-5.07	116	.00
14	P2CubicSplineFitting	-3.25	9.88	.86	-4.96	-1.54	-3.76	130	.00
15	P2CubicSpline4DPts.	4.25	8.48	.91	2.43	6.06	4.64	85	.00
16	P2SubgSubsMean	18.63	12.15	1.30	16.04	21.22	14.31	86	.00
17	P2SubgSubsMed.	15.61	12.23	1.30	13.03	18.19	12.04	88	.00
18	P2SubgSubsMax.	-.33	10.54	.98	-2.28	1.61	-.34	114	.73
19	P2SubgSubsMin.	43.98	29.33	4.11	35.73	52.23	10.71	50	.00

Table B90. Paired Samples T-Tests of Predicted Distress Scores According to Middle Age (1999-2004) for Three Years Missing Data points Case (3).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	**Mean Nearby Points**	-.26	6.24	.19	-.64	.12	-1.33	1032	.18
2	**Med. Nearby Pts.**	.44	5.22	.16	.12	.75	2.72	1063	.01
3	**Linear Interpolation**	.44	5.22	.16	.12	.75	2.72	1063	.01
4	**Linear Trend Pts.**	-.24	7.52	.24	-.71	.24	-.98	962	.33
5	**Moving Average**	.35	5.19	.16	.04	.65	2.23	1115	.03
6	**Cubic Spline Fitting**	-.05	6.32	.19	-.43	.32	-.28	1083	.78
7	**Cubic Spline4 D. Pts.**	-.21	6.12	.19	-.58	.15	-1.15	1090	.25
8	**Sub. Subs. Mean**	.61	5.05	.15	.31	.91	4.03	1105	.00
9	**Sub. Subs. Med.**	.57	5.12	.15	.26	.87	3.69	1120	.00
10	**Sub. Subs. Max.**	.70	5.07	.15	.40	.99	4.67	1153	.00
11	**Sub. Subs. Min.**	.47	5.27	.16	.16	.79	2.94	1081	.00
12	**P2LinearTrendatPts.**	-8.41	15.21	.54	-9.47	-7.34	-15.51	787	.00
13	**P2MovingAverage**	-4.57	12.81	.45	-5.46	-3.68	-10.07	795	.00
14	**P2CubicSplineFitting**	-3.87	13.77	.45	-4.74	-2.99	-8.67	953	.00
15	**P2CubicSpline4DPts.**	2.73	13.51	.49	1.76	3.70	5.52	747	.00
16	**P2SubgSubsMean**	16.18	15.72	.61	14.98	17.39	26.38	656	.00
17	**P2SubgSubsMed.**	11.69	15.81	.60	10.51	12.87	19.42	689	.00
18	**P2SubgSubsMax.**	-2.49	13.90	.48	-3.42	-1.55	-5.20	845	.00
19	**P2SubgSubsMin.**	42.69	27.42	1.43	39.88	45.50	29.83	366	.00

Table B91. Paired Samples T-Tests of Predicted Distress Scores According to Late Age (2005-2010) for Three Years Missing Data points Case (3).

Pair	Do Nothing	Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
1	**Mean Nearby Points**	-3.32	5.95	1.33	-6.11	-.54	-2.50	19	.02
2	**Med. Nearby Pts.**	-2.65	5.73	1.25	-5.26	-.04	-2.12	20	.05
3	**Linear Interpolation**	-2.65	5.73	1.25	-5.26	-.04	-2.12	20	.05
4	**Linear Trend Pts.**	-2.83	7.23	1.62	-6.21	.56	-1.75	19	.10
5	**Moving Average**	-2.76	5.91	1.14	-5.10	-.42	-2.42	26	.02
6	**Cubic Spline Fitting**	-1.12	3.69	.80	-2.80	.55	-1.40	20	.18
7	**Cubic Spline4 D. Pts.**	-1.51	4.92	1.02	-3.64	.61	-1.48	22	.15
8	**Sub. Subs. Mean**	-.68	3.48	.72	-2.19	.82	-.94	22	.36
9	**Sub. Subs. Med.**	-.15	4.82	1.01	-2.23	1.94	-.15	22	.89
10	**Sub. Subs. Max.**	.73	5.63	1.15	-1.65	3.10	.63	23	.53
11	**Sub. Subs. Min.**	-2.38	5.81	1.21	-4.89	.13	-1.97	22	.06
12	**P2LinearTrendatPts.**	-9.30	11.41	2.55	-14.64	-3.96	-3.65	19	.00
13	**P2MovingAverage**	-5.03	8.17	1.87	-8.97	-1.09	-2.68	18	.02
14	**P2CubicSplineFitting**	-4.08	8.58	1.83	-7.88	-.27	-2.23	21	.04
15	**P2CubicSpline4DPts.**	.92	5.82	1.33	-1.88	3.73	.69	18	.50
16	**P2SubgSubsMean**	21.34	11.89	3.30	14.15	28.53	6.47	12	.00
17	**P2SubgSubsMed.**	15.18	13.88	4.63	4.52	25.85	3.28	8	.01
18	**P2SubgSubsMax.**	-1.22	4.83	1.25	-3.89	1.46	-.98	14	.35
19	**P2SubgSubsMin.**	50.77	44.32	25.59	-59.33	160.86	1.98	2	.19

Appendix C

Average Efficiency and Statistical Significance of Predicted Distress Scores:

Statistical Significance: Paired Sample T-Test

Missing Data Points of CRCP 1993-2010

Table C0. Abbreviations of Statistical Summary Used for Predicted Distress Scores.

Abbreviation	Explanation	Note
Eff.	Efficiency	
Sig.	Significance	
Obs.	Observation	
Mean	Mean	
Med.	Median	
Min.	Minimum	
Max.	Maximum	
%	Percentage	
Missing Data Techniques Brief	**Missing Data Techniques Explanation**	**Predicting By**
Do Nothing	Do Nothing	**Pavement Performance Model**
Mean Nearby Points	Mean of Nearby Points Using	
Med. Nearby Pts.	Median of Nearby Points	
Linear Interpolation	Linear Interpolation	
Linear Trend Pts.	Linear Trend at Points	
Moving Average	Moving Average	
Cubic Spline Fitting	Cubic Spline Fitting	
Cubic Spline4 D. Pts.	Cubic Spline 4 Data Points	
Sub. Subs. Mean	Subgroup Substitutions Mean	
Sub. Subs. Med.	Subgroup Substitutions Median	
Sub. Subs. Max.	Subgroup Substitutions Maximum	
Sub. Subs. Min.	Subgroup Substitutions Minimum	
P2LinearTrendatPts	Linear Trend at Points	**Missing Data Techniques**
P2MovingAverage	Moving Average Using	
P2CubicSplineFitting	Cubic Spline Fitting Using	
P2CubicSpline4DPts	Cubic Spline 4 Data Points	
P2SubgSubsMean	Subgroup Substitutions	
P2SubgSubsMed	Subgroup Substitutions	
P2SubgSubsMax	Subgroup Substitutions Maximum	
P2SubgSubsMin	Subgroup Substitutions Minimum	

Table C1. Average Efficiency and Statistical Significance of the Predicted Distress Scores in Cases 1, 2, and 3.

Predicting By	Case	Case (1) One Data Point Missing			Case (2) Two Data Points Missing			Case (3) Three Data Points Missing		
	Technique	Eff. (%)	Sig.	Obs.	Eff. (%)	Sig.	Obs.	Eff. (%)	Sig.	Obs.
Pavement Performance Model	Mean Nearby Points	13.13	0.08	1116	4.88	0.03	3236	5.99	0.00	5877
	Med. Nearby Pts.	11.91	0.00	1124	3.45	0.12	3315	3.59	0.01	6029
	Linear Interpolation	11.91	0.00	1124	3.45	0.12	3315	3.59	0.01	6029
	Linear Trend Pts.	14.03	0.76	1086	7.10	0.24	3085	9.59	0.34	5625
	Moving Average	13.11	0.06	1143	5.49	0.28	3385	9.34	0.11	6327
	Cubic Spline Fitting	12.70	0.00	1122	4.17	0.39	3298	5.35	0.71	6054
	Cubic Spline4 D. Pts.	11.83	0.00	1122	1.73	0.99	3310	3.30	0.08	5988
	Sub. Subs. Mean	13.49	0.00	1134	5.46	0.01	3383	7.16	0.00	6196
	Sub. Subs. Med.	13.25	0.00	1133	5.71	0.05	3399	6.96	0.00	6226
	Sub. Subs. Max.	12.96	0.00	1142	5.55	0.00	3442	7.62	0.00	6451
	Sub. Subs. Min.	13.37	0.02	1136	6.18	0.66	3349	8.47	0.79	6121
Missing Data Techniques	P2LinearTrendatPts	-11.47	0.00	652	-15.68	0.00	2124	-15.22	0.00	3936
	P2MovingAverage	36.79	0.00	1146	-4.20	0.00	2220	-3.51	0.00	4351
	P2CubicSplineFitting	17.32	0.00	883	19.04	0.00	2853	19.26	0.00	5187
	P2CubicSpline4DPts	19.38	0.00	681	7.11	0.00	1895	3.67	0.00	3679
	P2SubgSubsMean	44.25	0.00	566	41.73	0.00	1698	40.46	0.00	3616
	P2SubgSubsMed	38.50	0.00	632	35.54	0.00	1793	41.71	0.00	3661
	P2SubgSubsMax	42.25	0.00	1032	13.98	0.00	2206	16.41	0.00	4513
	P2SubgSubsMin	22.88	0.00	373	6.92	0.00	1029	-0.46	0.00	2106

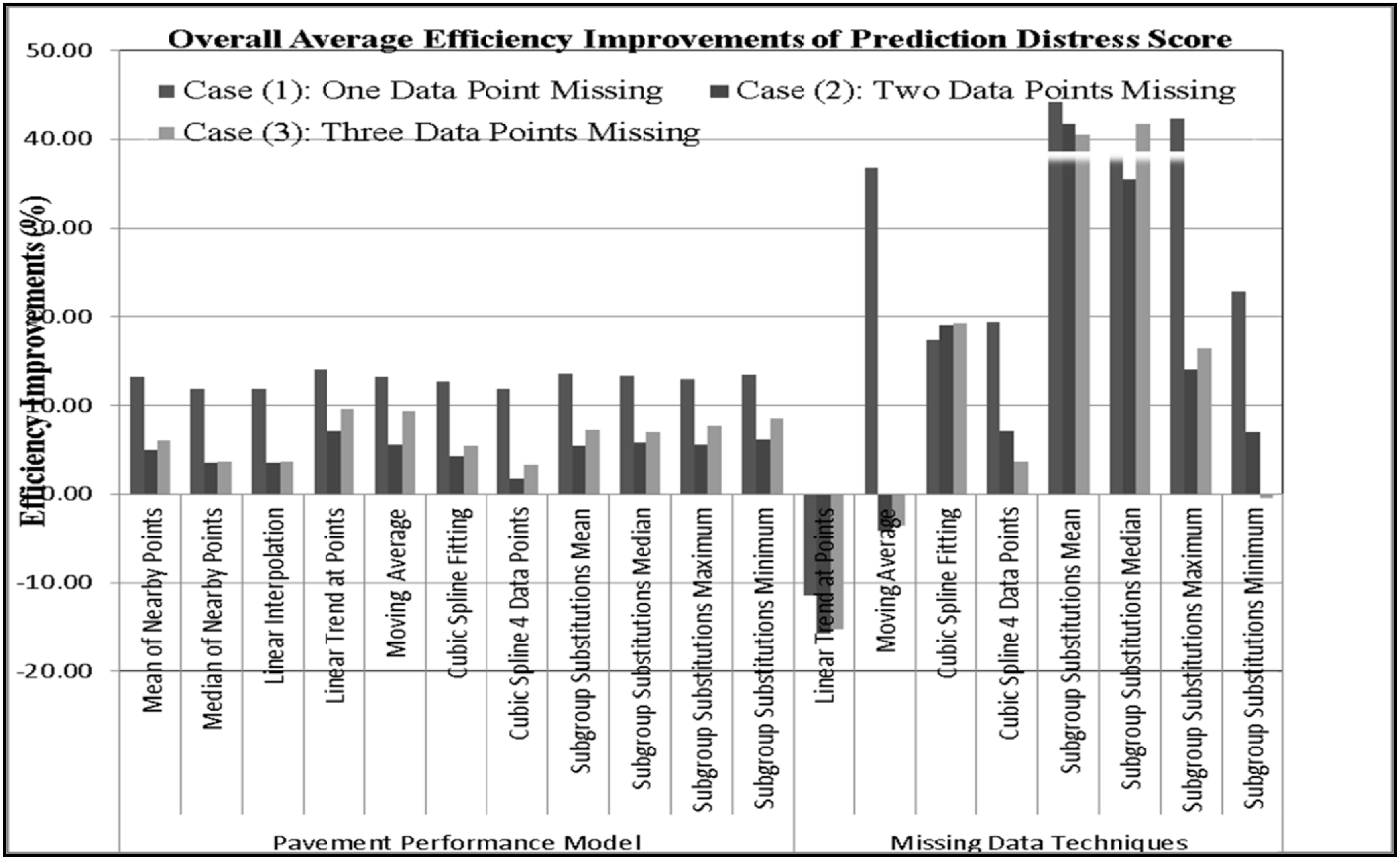

Figure C1. Average Efficiency of the Predicted Distress Scores in Cases 1, 2, and 3.

Table C2. Average Efficiency and Significance of the Predicted Distress Scores According to One Missing Year Classification Categories.

Predicting By	Case	Very Good (90 - 100)			Good (80 - 99)			Fair (70 - 79)			Poor (60 - 69)			Very Poor (1 - 59)		
	Technique	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**
Pavement Performance Model	**Mean Nearby Points**	9.50	0.96	935	33.56	0.44	63	22.25	0.36	48	44.62	0.01	24	44.25	0.00	46
	Med. Nearby Pts.	8.51	0.10	942	30.37	0.41	64	19.26	0.06	50	44.82	0.01	24	43.34	0.00	44
	Linear Interpolation	8.51	0.10	942	30.37	0.41	64	19.26	0.06	50	44.82	0.01	24	43.34	0.00	44
	Linear Trend Pts.	9.85	0.28	910	35.66	0.71	61	24.59	0.38	48	40.87	0.02	24	54.17	0.00	43
	Moving Average	11.63	0.32	960	27.29	0.61	61	15.05	0.96	53	24.04	0.28	22	32.23	0.00	47
	Cubic Spline Fitting	9.25	0.33	940	33.65	0.20	63	16.63	0.00	51	42.58	0.00	24	44.39	0.00	44
	Cubic Spline4 D. Pts.	8.63	0.33	944	33.63	0.55	64	16.89	0.01	50	47.50	0.01	24	37.55	0.00	40
	Sub. Subs. Mean	10.89	0.07	953	35.23	0.21	60	15.37	0.01	52	29.50	0.01	25	43.44	0.00	44
	Sub. Subs. Med.	11.08	0.09	956	31.31	0.20	59	11.74	0.01	50	37.55	0.01	25	39.55	0.00	43
	Sub. Subs. Max.	10.74	0.08	957	26.85	0.04	62	15.83	0.00	51	34.93	0.00	25	38.48	0.00	47
	Sub. Subs. Min.	11.27	0.21	952	30.76	0.75	63	15.74	0.87	52	32.76	0.05	23	34.61	0.00	46
Missing Data Techniques	**P2LinearTrendatPts**	-12.5	0.00	560	-15.5	0.19	30	-21.6	0.21	28	-18.1	0.29	12	32.81	0.00	22
	P2MovingAverage	33.95	0.00	952	57.45	0.03	65	45.22	0.17	56	45.87	0.98	24	56.05	0.00	49
	P2CubicSplineFitting	14.64	0.00	737	34.77	0.36	50	16.68	0.57	43	39.73	0.22	18	39.77	0.00	35
	P2CubicSpline4DPts	17.63	0.00	595	26.57	0.53	30	24.86	0.22	25	62.44	0.33	6	36.66	0.00	24
	P2SubgSubsMean	43.65	0.00	477	36.64	0.00	21	31.62	0.00	24	44.32	0.11	8	62.02	0.00	36
	P2SubgSubsMed	38.04	0.00	537	32.65	0.00	22	24.71	0.00	26	31.09	0.06	10	57.71	0.00	37
	P2SubgSubsMax	39.88	0.00	864	56.66	0.71	57	50.77	0.12	50	35.19	0.06	20	62.68	0.00	41
	P2SubgSubsMin	19.37	0.00	303	17.62	0.00	12	36.99	0.00	17	26.06	0.09	7	45.64	0.00	34

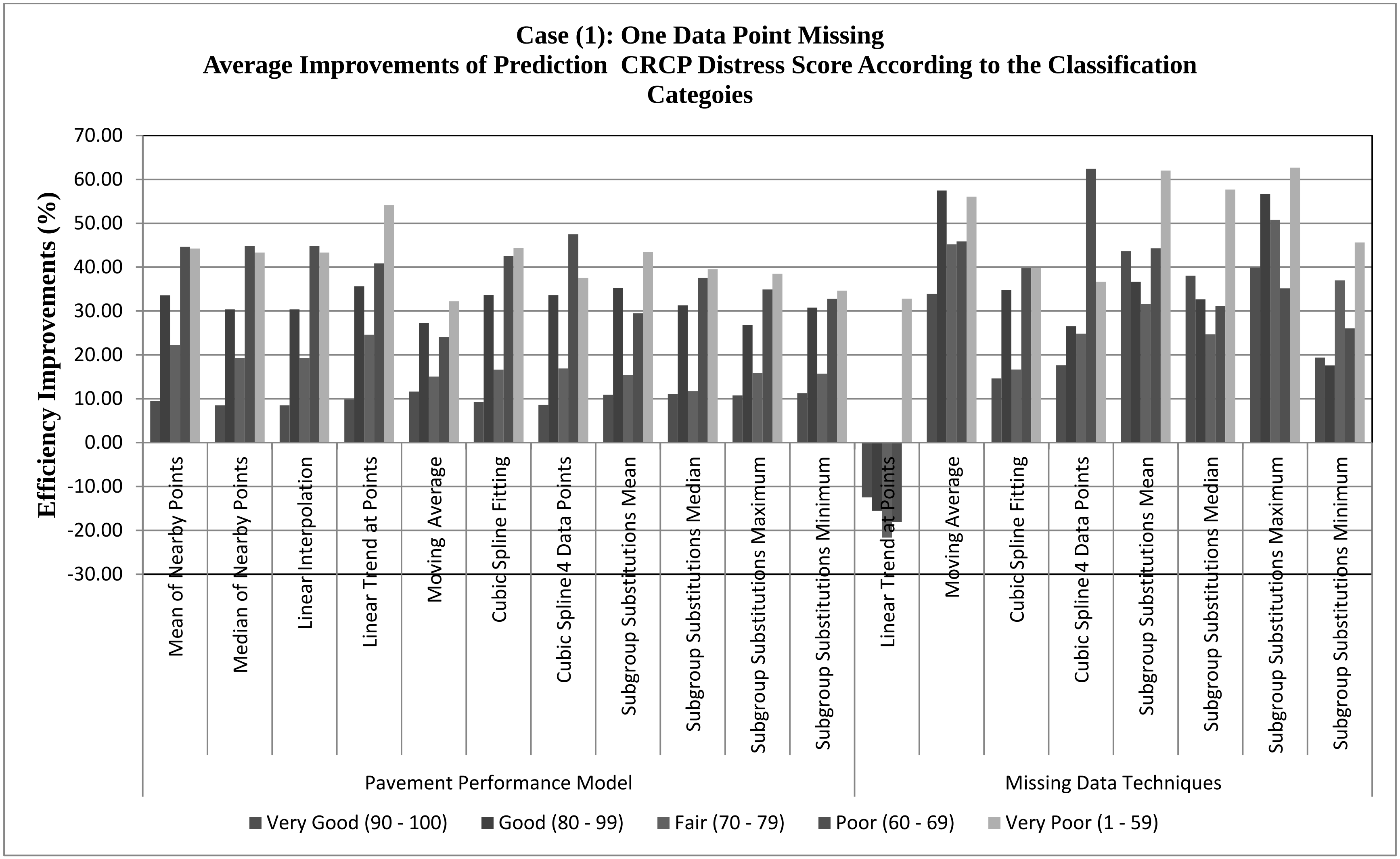

Figure C2. Average Efficiency of the Predicted Distress Scores According to One Missing Year Classification Categories.

Table C3. Average Efficiency and Significance of the Predicted Distress Scores According to Two Missing Years Classification Categories.

Predicting By	Case	Very Good (90 - 100)			Good (80 - 99)			Fair (70 - 79)			Poor (60 - 69)			Very Poor (1 - 59)		
	Technique	Eff. (%)	Sig.	Obs.	Eff. (%)	Sig.	Obs.	Eff. (%)	Sig.	Obs.	Eff. (%)	Sig.	Obs.	Eff. (%)	Sig.	Obs.
Pavement Performance Model	Mean Nearby Points	3.37	0.00	2562	2.14	0.05	46	10.8	0.12	15	17.9	0.07	5	43.7	0.00	29
	Med. Nearby Pts.	2.07	0.38	2609	6.10	0.01	47	12.9	0.13	15	77.7	0.17	5	38.6	0.00	30
	Linear Interpolation	2.07	0.38	2609	6.10	0.01	47	12.9	0.13	15	77.7	0.17	5	38.6	0.00	30
	Linear Trend Pts.	5.72	0.01	2428	8.28	0.02	50	17.6	0.13	13	38.6	0.13	5	43.2	0.00	28
	Moving Average	5.24	0.64	2644	4.62	0.57	42	27.4	0.08	15	67.0	0.44	7	38.7	0.00	36
	Cubic Spline Fitting	2.73	0.21	2601	-0.84	0.07	50	14.3	0.13	14	18.2	0.18	5	37.9	0.00	28
	Cubic Spline4 D. Pts.	0.65	0.37	2634	-6.66	0.02	41	16.8	0.14	15	49.5	0.53	6	41.9	0.00	29
	Sub. Subs. Mean	4.80	0.18	2664	7.22	0.24	45	6.1	0.24	14	25.2	0.07	6	37.5	0.00	32
	Sub. Subs. Med.	5.38	0.30	2674	8.65	0.21	42	5.7	0.23	13	36.0	0.08	6	34.1	0.00	35
	Sub. Subs. Max.	5.68	0.37	2698	2.47	0.35	44	-6.1	0.20	14	34.4	0.08	5	42.1	0.00	32
	Sub. Subs. Min.	5.39	0.90	2619	3.88	0.76	41	27.6	0.15	13	67.1	0.37	7	31.4	0.00	34
Missing Data Techniques	P2LinearTrendatPts	-13.3	0.00	1688	-24.1	0.87	32	-15.1	0.34	13	21.5	0.53	2	55.5	0.00	28
	P2MovingAverage	-3.02	0.00	1799	-16.9	0.02	9	-22.5	0.13	6	-3.0	0.51	3	45.6	0.00	24
	P2CubicSplineFitting	16.3	0.00	2136	41.0	0.21	61	30.3	0.15	16	14.4	0.92	5	40.5	0.00	33
	P2CubicSpline4DPts	8.56	0.00	1568	-6.49	0.96	13	38.0	0.04	14	41.7	0.48	2	35.3	0.00	28
	P2SubgSubsMean	42.1	0.00	1348	13.5	0.02	13	32.6	0.00	9	0.00			77.4	0.00	26
	P2SubgSubsMed	35.8	0.00	1450	10.0	0.05	14	36.1	0.00	9	0.00			69.5	0.00	26
	P2SubgSubsMax	13.5	0.00	1781	-24.8	0.29	10	39.4	0.06	6	-47.4			58.3	0.00	26
	P2SubgSubsMin	6.31	0.00	797	-51.7	0.17	5	-8.10	0.00	6	0.00			53.7	0.00	25

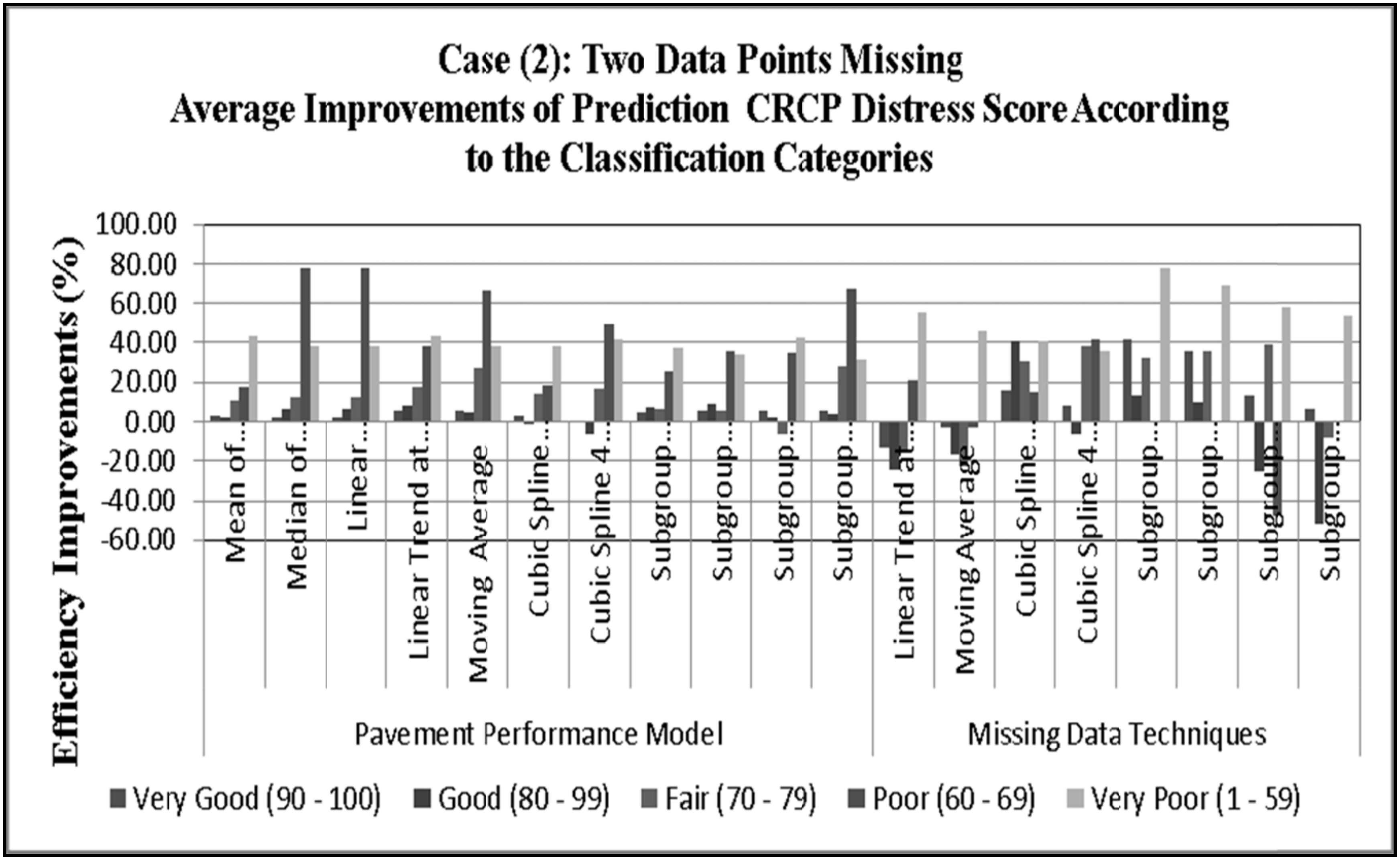

Figure C3. Average Efficiency of the Predicted Distress Scores According to Two Missing Years Classification Categories.

Table C4. Average Efficiency and Significance of the Predicted Distress Scores According to Three Missing Years Classification Categories.

Predicting By	Case	Very Good (90 - 100)			Good (80 - 99)			Fair (70 - 79)			Poor (60 - 69)			Very Poor (1 - 59)		
	Technique	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**
Pavement Performance Model	**Mean Nearby Points**	5.09	0.00	4501	-6.64	0.09	3	10.41		1	44.94		2	44.58	0.00	29
	Med. Nearby Pts.	2.95	0.00	4599	6.61	0.09	4	10.73		1	44.94		2	48.68	0.00	29
	Linear Interpolation	2.95	0.00	4599	6.61	0.09	4	10.73		1	44.94		2	48.68	0.00	29
	Linear Trend Pts.	9.11	0.00	4281	-26.0	0.06	4	9.91		1	44.94		2	47.46	0.00	29
	Moving Average	8.15	0.15	4705	-6.43	0.06	3	13.00		1	44.94		2	48.91	0.00	35
	Cubic Spline Fitting	4.61	0.01	4629	-3.96	0.22	3	9.81		1	86.30		2	46.76	0.00	29
	Cubic Spline4 D. Pts.	3.19	0.04	4600	-18.04	0.28	4	11.73		1	44.94		2	46.05	0.00	29
	Sub. Subs. Mean	6.47	0.00	4695	11.84	0.27	4	10.93		1	44.94		2	48.93	0.00	31
	Sub. Subs. Med.	6.45	0.00	4694	-0.83	0.21	4	13.00		1	44.94		2	46.14	0.00	32
	Sub. Subs. Max.	8.15	0.00	4795	13.84	0.10	4	13.00		1	44.94		2	45.83	0.00	30
	Sub. Subs. Min.	7.56	0.11	4602	-4.13	0.26	3	12.21		1	44.94		2	45.03	0.00	31
Missing Data Techniques	**P2LinearTrendatPts**	-12.2	0.00	3113	-4.5	0.02	3	14.77		1	39.50		1	83.50	0.00	28
	P2MovingAverage	-1.5	0.00	3261	-19.7	0.06	3	13.00		1	44.94		2	48.52	0.00	28
	P2CubicSplineFitting	19.73	0.00	3905	-19.2	0.03	3	9.78		1	82.07		1	35.57	0.00	30
	P2CubicSpline4DPts	8.13	0.00	2863	-14.4	0.04	3	14.81		1	44.94		2	54.23	0.00	28
	P2SubgSubsMean	39.20	0.00	2654	35.22	0.17	4	-4.60		1	0.00		0	84.49	0.00	29
	P2SubgSubsMed	41.42	0.00	2731	26.32	0.34	4	-3.00		1	0.00		0	71.39	0.00	29
	P2SubgSubsMax	14.80	0.00	3321	-19.7	0.06	3	2.00		1	-30.7		1	60.48	0.00	29
	P2SubgSubsMin	-1.3	0.00	1457				-11.0		1	0.00		0	60.48	0.00	29

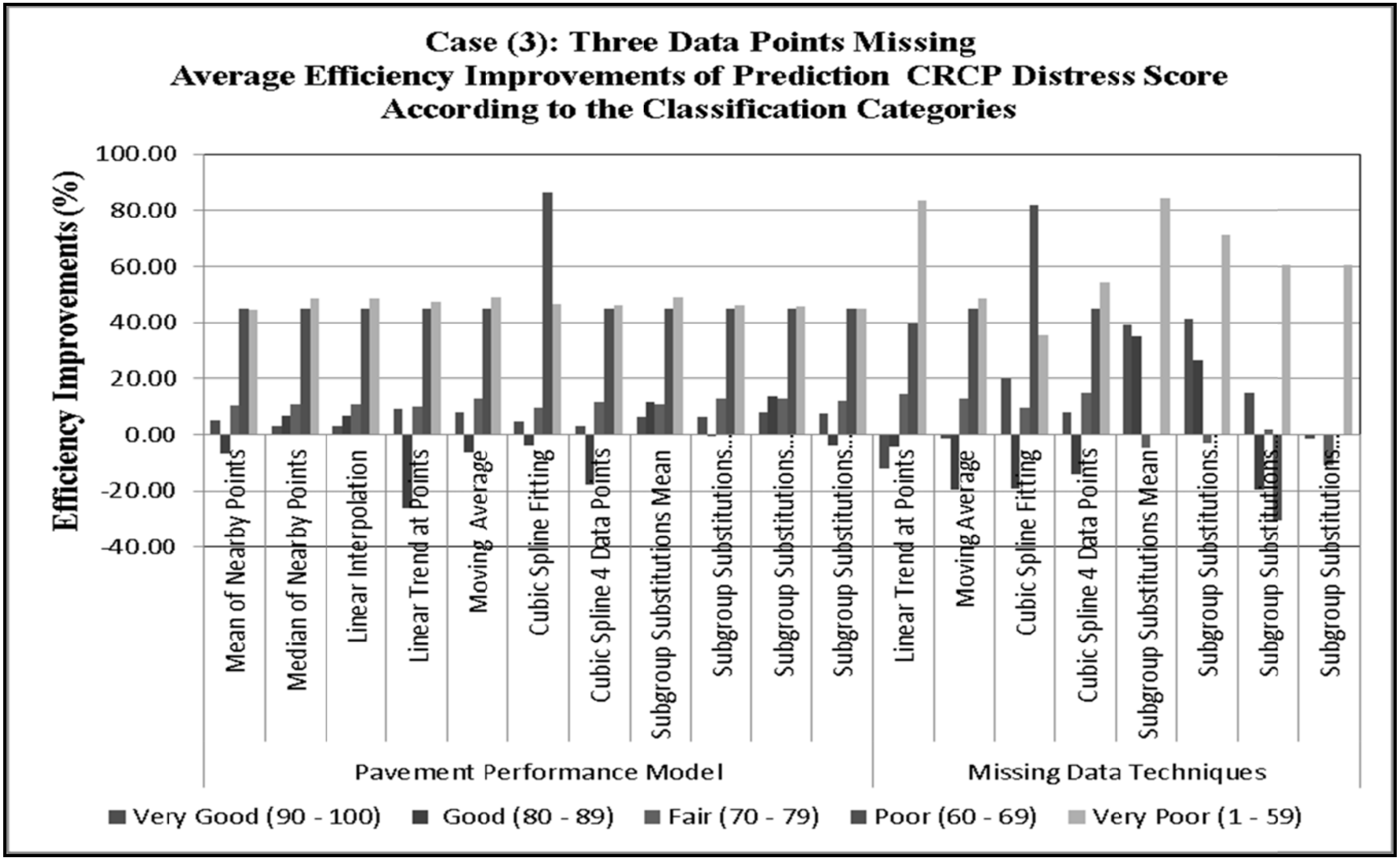

Figure C4. Average Efficiency of the Predicted Distress Scores According to Three Missing Years Classification Categories.

Table C5. Average Efficiency and Significance of the Predicted Distress Scores According to the Period of Time the One Year Missing Data Point is Belonging.

Predicting By	Case	Early Age (1993 - 1998)			Middle Age (1999 - 2004)			Late Age (2005 - 2010)		
	Technique	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**
Pavement Performance Model	**Mean Nearby Points**	16.2	0.37	393	10.8	0.04	608	21.4	0.33	115
	Med. Nearby Pts.	16.2	0.39	392	10.3	0.00	616	12.8	0.33	116
	Linear Interpolation	16.2	0.39	392	10.3	0.00	616	12.8	0.33	116
	Linear Trend Pts.	15.7	0.09	383	12.3	0.75	591	22.4	0.25	112
	Moving Average	16.5	0.45	390	11.4	0.06	631	18.1	0.94	122
	Cubic Spline Fitting	15.4	0.50	392	12.3	0.00	618	10.2	0.21	112
	Cubic Spline4 D. Pts.	15.7	0.49	392	10.6	0.01	617	12.1	0.23	113
	Sub. Subs. Mean	16.2	0.38	391	13.0	0.00	628	14.4	0.06	115
	Sub. Subs. Med.	16.0	0.45	389	12.5	0.00	628	15.2	0.08	116
	Sub. Subs. Max.	16.1	0.44	389	11.9	0.00	633	15.4	0.07	120
	Sub. Subs. Min.	16.0	0.38	389	12.2	0.03	626	17.3	0.54	121
Missing Data Techniques	**P2LinearTrendatPts**	-12.1	0.00	210	-11.7	0.00	367	-8.9	0.00	75
	P2MovingAverage	36.9	0.00	383	34.9	0.00	635	47.7	0.00	128
	P2CubicSplineFitting	17.7	0.00	295	15.2	0.00	492	27.1	0.01	96
	P2CubicSpline4DPts	18.1	0.00	223	20.2	0.00	389	18.8	0.67	69
	P2SubgSubsMean	43.7	0.00	195	44.3	0.00	313	46.1	0.00	55
	P2SubgSubsMed	36.3	0.00	217	39.0	0.00	354	43.3	0.00	61
	P2SubgSubsMax	43.5	0.36	352	40.1	0.01	567	49.3	0.28	113
	P2SubgSubsMin	24.0	0.00	144	22.8	0.00	196	18.3	00000	33

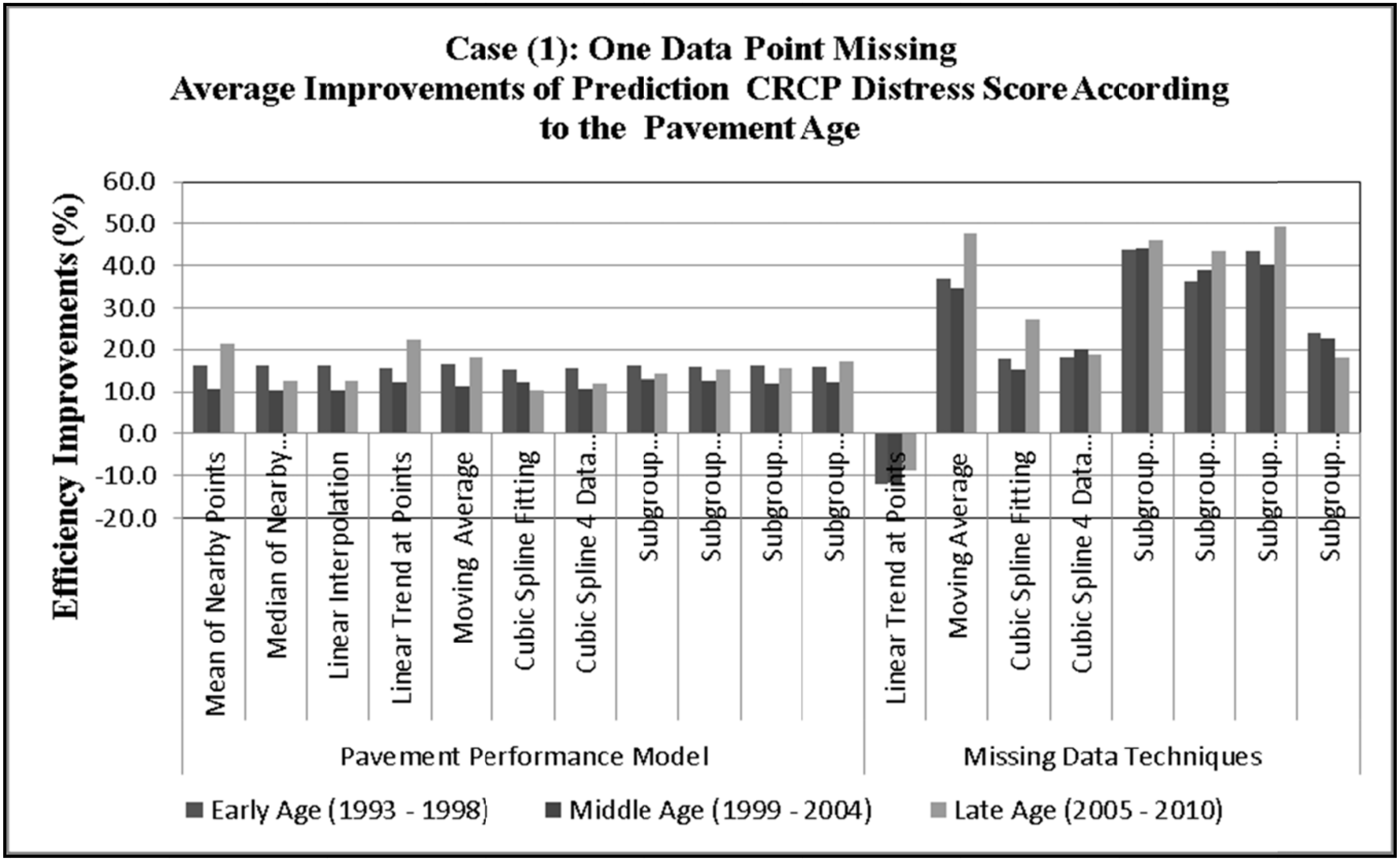

Figure C5. Average Efficiency of the Predicted Distress Scores According to the Period of Time the One Year Missing Data Point is Belonging.

Table C6. Average Efficiency and Significance of the Predicted Distress Scores According to the Period of Time the Two Years Missing Data Points are Belonging.

Predicting By	Case	Early Age (1993 - 1998)			Middle Age (1999 - 2004)			Late Age (2005 - 2010)		
	Technique	Eff. (%)	Sig.	Obs.	Eff. (%)	Sig.	Obs.	Eff. (%)	Sig.	Obs.
Pavement Performance Model	Mean Nearby Points	4.3	0.30	390	4.3	0.27	1014	7.1	0.01	60
	Med. Nearby Pts.	5.9	0.04	395	2.5	0.34	1039	2.5	0.25	63
	Linear Interpolation	5.9	0.04	395	2.5	0.34	1039	2.5	0.25	63
	Linear Trend Pts.	7.9	0.02	367	6.4	0.19	963	19.0	0.20	54
	Moving Average	5.2	0.02	387	3.3	0.72	1056	22.2	0.01	73
	Cubic Spline Fitting	4.6	0.25	382	4.2	0.36	1049	-0.3	0.54	58
	Cubic Spline4 D. Pts.	3.5	0.02	392	2.1	0.41	1053	2.0	0.05	61
	Sub. Subs. Mean	5.5	0.03	391	4.5	0.18	1052	6.5	0.77	66
	Sub. Subs. Med.	5.5	0.01	391	3.5	0.32	1080	16.3	0.74	68
	Sub. Subs. Max.	5.6	0.01	391	3.5	0.07	1078	13.7	0.58	68
	Sub. Subs. Min.	4.1	0.03	392	5.1	0.64	1044	18.6	0.03	69
Missing Data Techniques	P2LinearTrendatPts	-9.9	0.00	217	-15.2	0.00	694	-9.4	0.00	46
	P2MovingAverage	-1.4	0.00	248	-4.8	0.00	720	3.5	0.00	44
	P2CubicSplineFitting	20.1	0.00	314	16.5	0.00	902	17.5	0.00	59
	P2CubicSpline4DPts	4.9	0.00	190	11.7	0.00	655	0.9	0.11	42
	P2SubgSubsMean	34.2	0.00	177	47.2	0.00	560	43.7	0.00	31
	P2SubgSubsMed	20.0	0.00	197	42.0	0.00	605	43.4	0.00	28
	P2SubgSubsMax	19.9	0.18	253	12.4	0.00	725	6.0	0.60	35
	P2SubgSubsMin	13.3	0.00	119	8.9	0.00	337	-3.5	0.00	14

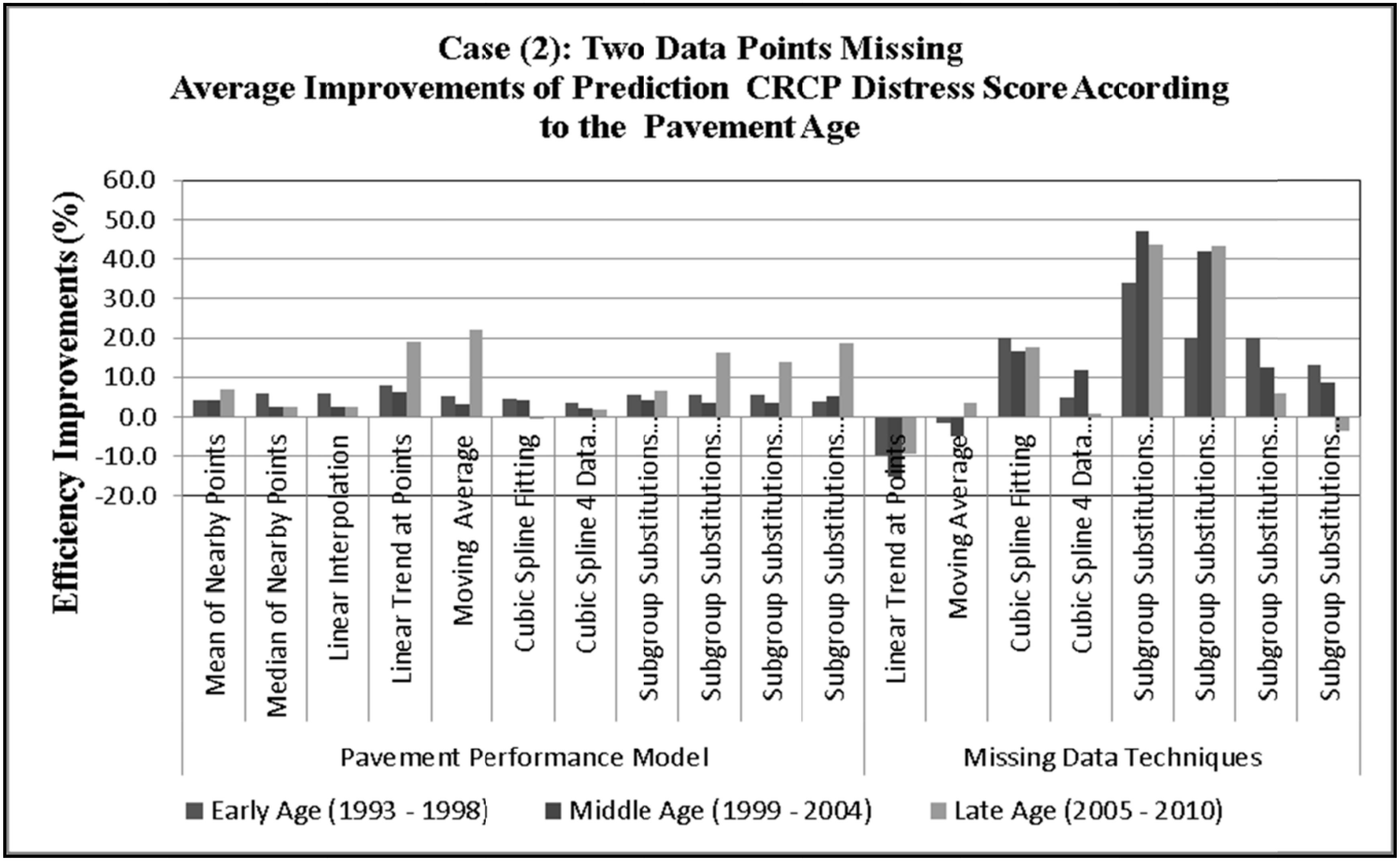

Figure C6. Average Efficiency of the Predicted Distress Scores According to the Period of Time the Two Years Missing Data Points are Belonging.

Table C7. Average Efficiency and Significance of the Predicted Distress Scores According to the Period of Time the Three Years Missing Data Points are Belonging.

Predicting By	Case	Early Age (1993 - 1998)			Middle Age (1999 - 2004)			Late Age (2005 - 2010)		
	Technique	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**	**Eff. (%)**	**Sig.**	**Obs.**
Pavement Performance Model	**Mean Nearby Points**	10.7	0.11	162	7.1	0.18	1033	22.1	0.02	20
	Med. Nearby Pts.	11.0	0.84	166	2.7	0.01	1064	17.7	0.05	21
	Linear Interpolation	11.0	0.84	166	2.7	0.01	1064	17.7	0.05	21
	Linear Trend Pts.	10.5	0.00	158	9.5	0.33	963	26.6	0.10	20
	Moving Average	11.1	0.96	164	5.1	0.03	1116	31.2	0.02	27
	Cubic Spline Fitting	6.9	0.90	166	6.1	0.78	1084	21.7	0.18	21
	Cubic Spline4 D. Pts.	9.6	0.83	164	4.7	0.25	1091	9.0	0.15	23
	Sub. Subs. Mean	11.2	0.63	166	5.3	0.00	1106	11.8	0.36	23
	Sub. Subs. Med.	10.3	0.67	165	4.5	0.00	1121	6.7	0.89	23
	Sub. Subs. Max.	10.7	0.78	165	4.4	0.00	1154	10.6	0.53	24
	Sub. Subs. Min.	10.7	0.89	167	5.0	0.00	1082	26.2	0.06	23
Missing Data Techniques	**P2LinearTrendatPts**	-5.5	0.00	93	-13.3	0.00	788	-13.8	0.00	20
	P2MovingAverage	-4.3	0.00	117	-3.1	0.00	796	10.3	0.02	19
	P2CubicSplineFitting	16.2	0.00	131	17.1	0.00	954	24.0	0.04	22
	P2CubicSpline4DPts	2.9	0.00	86	11.9	0.00	748	1.1	0.50	19
	P2SubgSubsMean	22.8	0.00	87	46.8	0.00	657	7.4	0.00	13
	P2SubgSubsMed	20.3	0.00	89	47.7	0.00	690	37.5	0.01	9
	P2SubgSubsMax	21.5	0.73	115	15.2	0.00	846	14.6	0.35	15
	P2SubgSubsMin	13.5	0.00	51	5.0	0.00	367	9.5	0.19	3

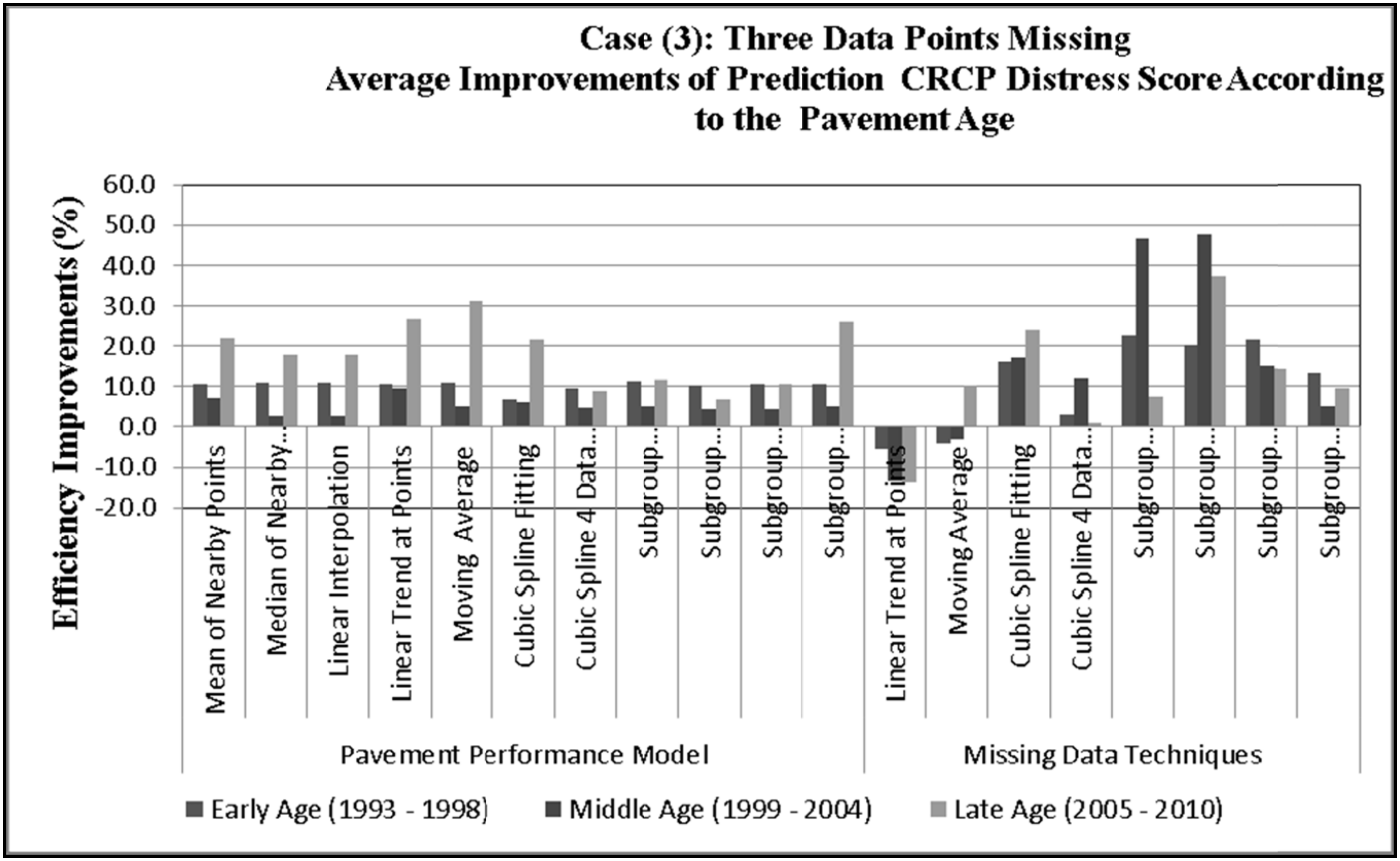

Figure C7. Average Efficiency of the Predicted Distress Scores According to the Period of Time the Three Years Missing Data Points are Belonging.

Table C3. General Statistics of Predicted Distress Scores According to Very Good (90-100) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1025	0	72.27	.67	77.75	21.55	464.5	98.73	.92	99.65	58.08	77.75	88.99
Mean Nearby Points	935	90	72.77	.72	77.99	21.95	481.7	98.31	.69	99.00	61.94	77.99	89.00
Med. Nearby Pts.	942	83	72.63	.72	77.98	21.98	483.1	98.31	.69	99.00	61.93	77.98	89.00
Linear Interpolation	942	83	72.63	.72	77.98	21.98	483.1	98.31	.69	99.00	61.93	77.98	89.00
Linear Trend Pts.	910	115	73.15	.72	77.99	21.80	475.2	98.00	1.00	99.00	61.54	77.99	89.00
Moving Average	960	65	72.64	.71	77.99	21.88	478.6	98.31	.69	99.00	61.99	77.99	89.00
Cubic Spline Fitting	940	85	72.74	.71	77.97	21.75	472.9	98.13	.87	99.00	59.63	77.97	89.00
Cubic Spline4 D. Pts.	944	81	72.71	.71	77.98	21.93	481.0	98.31	.69	99.00	61.99	77.98	89.00
Sub. Subs. Mean	953	72	72.54	.71	77.97	21.88	478.7	98.31	.69	99.00	62.00	77.97	89.00
Sub. Subs. Med.	956	69	72.51	.71	77.97	21.94	481.5	98.31	.69	99.00	61.88	77.97	89.00
Sub. Subs. Max.	957	68	72.52	.71	77.97	21.89	479.2	98.31	.69	99.00	61.99	77.97	89.00
Sub. Subs. Min.	952	73	72.80	.71	77.99	21.81	475.5	98.31	.69	99.00	62.00	77.99	89.00
P2LinearTrendatPts	560	465	86.89	.67	91.63	15.78	249.1	89.98	9.79	99.77	83.01	91.63	97.11
P2MovingAverage	952	73	76.40	.67	82.00	20.60	424.4	91.00	8.00	99.00	69.00	82.00	91.00
P2CubicSplineFitting	737	288	78.94	.72	87.01	19.60	384.1	95.05	4.30	99.35	71.18	87.01	91.58
P2CubicSpline4DPts	595	430	71.99	1.03	78.00	25.05	627.7	97.00	3.00	100.00	57.00	78.00	92.00
P2SubgSubsMean	477	548	54.58	.78	60.40	16.98	288.3	84.00	5.00	89.00	44.97	60.40	66.43
P2SubgSubsMed	537	488	58.78	.82	65.00	18.90	357.4	84.00	5.00	89.00	45.25	65.00	73.00
P2SubgSubsMax	864	161	75.10	.70	79.00	20.71	429.1	94.00	5.00	99.00	69.00	79.00	89.00
P2SubgSubsMin	303	722	26.26	1.14	20.00	19.86	394.3	85.00	4.00	89.00	13.00	20.00	32.00

Table C4. General Statistics of Predicted Distress Scores According to Good (80-89) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	70	0	67.79	2.43	75.92	20.30	412.0	77.20	12.39	89.59	60.98	75.92	78.89
Mean Nearby Points	63	7	67.24	2.51	75.75	19.92	396.8	77.03	11.97	89.00	62.00	75.75	78.00
Med. Nearby Pts.	64	6	66.71	2.53	74.05	20.26	410.6	76.99	12.01	89.00	59.19	74.05	78.00
Linear Interpolation	64	6	66.71	2.53	74.05	20.26	410.6	76.99	12.01	89.00	59.19	74.05	78.00
Linear Trend Pts.	61	9	66.66	2.46	72.00	19.20	368.5	76.18	12.82	89.00	57.88	72.00	78.00
Moving Average	61	9	67.77	2.54	75.54	19.86	394.6	75.78	13.22	89.00	62.00	75.54	78.00
Cubic Spline Fitting	63	7	65.81	2.53	72.00	20.11	404.5	76.86	12.14	89.00	55.48	72.00	78.00
Cubic Spline4 D. Pts.	64	6	66.20	2.52	72.00	20.17	406.7	77.09	11.91	89.00	57.60	72.00	78.00
Sub. Subs. Mean	60	10	67.00	2.54	73.91	19.69	387.7	75.78	13.22	89.00	59.44	73.91	78.00
Sub. Subs. Med.	59	11	66.98	2.59	75.81	19.86	394.4	75.78	13.22	89.00	59.00	75.81	78.00
Sub. Subs. Max.	62	8	66.56	2.60	73.91	20.45	418.0	75.78	13.22	89.00	60.18	73.91	78.00
Sub. Subs. Min.	63	7	67.76	2.50	75.52	19.82	392.9	76.49	12.51	89.00	60.59	75.52	78.00
P2LinearTrendatPts	30	40	73.87	3.07	75.45	16.82	283.0	84.32	9.05	93.37	71.55	75.45	80.77
P2MovingAverage	65	5	71.37	2.07	78.00	16.70	278.7	75.00	14.00	89.00	69.00	78.00	78.00
P2CubicSplineFitting	50	20	70.84	2.06	76.82	14.56	211.9	74.06	15.50	89.56	66.98	76.82	78.10
P2CubicSpline4DPts	30	40	67.38	4.86	78.00	26.62	708.5	96.33	3.67	100.00	54.00	78.00	87.50
P2SubgSubsMean	21	49	44.99	3.84	48.10	17.61	310.3	61.00	10.00	71.00	28.44	48.10	60.34
P2SubgSubsMed	22	48	45.14	3.94	44.50	18.49	342.0	68.00	10.00	78.00	31.00	44.50	60.63
P2SubgSubsMax	57	13	69.37	2.49	78.00	18.78	352.7	79.00	10.00	89.00	62.00	78.00	78.00
P2SubgSubsMin	12	58	25.67	4.63	22.50	16.05	257.5	48.00	9.00	57.00	9.25	22.50	35.75

Table C5. General Statistics of Predicted Distress Scores According to Fair (70-79) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	59	0	60.52	2.19	67.35	16.85	283.9	61.92	22.17	84.09	47.65	67.35	75.75
Mean Nearby Points	48	11	59.84	2.22	66.80	15.37	236.2	56.00	22.00	78.00	47.86	66.80	71.68
Med. Nearby Pts.	50	9	59.69	2.20	66.68	15.57	242.5	56.00	22.00	78.00	47.57	66.68	71.44
Linear Interpolation	50	9	59.69	2.20	66.68	15.57	242.5	56.00	22.00	78.00	47.57	66.68	71.44
Linear Trend Pts.	48	11	59.89	2.21	66.36	15.30	234.0	56.00	22.00	78.00	48.43	66.36	71.72
Moving Average	53	6	61.30	2.07	68.38	15.05	226.5	56.00	22.00	78.00	49.50	68.38	74.23
Cubic Spline Fitting	51	8	58.30	2.33	66.06	16.67	277.8	56.28	21.72	78.00	46.16	66.06	71.53
Cubic Spline4 D. Pts.	50	9	58.28	2.37	64.17	16.75	280.6	56.53	21.47	78.00	46.13	64.17	70.96
Sub. Subs. Mean	52	7	59.89	2.19	66.61	15.77	248.8	56.00	22.00	78.00	48.00	66.61	72.16
Sub. Subs. Med.	50	9	59.58	2.23	65.66	15.78	249.0	56.00	22.00	78.00	47.75	65.66	72.16
Sub. Subs. Max.	51	8	59.65	2.21	65.60	15.76	248.3	56.00	22.00	78.00	47.32	65.60	72.00
Sub. Subs. Min.	52	7	60.91	2.09	67.75	15.09	227.9	56.00	22.00	78.00	49.25	67.75	73.15
P2LinearTrendatPts	28	31	65.64	3.41	71.96	18.05	325.7	75.72	12.86	88.59	59.45	71.96	75.93
P2MovingAverage	56	3	62.46	2.01	69.00	15.04	226.1	57.00	22.00	79.00	49.25	69.00	75.00
P2CubicSplineFitting	43	16	59.79	2.37	63.76	15.56	242.1	57.19	21.80	78.99	44.35	63.76	71.23
P2CubicSpline4DPts	25	34	56.17	5.36	60.67	26.80	718.5	97.83	.50	98.33	30.50	60.67	78.00
P2SubgSubsMean	24	35	39.70	2.41	41.95	11.81	139.6	43.25	13.00	56.25	30.15	41.95	48.10
P2SubgSubsMed	26	33	41.71	2.59	44.00	13.22	174.7	59.00	13.00	72.00	33.50	44.00	50.00
P2SubgSubsMax	50	9	60.34	2.49	67.00	17.61	310.1	65.00	13.00	78.00	47.75	67.00	75.75
P2SubgSubsMin	17	42	22.29	2.21	20.00	9.12	83.2	28.00	11.00	39.00	13.00	20.00	30.00

Table C6. General Statistics of Predicted Distress Scores According to Poor (60-69) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	26	0	45.84	3.65	45.19	18.64	347.3	65.02	7.54	72.56	30.85	45.19	62.02
Mean Nearby Points	24	2	46.06	3.39	45.23	16.60	275.4	55.18	13.82	69.00	32.03	45.23	62.00
Med. Nearby Pts.	24	2	46.02	3.41	45.38	16.70	278.8	55.67	13.33	69.00	32.39	45.38	62.00
Linear Interpolation	24	2	46.02	3.41	45.38	16.70	278.8	55.67	13.33	69.00	32.39	45.38	62.00
Linear Trend Pts.	24	2	46.12	3.39	45.10	16.59	275.2	55.94	13.06	69.00	32.04	45.10	62.00
Moving Average	22	4	45.11	3.44	45.00	16.14	260.5	51.35	13.65	65.00	32.18	45.00	62.00
Cubic Spline Fitting	24	2	45.92	3.41	45.40	16.72	279.5	55.62	13.38	69.00	31.98	45.40	61.97
Cubic Spline4 D. Pts.	24	2	46.03	3.44	46.14	16.85	283.8	56.55	12.45	69.00	32.69	46.14	62.00
Sub. Subs. Mean	25	1	45.34	3.48	45.00	17.41	303.2	61.50	7.50	69.00	32.21	45.00	61.95
Sub. Subs. Med.	25	1	45.38	3.50	45.00	17.49	305.8	61.45	7.55	69.00	32.23	45.00	61.99
Sub. Subs. Max.	25	1	43.53	3.63	43.27	18.13	328.8	61.45	7.55	69.00	28.34	43.27	62.00
Sub. Subs. Min.	23	3	44.57	3.31	45.00	15.88	252.0	51.32	13.68	65.00	32.00	45.00	59.33
P2LinearTrendatPts	12	14	44.28	5.66	49.82	19.60	384.1	61.34	8.76	70.10	27.45	49.82	56.83
P2MovingAverage	24	2	46.08	3.62	48.00	17.71	313.8	61.00	8.00	69.00	33.25	48.00	62.00
P2CubicSplineFitting	18	8	45.01	3.51	46.71	14.87	221.2	47.64	18.06	65.70	33.57	46.71	57.57
P2CubicSpline4DPts	6	20	48.78	9.33	57.17	22.86	522.7	51.67	20.00	71.67	21.25	57.17	66.67
P2SubgSubsMean	8	18	32.41	5.77	28.88	16.32	266.5	49.00	13.00	62.00	20.00	28.88	45.38
P2SubgSubsMed	10	16	36.05	4.89	38.50	15.47	239.2	49.00	13.00	62.00	20.00	38.50	49.25
P2SubgSubsMax	20	6	41.70	2.88	43.00	12.88	165.9	49.00	13.00	62.00	35.00	43.00	50.00
P2SubgSubsMin	7	19	26.29	6.49	20.00	17.17	294.9	50.00	12.00	62.00	13.00	20.00	32.00

Table C7. General Statistics of Predicted Distress Scores According to Very Poor (1-59) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	53	0	32.35	1.72	31.71	12.52	156.8	45.59	11.39	56.98	21.98	31.71	42.60
Mean Nearby Points	47	6	30.02	1.90	27.00	13.03	169.9	48.72	8.28	57.00	20.00	27.00	43.10
Med. Nearby Pts.	45	8	29.61	1.89	27.00	12.70	161.4	48.28	8.72	57.00	20.00	27.00	38.83
Linear Interpolation	45	8	29.61	1.89	27.00	12.70	161.4	48.28	8.72	57.00	20.00	27.00	38.83
Linear Trend Pts.	44	9	28.88	1.89	26.50	12.54	157.2	48.22	8.78	57.00	20.00	26.50	36.39
Moving Average	48	5	29.89	1.88	26.83	13.05	170.3	45.32	11.53	56.85	20.00	26.83	41.24
Cubic Spline Fitting	45	8	29.23	1.85	27.00	12.38	153.2	49.41	7.59	57.00	20.00	27.00	37.64
Cubic Spline4 D. Pts.	41	12	29.80	1.97	27.00	12.61	159.0	46.97	9.07	56.04	20.00	27.00	39.33
Sub. Subs. Mean	45	8	29.36	1.92	27.00	12.86	165.4	49.31	7.69	57.00	19.99	27.00	38.81
Sub. Subs. Med.	44	9	30.27	2.01	27.00	13.31	177.1	49.05	7.95	57.00	19.97	27.00	42.21
Sub. Subs. Max.	48	5	29.67	1.91	27.00	13.24	175.2	52.68	4.32	57.00	19.98	27.00	42.20
Sub. Subs. Min.	47	6	29.90	1.86	27.00	12.78	163.3	45.42	11.58	57.00	20.00	27.00	41.99
P2LinearTrendatPts	23	30	22.75	2.79	19.11	13.38	179.1	48.80	8.73	57.52	13.04	19.11	29.92
P2MovingAverage	50	3	30.18	1.81	26.50	12.78	163.2	44.00	13.00	57.00	20.00	26.50	39.75
P2CubicSplineFitting	36	17	28.58	1.86	26.62	11.18	124.9	40.70	13.86	54.56	19.71	26.62	33.44
P2CubicSpline4DPts	25	28	18.73	3.23	18.00	16.13	260.1	64.00	1.00	65.00	7.00	18.00	20.75
P2SubgSubsMean	37	16	20.67	1.25	20.00	7.58	57.4	30.50	8.50	39.00	17.87	20.00	20.75
P2SubgSubsMed	38	15	22.32	1.50	20.00	9.25	85.5	40.50	8.50	49.00	18.50	20.00	22.00
P2SubgSubsMax	42	11	26.07	1.79	22.50	11.63	135.1	43.00	9.00	52.00	20.00	22.50	35.00
P2SubgSubsMin	35	18	16.57	1.25	20.00	7.42	55.0	25.00	7.00	32.00	10.00	20.00	20.00

Table C8. General Statistics of Predicted Distress Scores According Age (1993-2010) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1232	0	69.21	.65	75.71	22.73	516.7	98.73	.92	99.65	53.99	75.71	88.75
Mean Nearby Points	1116	116	69.57	.69	76.00	23.17	537.0	98.31	.69	99.00	53.99	76.00	88.97
Med. Nearby Pts.	1124	108	69.47	.69	75.95	23.17	536.9	98.31	.69	99.00	54.25	75.95	88.97
Linear Interpolation	1124	108	69.47	.69	75.95	23.17	536.9	98.31	.69	99.00	54.25	75.95	88.97
Linear Trend Pts.	1086	146	69.86	.70	75.97	23.09	533.2	98.00	1.00	99.00	54.71	75.97	88.98
Moving Average	1143	89	69.58	.68	75.95	23.06	531.7	98.31	.69	99.00	55.12	75.95	88.98
Cubic Spline Fitting	1122	110	69.42	.69	75.51	23.08	532.9	98.13	.87	99.00	53.99	75.51	88.98
Cubic Spline4 D. Pts.	1122	110	69.60	.69	75.98	23.10	533.6	98.31	.69	99.00	55.47	75.98	88.97
Sub. Subs. Mean	1134	98	69.40	.69	75.89	23.10	533.7	98.31	.69	99.00	54.68	75.89	88.97
Sub. Subs. Med.	1133	99	69.46	.69	75.95	23.09	533.4	98.31	.69	99.00	54.07	75.95	88.98
Sub. Subs. Max.	1142	90	69.23	.69	75.88	23.25	540.8	98.31	.69	99.00	53.99	75.88	88.97
Sub. Subs. Min.	1136	96	69.67	.68	76.09	23.02	529.8	98.31	.69	99.00	56.00	76.09	88.98
P2LinearTrendatPts	652	580	82.45	.81	90.81	20.75	430.4	91.05	8.73	99.77	75.88	90.81	95.66
P2MovingAverage	1146	86	72.83	.66	78.00	22.37	500.3	91.00	8.00	99.00	59.00	78.00	89.00
P2CubicSplineFitting	883	349	74.87	.74	81.48	21.94	481.4	95.05	4.30	99.35	64.54	81.48	90.89
P2CubicSpline4DPts	681	551	69.05	1.03	78.00	26.97	727.4	99.50	.50	100.00	52.00	78.00	92.00
P2SubgSubsMean	566	666	51.14	.78	56.10	18.62	346.7	84.00	5.00	89.00	38.40	56.10	65.62
P2SubgSubsMed	632	600	55.12	.82	59.00	20.50	420.3	84.00	5.00	89.00	41.00	59.00	72.00
P2SubgSubsMax	1032	200	71.49	.71	78.00	22.73	516.6	94.00	5.00	99.00	62.00	78.00	89.00
P2SubgSubsMin	373	859	25.19	.97	20.00	18.68	349.0	85.00	4.00	89.00	13.00	20.00	30.50

Table C9. General Statistics of Predicted Distress Scores According to Early Age (1993-1998) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	406	0	66.17	1.22	73.00	24.53	601.6	98.36	.92	99.28	48.60	73.00	87.36
Mean Nearby Points	393	13	66.35	1.26	72.97	24.91	620.4	98.20	.69	98.89	49.41	72.97	88.97
Med. Nearby Pts.	392	14	66.33	1.26	72.99	24.95	622.7	98.20	.69	98.89	49.41	72.99	88.98
Linear Interpolation	392	14	66.33	1.26	72.99	24.95	622.7	98.20	.69	98.89	49.41	72.99	88.98
Linear Trend Pts.	383	23	66.64	1.26	72.67	24.64	607.1	98.00	1.00	99.00	49.02	72.67	88.98
Moving Average	390	16	66.28	1.26	72.99	24.98	623.8	98.20	.69	98.89	49.23	72.99	88.98
Cubic Spline Fitting	392	14	66.59	1.25	72.82	24.67	608.5	97.91	1.09	99.00	49.76	72.82	88.98
Cubic Spline4 D. Pts.	392	14	66.50	1.25	73.00	24.83	616.7	98.20	.69	98.89	49.41	73.00	88.98
Sub. Subs. Mean	391	15	66.42	1.26	73.00	24.83	616.4	98.20	.69	98.89	49.41	73.00	88.97
Sub. Subs. Med.	389	17	66.42	1.26	73.00	24.91	620.4	98.20	.69	98.89	49.41	73.00	88.98
Sub. Subs. Max.	389	17	66.44	1.26	73.00	24.91	620.4	98.20	.69	98.89	49.41	73.00	88.98
Sub. Subs. Min.	389	17	66.38	1.26	73.00	24.90	620.2	98.20	.69	98.89	49.41	73.00	88.97
P2LinearTrendatPts	210	196	80.18	1.51	89.49	21.95	481.9	90.73	9.05	99.77	71.93	89.49	95.52
P2MovingAverage	383	23	69.28	1.24	78.00	24.24	587.5	91.00	8.00	99.00	52.00	78.00	89.00
P2CubicSplineFitting	295	111	71.88	1.37	77.62	23.52	553.1	95.05	4.30	99.35	54.81	77.62	89.81
P2CubicSpline4DPts	223	183	64.88	1.92	74.00	28.67	821.8	96.00	3.00	99.00	39.00	74.00	92.00
P2SubgSubsMean	195	211	47.52	1.39	50.33	19.40	376.4	73.80	5.00	78.80	34.44	50.33	62.55
P2SubgSubsMed	217	189	51.40	1.48	54.00	21.80	475.3	84.00	5.00	89.00	38.50	54.00	69.00
P2SubgSubsMax	352	54	67.92	1.31	78.00	24.49	599.6	94.00	5.00	99.00	49.00	78.00	89.00
P2SubgSubsMin	144	262	24.06	1.27	20.00	15.22	231.7	74.00	4.00	78.00	15.25	20.00	29.00

Table C10. General Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	687	0	70.13	.84	75.51	21.93	480.9	92.11	7.54	99.65	56.04	75.51	88.96
Mean Nearby Points	608	79	70.78	.90	76.29	22.22	493.7	90.72	8.28	99.00	56.00	76.29	88.96
Med. Nearby Pts.	616	71	70.74	.89	76.17	22.20	492.8	90.28	8.72	99.00	56.48	76.17	88.96
Linear Interpolation	616	71	70.74	.89	76.17	22.20	492.8	90.28	8.72	99.00	56.48	76.17	88.96
Linear Trend Pts.	591	96	71.07	.91	76.29	22.24	494.6	96.96	2.04	99.00	56.05	76.29	88.98
Moving Average	631	56	70.58	.88	76.09	22.14	490.1	88.14	10.86	99.00	56.65	76.09	88.98
Cubic Spline Fitting	618	69	70.58	.89	75.68	22.03	485.5	91.41	7.59	99.00	56.00	75.68	88.97
Cubic Spline4 D. Pts.	617	70	70.80	.89	76.29	22.19	492.3	89.93	9.07	99.00	56.69	76.29	88.96
Sub. Subs. Mean	628	59	70.58	.89	76.09	22.25	495.2	91.50	7.50	99.00	56.51	76.09	88.96
Sub. Subs. Med.	628	59	70.66	.89	76.09	22.20	493.0	91.45	7.55	99.00	56.88	76.09	88.98
Sub. Subs. Max.	633	54	70.23	.90	76.09	22.57	509.5	94.68	4.32	99.00	56.05	76.09	88.97
Sub. Subs. Min.	626	61	70.81	.88	76.09	22.08	487.5	88.14	10.86	99.00	57.17	76.09	88.98
P2LinearTrendatPts	367	320	83.46	1.04	91.10	19.83	393.3	91.05	8.73	99.77	76.80	91.10	96.65
P2MovingAverage	635	52	73.92	.85	78.00	21.52	463.1	91.00	8.00	99.00	62.00	78.00	90.00
P2CubicSplineFitting	492	195	76.06	.94	82.08	20.92	437.5	87.34	12.02	99.35	67.98	82.08	91.13
P2CubicSpline4DPts	389	298	69.87	1.33	78.00	26.29	691.4	99.50	.50	100.00	57.00	78.00	92.00
P2SubgSubsMean	313	374	52.91	1.02	58.58	17.97	322.9	80.50	8.50	89.00	41.64	58.58	66.14
P2SubgSubsMed	354	333	57.00	1.04	62.00	19.53	381.4	80.50	8.50	89.00	42.00	62.00	73.00
P2SubgSubsMax	567	120	72.82	.91	78.00	21.65	468.8	90.00	9.00	99.00	65.00	78.00	89.00
P2SubgSubsMin	196	491	26.46	1.50	20.00	21.03	442.1	85.00	4.00	89.00	13.00	20.00	32.00

Table C11. General Statistics of Predicted Distress Scores According to Late Age (2005-2010) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	139	0	73.55	1.70	77.98	20.06	402.6	84.48	14.94	99.43	65.65	77.98	88.97
Mean Nearby Points	115	24	74.20	1.92	78.00	20.60	424.5	82.91	16.09	99.00	64.95	78.00	89.00
Med. Nearby Pts.	116	23	73.35	1.93	77.98	20.81	433.2	84.43	14.57	99.00	64.39	77.98	88.98
Linear Interpolation	116	23	73.35	1.93	77.98	20.81	433.2	84.43	14.57	99.00	64.39	77.98	88.98
Linear Trend Pts.	112	27	74.46	1.96	78.00	20.70	428.6	82.79	16.21	99.00	65.64	78.00	89.00
Moving Average	122	17	74.94	1.79	78.00	19.80	391.9	85.50	13.50	99.00	66.46	78.00	88.99
Cubic Spline Fitting	112	27	72.99	2.09	77.98	22.15	490.7	98.13	.87	99.00	62.03	77.98	89.00
Cubic Spline4 D. Pts.	113	26	73.87	1.93	77.98	20.50	420.3	85.30	13.70	99.00	64.79	77.98	88.99
Sub. Subs. Mean	115	24	73.10	1.91	77.91	20.49	419.9	85.58	13.42	99.00	64.95	77.91	88.98
Sub. Subs. Med.	116	23	73.13	1.90	77.97	20.41	416.6	85.50	13.50	99.00	64.95	77.97	88.97
Sub. Subs. Max.	120	19	73.00	1.85	77.97	20.27	411.0	85.67	13.33	99.00	64.39	77.97	88.97
Sub. Subs. Min.	121	18	74.39	1.82	78.00	20.06	402.4	85.50	13.50	99.00	65.52	78.00	88.99
P2LinearTrendatPts	75	64	83.86	2.47	91.68	21.40	458.1	87.93	11.80	99.73	80.77	91.68	95.37
P2MovingAverage	128	11	78.07	1.68	87.00	18.98	360.3	80.00	19.00	99.00	73.00	87.00	89.00
P2CubicSplineFitting	96	43	77.89	2.17	87.41	21.26	451.8	83.66	15.65	99.31	71.43	87.41	91.08
P2CubicSpline4DPts	69	70	77.91	2.71	87.00	22.49	505.6	91.00	9.00	100.00	71.42	87.00	96.00
P2SubgSubsMean	58	81	53.75	2.34	61.14	17.85	318.5	67.83	13.00	80.83	42.92	61.14	66.79
P2SubgSubsMed	61	78	57.48	2.53	69.00	19.72	389.0	70.50	13.00	83.50	44.50	69.00	75.00
P2SubgSubsMax	113	26	75.88	1.97	87.00	20.95	439.0	86.00	13.00	99.00	73.00	87.00	89.00
P2SubgSubsMin	33	106	22.58	3.04	13.00	17.45	304.4	66.00	7.00	73.00	13.00	13.00	28.00

Table C12. General Statistics of Predicted Distress Scores for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	4144	0	71.10	.33	77.60	21.44	459.47	97.77	2.23	100.00	56.00	77.60	88.95
Mean Nearby Points	3236	908	72.22	.38	77.36	21.38	457.23	98.15	.85	99.00	56.28	77.36	88.99
Med. Nearby Pts.	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Interpolation	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Trend Pts.	3085	1059	72.11	.38	76.95	21.24	451.11	98.58	.42	99.00	55.98	76.95	88.98
Moving Average	3385	759	72.12	.37	77.96	21.43	459.24	98.15	.85	99.00	57.17	77.96	88.99
Cubic Spline Fitting	3298	846	71.73	.37	76.82	21.42	458.68	98.13	.87	99.00	55.94	76.82	88.98
Cubic Spline4 D. Pts.	3310	834	71.93	.37	76.95	21.54	464.04	98.15	.85	99.00	56.45	76.95	88.98
Sub. Subs. Mean	3383	761	71.65	.37	76.79	21.62	467.22	98.15	.85	99.00	56.30	76.79	88.99
Sub. Subs. Med.	3399	745	71.42	.37	76.71	21.76	473.57	98.15	.85	99.00	56.05	76.71	88.98
Sub. Subs. Max.	3442	702	71.45	.37	76.79	21.67	469.50	98.15	.85	99.00	56.05	76.79	88.98
Sub. Subs. Min.	3349	795	72.21	.37	77.97	21.44	459.75	98.15	.85	99.00	57.77	77.97	88.99
P2LinearTrendatPts	2124	2020	84.80	.37	90.86	17.02	289.65	99.70	.07	99.77	78.97	90.86	95.69
P2MovingAverage	2220	1924	77.51	.44	87.00	20.71	428.99	85.00	14.00	99.00	62.00	87.00	92.00
P2CubicSplineFitting	2853	1291	76.89	.37	82.18	19.65	386.19	93.17	6.18	99.35	69.30	82.18	90.98
P2CubicSpline4DPts	1895	2249	72.92	.58	83.00	25.22	635.94	99.50	.50	100.00	59.67	83.00	93.50
P2SubgSubsMean	1698	2446	54.08	.37	57.33	15.32	234.58	84.00	5.00	89.00	42.00	57.33	65.62
P2SubgSubsMed	1793	2351	58.27	.40	62.00	17.09	291.97	84.00	5.00	89.00	44.00	62.00	72.00
P2SubgSubsMax	2206	1938	73.52	.46	78.00	21.50	462.32	94.00	5.00	99.00	57.00	78.00	89.00
P2SubgSubsMin	1029	3115	24.62	.54	20.00	17.40	302.72	85.00	4.00	89.00	13.00	20.00	32.00

Table C13. General Statistics of Predicted Distress Scores According to Very Good (90-100) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	3111	1	74.61	.37	78.84	20.37	414.82	97.77	2.23	100.00	64.87	78.84	89.00
Mean Nearby Points	2562	550	75.72	.40	81.91	20.32	413.07	98.15	.85	99.00	64.73	81.91	90.79
Med. Nearby Pts.	2609	503	75.27	.40	80.46	20.67	427.41	98.15	.85	99.00	64.73	80.46	90.68
Linear Interpolation	2609	503	75.27	.40	80.46	20.67	427.41	98.15	.85	99.00	64.73	80.46	90.68
Linear Trend Pts.	2428	684	75.77	.41	82.32	20.09	403.68	98.58	.42	99.00	64.11	82.32	90.70
Moving Average	2644	468	75.50	.40	80.98	20.39	415.64	98.15	.85	99.00	64.95	80.98	90.13
Cubic Spline Fitting	2601	511	75.20	.40	80.94	20.43	417.58	98.13	.87	99.00	62.94	80.94	90.63
Cubic Spline4 D. Pts.	2634	478	75.32	.40	80.05	20.55	422.28	98.15	.85	99.00	64.95	80.05	90.29
Sub. Subs. Mean	2664	448	74.98	.40	79.09	20.66	427.04	98.15	.85	99.00	64.63	79.09	90.66
Sub. Subs. Med.	2674	438	74.83	.40	78.27	20.72	429.44	98.15	.85	99.00	64.21	78.27	90.28
Sub. Subs. Max.	2698	414	74.88	.40	78.00	20.59	423.96	98.15	.85	99.00	64.21	78.00	89.41
Sub. Subs. Min.	2619	493	75.67	.40	80.98	20.31	412.57	98.15	.85	99.00	66.34	80.98	90.66
P2LinearTrendatPts	1688	1424	89.09	.31	91.95	12.85	165.12	84.08	15.69	99.77	87.15	91.95	97.72
P2MovingAverage	1799	1313	82.42	.42	89.00	17.79	316.41	81.00	18.00	99.00	78.00	89.00	93.00
P2CubicSplineFitting	2136	976	81.89	.37	87.48	17.01	289.26	89.93	9.42	99.35	74.52	87.48	92.65
P2CubicSpline4DPts	1568	1544	76.10	.59	86.00	23.19	537.82	97.00	3.00	100.00	63.33	86.00	94.17
P2SubgSubsMean	1348	1764	57.66	.36	61.14	13.19	174.06	81.00	8.00	89.00	50.62	61.14	66.55
P2SubgSubsMed	1450	1662	62.22	.39	68.00	14.80	219.15	81.00	8.00	89.00	53.50	68.00	73.00
P2SubgSubsMax	1781	1331	78.11	.45	86.00	18.96	359.31	83.00	16.00	99.00	72.00	86.00	91.00
P2SubgSubsMin	797	2315	24.66	.67	17.00	18.79	353.22	85.00	4.00	89.00	13.00	17.00	28.00

Table C14. General Statistics of Predicted Distress Scores According to Good (80-89) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	74	0	73.93	1.49	76.89	12.79	163.57	75.52	14.21	89.72	75.40	76.89	78.58
Mean Nearby Points	46	28	71.95	1.97	76.21	13.35	178.15	74.12	14.88	89.00	71.21	76.21	76.82
Med. Nearby Pts.	47	27	71.82	2.09	76.09	14.33	205.48	71.70	17.30	89.00	71.19	76.09	76.78
Linear Interpolation	47	27	71.82	2.09	76.09	14.33	205.48	71.70	17.30	89.00	71.19	76.09	76.78
Linear Trend Pts.	50	24	72.52	1.92	76.41	13.60	185.07	69.57	19.43	89.00	71.40	76.41	77.11
Moving Average	42	32	73.40	2.07	76.09	13.38	179.10	75.78	13.22	89.00	71.32	76.09	76.76
Cubic Spline Fitting	50	24	71.73	1.88	76.08	13.29	176.63	65.90	23.10	89.00	70.82	76.08	76.99
Cubic Spline4 D. Pts.	41	33	71.05	2.28	76.19	14.58	212.67	67.07	21.93	89.00	70.89	76.19	76.69
Sub. Subs. Mean	45	29	74.10	1.88	76.38	12.64	159.79	68.23	20.77	89.00	71.19	76.38	77.23
Sub. Subs. Med.	42	32	73.71	2.03	76.09	13.13	172.32	69.17	19.83	89.00	71.19	76.09	76.61
Sub. Subs. Max.	44	30	71.94	2.28	76.02	15.10	227.95	61.17	27.83	89.00	71.19	76.02	76.61
Sub. Subs. Min.	41	33	73.53	2.13	76.09	13.65	186.20	73.06	15.94	89.00	71.28	76.09	76.31
P2LinearTrendatPts	32	42	77.74	1.01	75.62	5.70	32.50	25.42	64.01	89.43	75.31	75.62	79.42
P2MovingAverage	9	65	71.78	5.96	78.00	17.88	319.69	53.00	36.00	89.00	61.00	78.00	89.00
P2CubicSplineFitting	61	13	76.30	1.02	77.40	7.99	63.87	57.64	31.93	89.56	76.91	77.40	77.89
P2CubicSpline4DPts	13	61	73.89	6.10	79.28	22.00	484.19	76.11	12.39	88.50	72.33	79.28	87.58
P2SubgSubsMean	13	61	52.64	4.21	48.10	15.19	230.71	42.56	28.44	71.00	40.00	48.10	67.20
P2SubgSubsMed	14	60	53.75	4.80	52.00	17.95	322.03	53.00	25.00	78.00	40.00	52.00	70.00
P2SubgSubsMax	10	64	69.50	5.72	71.50	18.08	326.72	47.00	42.00	89.00	53.50	71.50	89.00
P2SubgSubsMin	5	69	27.40	5.10	32.00	11.41	130.30	30.00	9.00	39.00	17.00	32.00	35.50

Table C15. General Statistics of Predicted Distress Scores According to Fair (70-79) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	19	0	65.79	3.82	68.15	16.65	277.24	62.14	23.16	85.30	52.80	68.15	76.85
Mean Nearby Points	15	4	63.89	3.11	67.60	12.04	144.93	42.03	35.00	77.03	52.85	67.60	76.02
Med. Nearby Pts.	15	4	64.00	3.12	67.80	12.09	146.21	41.82	35.00	76.82	53.21	67.80	76.09
Linear Interpolation	15	4	64.00	3.12	67.80	12.09	146.21	41.82	35.00	76.82	53.21	67.80	76.09
Linear Trend Pts.	13	6	62.65	3.44	66.82	12.40	153.77	42.45	35.00	77.45	52.12	66.82	72.79
Moving Average	15	4	64.35	3.04	68.38	11.77	138.60	42.97	35.00	77.97	54.37	68.38	73.00
Cubic Spline Fitting	14	5	63.01	3.23	67.21	12.07	145.66	42.41	35.00	77.41	52.15	67.21	70.45
Cubic Spline4 D. Pts.	15	4	64.05	3.14	68.09	12.16	147.76	42.30	35.00	77.30	53.54	68.09	76.03
Sub. Subs. Mean	14	5	63.50	3.37	67.09	12.59	158.62	42.89	35.00	77.89	53.07	67.09	76.14
Sub. Subs. Med.	13	6	63.07	3.62	66.09	13.04	170.01	42.97	35.00	77.97	52.70	66.09	76.30
Sub. Subs. Max.	14	5	63.67	3.39	66.31	12.70	161.36	41.60	35.00	76.60	53.07	66.31	76.22
Sub. Subs. Min.	13	6	62.79	3.50	67.98	12.63	159.50	42.97	35.00	77.97	52.70	67.98	72.45
P2LinearTrendatPts	13	6	63.87	3.40	65.93	12.25	150.14	47.05	29.33	76.38	59.49	65.93	73.58
P2MovingAverage	6	13	54.50	4.08	56.00	9.99	99.90	27.00	35.00	62.00	50.75	56.00	62.00
P2CubicSplineFitting	16	3	64.96	2.83	69.24	11.30	127.73	39.97	37.20	77.17	54.72	69.24	72.82
P2CubicSpline4DPts	14	5	61.51	5.35	73.25	20.02	400.94	58.39	20.00	78.39	46.92	73.25	77.11
P2SubgSubsMean	9	10	43.91	3.04	47.00	9.11	83.06	26.50	26.50	53.00	38.40	47.00	53.00
P2SubgSubsMed	9	10	45.11	2.78	48.00	8.34	69.61	24.00	29.00	53.00	40.00	48.00	53.00
P2SubgSubsMax	6	13	49.00	4.40	45.00	10.79	116.40	27.00	35.00	62.00	42.50	45.00	62.00
P2SubgSubsMin	6	13	30.50	1.91	32.00	4.68	21.90	12.00	25.00	37.00	25.00	32.00	33.25

Table C16. General Statistics of Predicted Distress Scores According to Poor (60-69) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	8	0	53.97	4.05	51.15	11.46	131.32	29.72	43.78	73.50	43.93	51.15	62.10
Mean Nearby Points	5	3	46.62	4.61	42.52	10.30	106.07	23.90	41.10	65.00	41.33	42.52	53.97
Med. Nearby Pts.	5	3	47.43	4.40	43.09	9.83	96.59	22.54	42.46	65.00	42.76	43.09	54.27
Linear Interpolation	5	3	47.43	4.40	43.09	9.83	96.59	22.54	42.46	65.00	42.76	43.09	54.27
Linear Trend Pts.	5	3	47.13	4.48	42.99	10.02	100.33	23.04	41.96	65.00	41.98	42.99	54.35
Moving Average	7	1	51.60	4.05	44.01	10.72	114.99	23.13	41.87	65.00	42.95	44.01	62.00
Cubic Spline Fitting	5	3	47.40	4.43	43.52	9.90	97.98	23.33	41.67	65.00	42.00	43.52	54.74
Cubic Spline4 D. Pts.	6	2	50.15	4.21	43.96	10.31	106.32	22.33	42.67	65.00	43.33	43.96	62.58
Sub. Subs. Mean	6	2	49.20	4.53	42.57	11.10	123.16	23.86	41.14	65.00	41.81	42.57	62.68
Sub. Subs. Med.	6	2	49.27	4.52	42.67	11.06	122.32	23.89	41.11	65.00	41.94	42.67	62.70
Sub. Subs. Max.	5	3	46.73	4.58	42.63	10.23	104.69	23.89	41.11	65.00	41.66	42.63	53.85
Sub. Subs. Min.	7	1	51.41	4.12	43.72	10.90	118.89	23.47	41.53	65.00	42.71	43.72	62.00
P2LinearTrendatPts	2	6	57.64	1.12	57.64	1.58	2.49	2.23	56.52	58.76	56.52	57.64	
P2MovingAverage	3	5	51.67	6.67	45.00	11.55	133.33	20.00	45.00	65.00	45.00	45.00	
P2CubicSplineFitting	5	3	52.55	5.00	44.80	11.19	125.22	21.83	44.20	66.03	44.20	44.80	64.76
P2CubicSpline4DPts	2	6	61.31	3.69	61.31	5.22	27.30	7.39	57.61	65.00	57.61	61.31	
P2SubgSubsMean	0	8											
P2SubgSubsMed	0	8											
P2SubgSubsMax	1	7	50.00		50.00			.00	50.00	50.00	50.00	50.00	50.00
P2SubgSubsMin	0	8											

Table C17. General Statistics of Predicted Distress Scores According to Very Poor (1-59) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	46	0	28.54	1.65	28.88	11.21	125.62	46.88	5.12	51.99	19.98	28.88	35.59
Mean Nearby Points	29	17	24.39	1.61	27.00	8.70	75.60	45.27	5.69	50.96	19.00	27.00	27.00
Med. Nearby Pts.	30	16	23.91	1.63	27.00	8.95	80.10	45.48	5.52	51.00	19.00	27.00	27.00
Linear Interpolation	30	16	23.91	1.63	27.00	8.95	80.10	45.48	5.52	51.00	19.00	27.00	27.00
Linear Trend Pts.	28	18	24.05	1.42	27.00	7.52	56.57	38.34	12.64	50.98	19.00	27.00	27.00
Moving Average	36	10	25.06	1.73	26.50	10.38	107.83	45.20	6.80	52.00	19.00	26.50	27.00
Cubic Spline Fitting	28	18	24.95	1.57	27.00	8.29	68.79	39.28	11.72	51.00	19.00	27.00	27.00
Cubic Spline4 D. Pts.	29	17	23.20	1.55	27.00	8.32	69.23	45.47	5.53	51.00	19.00	27.00	27.00
Sub. Subs. Mean	32	14	22.60	1.48	22.99	8.37	69.98	44.90	6.10	51.00	19.00	22.99	27.00
Sub. Subs. Med.	35	11	23.13	1.63	19.99	9.65	93.04	46.72	5.27	52.00	19.00	19.99	27.00
Sub. Subs. Max.	32	14	24.89	1.81	27.00	10.26	105.28	46.01	5.98	51.99	19.00	27.00	27.00
Sub. Subs. Min.	34	12	24.49	1.66	26.50	9.69	93.89	44.50	7.50	52.00	19.00	26.50	27.00
P2LinearTrendatPts	28	18	19.06	1.84	19.14	9.72	94.50	51.96	.07	52.03	13.55	19.14	20.32
P2MovingAverage	24	22	25.58	1.43	27.00	6.98	48.78	33.00	18.00	51.00	19.00	27.00	27.00
P2CubicSplineFitting	33	13	26.03	1.44	26.86	8.28	68.49	35.28	13.50	48.78	20.15	26.86	28.29
P2CubicSpline4DPts	28	18	13.25	2.14	10.10	11.34	128.64	54.61	1.00	55.61	7.00	10.10	21.76
P2SubgSubsMean	26	20	16.93	1.20	18.40	6.13	37.52	30.20	8.00	38.20	13.00	18.40	18.40
P2SubgSubsMed	26	20	18.94	1.43	22.00	7.27	52.89	33.00	8.00	41.00	13.00	22.00	22.00
P2SubgSubsMax	26	20	22.42	1.89	25.00	9.64	92.89	39.00	8.00	47.00	13.00	25.00	25.00
P2SubgSubsMin	25	21	9.92	.97	7.00	4.85	23.49	22.00	6.00	28.00	7.00	7.00	13.00

Table C18. General Statistics of Predicted Distress Scores According Age (1993-2010) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	4144	0	71.10	.33	77.60	21.44	459.47	97.77	2.23	100.00	56.00	77.60	88.95
Mean Nearby Points	3236	908	72.22	.38	77.36	21.38	457.23	98.15	.85	99.00	56.28	77.36	88.99
Med. Nearby Pts.	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Interpolation	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Trend Pts.	3085	1059	72.11	.38	76.95	21.24	451.11	98.58	.42	99.00	55.98	76.95	88.98
Moving Average	3385	759	72.12	.37	77.96	21.43	459.24	98.15	.85	99.00	57.17	77.96	88.99
Cubic Spline Fitting	3298	846	71.73	.37	76.82	21.42	458.68	98.13	.87	99.00	55.94	76.82	88.98
Cubic Spline4 D. Pts.	3310	834	71.93	.37	76.95	21.54	464.04	98.15	.85	99.00	56.45	76.95	88.98
Sub. Subs. Mean	3383	761	71.65	.37	76.79	21.62	467.22	98.15	.85	99.00	56.30	76.79	88.99
Sub. Subs. Med.	3399	745	71.42	.37	76.71	21.76	473.57	98.15	.85	99.00	56.05	76.71	88.98
Sub. Subs. Max.	3442	702	71.45	.37	76.79	21.67	469.50	98.15	.85	99.00	56.05	76.79	88.98
Sub. Subs. Min.	3349	795	72.21	.37	77.97	21.44	459.75	98.15	.85	99.00	57.77	77.97	88.99
P2LinearTrendatPts	2124	2020	84.80	.37	90.86	17.02	289.65	99.70	.07	99.77	78.97	90.86	95.69
P2MovingAverage	2220	1924	77.51	.44	87.00	20.71	428.99	85.00	14.00	99.00	62.00	87.00	92.00
P2CubicSplineFitting	2853	1291	76.89	.37	82.18	19.65	386.19	93.17	6.18	99.35	69.30	82.18	90.98
P2CubicSpline4DPts	1895	2249	72.92	.58	83.00	25.22	635.94	99.50	.50	100.00	59.67	83.00	93.50
P2SubgSubsMean	1698	2446	54.08	.37	57.33	15.32	234.58	84.00	5.00	89.00	42.00	57.33	65.62
P2SubgSubsMed	1793	2351	58.27	.40	62.00	17.09	291.97	84.00	5.00	89.00	44.00	62.00	72.00
P2SubgSubsMax	2206	1938	73.52	.46	78.00	21.50	462.32	94.00	5.00	99.00	57.00	78.00	89.00
P2SubgSubsMin	1029	3115	24.62	.54	20.00	17.40	302.72	85.00	4.00	89.00	13.00	20.00	32.00

Table C19. General Statistics of Predicted Distress Scores According to Early Age (1993-1998) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	449	0	66.42	1.16	73.50	24.67	608.48	87.30	11.47	98.77	48.69	73.50	88.93
Mean Nearby Points	390	59	67.01	1.26	73.79	24.92	621.13	89.56	9.33	98.89	49.30	73.79	88.99
Med. Nearby Pts.	395	54	66.90	1.25	72.00	24.83	616.36	85.95	12.94	98.89	49.41	72.00	88.99
Linear Interpolation	395	54	66.90	1.25	72.00	24.83	616.36	85.95	12.94	98.89	49.41	72.00	88.99
Linear Trend Pts.	367	82	67.80	1.27	74.74	24.28	589.58	89.80	9.09	98.89	48.97	74.74	88.99
Moving Average	387	62	67.11	1.26	72.97	24.75	612.76	85.74	13.15	98.89	49.41	72.97	88.99
Cubic Spline Fitting	382	67	67.01	1.26	72.00	24.69	609.73	85.44	13.49	98.93	48.69	72.00	88.99
Cubic Spline4 D. Pts.	392	57	67.10	1.25	72.98	24.73	611.68	85.95	12.94	98.89	49.41	72.98	88.98
Sub. Subs. Mean	391	58	67.49	1.23	73.00	24.42	596.12	86.34	12.55	98.89	50.00	73.00	88.99
Sub. Subs. Med.	391	58	67.52	1.23	73.00	24.41	595.81	86.38	12.51	98.89	50.00	73.00	88.99
Sub. Subs. Max.	391	58	67.52	1.23	73.00	24.40	595.49	86.38	12.51	98.89	50.00	73.00	88.99
Sub. Subs. Min.	392	57	67.15	1.24	72.22	24.62	606.30	88.55	10.34	98.89	49.41	72.22	88.99
P2LinearTrendatPts	217	232	79.81	1.54	90.80	22.75	517.74	89.96	9.81	99.77	67.91	90.80	95.67
P2MovingAverage	248	201	72.60	1.50	79.00	23.67	560.25	85.00	14.00	99.00	51.75	79.00	92.00
P2CubicSplineFitting	314	135	72.07	1.31	77.49	23.27	541.44	89.93	9.42	99.35	52.94	77.49	89.83
P2CubicSpline4DPts	190	259	67.70	2.03	78.50	28.04	786.32	96.00	3.00	99.00	40.00	78.50	92.00
P2SubgSubsMean	177	272	50.29	1.32	54.98	17.60	309.83	70.00	8.00	78.00	38.40	54.98	64.05
P2SubgSubsMed	197	252	55.68	1.42	56.00	19.99	399.50	81.00	8.00	89.00	41.00	56.00	71.00
P2SubgSubsMax	253	196	68.62	1.49	73.00	23.67	560.29	89.00	10.00	99.00	47.00	73.00	89.00
P2SubgSubsMin	119	330	23.18	1.18	20.00	12.83	164.69	74.00	4.00	78.00	15.00	20.00	29.00

Table C20. General Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1288	0	71.78	.57	76.92	20.58	423.67	97.49	2.23	99.72	56.99	76.92	88.94
Mean Nearby Points	1014	274	73.05	.65	77.79	20.66	426.96	93.31	5.69	99.00	58.75	77.79	88.96
Med. Nearby Pts.	1039	249	72.62	.65	76.97	21.08	444.55	93.48	5.52	99.00	57.99	76.97	88.97
Linear Interpolation	1039	249	72.62	.65	76.97	21.08	444.55	93.48	5.52	99.00	57.99	76.97	88.97
Linear Trend Pts.	963	325	72.95	.66	77.50	20.53	421.45	95.59	3.41	99.00	57.17	77.50	88.98
Moving Average	1056	232	72.51	.65	77.63	21.15	447.16	92.20	6.80	99.00	58.00	77.63	88.98
Cubic Spline Fitting	1049	239	72.80	.63	76.88	20.27	411.06	96.40	2.60	99.00	57.17	76.88	88.96
Cubic Spline4 D. Pts.	1053	235	72.93	.63	76.93	20.52	421.14	94.23	4.77	99.00	59.19	76.93	88.96
Sub. Subs. Mean	1052	236	72.41	.65	76.71	21.00	440.95	92.90	6.10	99.00	57.91	76.71	88.98
Sub. Subs. Med.	1080	208	72.20	.64	76.71	21.16	447.72	93.73	5.27	99.00	57.99	76.71	88.97
Sub. Subs. Max.	1078	210	72.38	.64	76.71	20.90	436.77	93.02	5.98	99.00	58.00	76.71	88.98
Sub. Subs. Min.	1044	244	72.76	.65	77.11	20.98	440.02	91.50	7.50	99.00	59.00	77.11	88.98
P2LinearTrendatPts	694	594	85.42	.65	91.26	17.09	292.21	99.70	.07	99.77	78.99	91.26	96.82
P2MovingAverage	720	568	79.01	.75	89.00	20.20	408.04	81.00	18.00	99.00	69.00	89.00	92.00
P2CubicSplineFitting	902	386	78.28	.63	84.58	18.96	359.34	85.85	13.50	99.35	70.62	84.58	91.52
P2CubicSpline4DPts	655	633	73.46	.94	80.50	24.09	580.36	99.00	1.00	100.00	62.00	80.50	93.00
P2SubgSubsMean	560	728	55.92	.63	60.40	14.94	223.13	81.00	8.00	89.00	48.10	60.40	66.41
P2SubgSubsMed	605	683	60.35	.67	68.00	16.49	272.06	81.00	8.00	89.00	48.00	68.00	73.00
P2SubgSubsMax	725	563	75.70	.77	83.00	20.69	428.03	91.00	8.00	99.00	69.00	83.00	90.00
P2SubgSubsMin	337	951	26.31	1.12	17.00	20.61	424.81	85.00	4.00	89.00	13.00	17.00	32.00

Table C21. General Statistics of Predicted Distress Scores According to Late Age (2005-2010) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	90	0	77.86	1.62	78.00	15.38	236.60	90.59	8.84	99.43	74.49	78.00	88.81
Mean Nearby Points	60	30	79.36	2.06	81.45	15.99	255.77	86.97	12.03	99.00	74.69	81.45	88.99
Med. Nearby Pts.	63	27	79.59	1.87	80.46	14.85	220.44	81.64	17.36	99.00	76.24	80.46	88.99
Linear Interpolation	63	27	79.59	1.87	80.46	14.85	220.44	81.64	17.36	99.00	76.24	80.46	88.99
Linear Trend Pts.	54	36	80.28	2.20	83.56	16.18	261.95	88.78	10.22	99.00	74.17	83.56	89.00
Moving Average	73	17	79.55	1.61	78.00	13.78	189.83	66.00	33.00	99.00	75.00	78.00	88.99
Cubic Spline Fitting	58	32	78.07	2.20	80.98	16.77	281.38	88.71	10.29	99.00	68.66	80.98	88.80
Cubic Spline4 D. Pts.	61	29	79.88	1.90	81.56	14.85	220.45	71.21	27.79	99.00	74.87	81.56	89.00
Sub. Subs. Mean	66	24	79.09	1.73	78.00	14.09	198.39	71.96	27.04	99.00	76.02	78.00	89.00
Sub. Subs. Med.	68	22	78.50	1.71	77.98	14.06	197.74	72.83	26.17	99.00	74.99	77.98	88.99
Sub. Subs. Max.	68	22	77.83	1.90	78.00	15.69	246.09	94.57	4.43	99.00	73.67	78.00	88.99
Sub. Subs. Min.	69	21	80.01	1.63	80.13	13.51	182.46	66.00	33.00	99.00	76.17	80.13	88.99
P2LinearTrendatPts	46	44	89.20	1.24	90.57	8.43	71.08	44.57	55.10	99.68	86.38	90.57	94.70
P2MovingAverage	44	46	84.50	1.96	89.00	13.02	169.60	66.00	33.00	99.00	78.00	89.00	92.00
P2CubicSplineFitting	59	31	81.85	1.90	85.53	14.58	212.60	73.13	26.17	99.30	75.78	85.53	90.11
P2CubicSpline4DPts	42	48	82.92	2.21	87.50	14.32	205.10	59.89	39.28	99.17	76.46	87.50	94.00
P2SubgSubsMean	31	59	60.06	2.15	61.30	11.99	143.85	59.43	21.40	80.83	54.98	61.30	66.79
P2SubgSubsMed	28	62	64.59	2.69	69.00	14.25	203.11	59.50	24.00	83.50	52.75	69.00	75.50
P2SubgSubsMax	35	55	81.29	2.30	85.00	13.59	184.62	75.00	24.00	99.00	78.00	85.00	89.00
P2SubgSubsMin	14	76	19.64	4.80	13.00	17.97	322.86	52.00	10.00	62.00	13.00	13.00	13.00

Table C22. General Statistics of Predicted Distress Scores for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	7554	0	71.17	.24	77.99	21.28	453.03	99.97	.03	100.00	53.99	77.99	88.96
Mean Nearby Points	5877	1677	73.05	.27	78.34	20.64	426.08	98.15	.85	99.00	54.75	78.34	88.99
Med. Nearby Pts.	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Interpolation	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Trend Pts.	5625	1929	72.67	.28	78.00	20.64	425.89	96.06	2.94	99.00	53.99	78.00	88.99
Moving Average	6327	1227	72.47	.26	78.00	21.02	441.98	98.15	.85	99.00	54.00	78.00	88.99
Cubic Spline Fitting	6054	1500	72.29	.27	78.00	20.71	428.98	91.83	7.17	99.00	53.99	78.00	88.98
Cubic Spline4 D. Pts.	5988	1566	72.75	.27	77.99	20.83	433.75	98.15	.85	99.00	54.12	77.99	88.98
Sub. Subs. Mean	6196	1358	72.15	.27	77.99	21.11	445.52	98.15	.85	99.00	54.00	77.99	88.99
Sub. Subs. Med.	6226	1328	71.31	.28	77.99	21.72	471.78	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Max.	6451	1103	71.43	.27	77.99	21.44	459.84	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Min.	6121	1433	72.83	.27	78.00	21.02	441.82	98.15	.85	99.00	55.12	78.00	88.99
P2LinearTrendatPts	3936	3618	85.86	.25	90.93	15.45	238.63	90.98	8.77	99.76	83.32	90.93	94.43
P2MovingAverage	4351	3203	77.37	.30	87.00	19.75	390.21	85.00	14.00	99.00	59.00	87.00	92.00
P2CubicSplineFitting	5187	2367	77.32	.27	84.72	19.30	372.47	89.31	10.02	99.33	68.72	84.72	90.96
P2CubicSpline4DPts	3679	3875	73.32	.41	83.00	24.80	615.05	99.00	1.00	100.00	57.81	83.00	93.33
P2SubgSubsMean	3616	3938	53.48	.23	55.12	14.01	196.27	81.00	8.00	89.00	40.57	55.12	64.05
P2SubgSubsMed	3661	3893	57.08	.26	58.00	15.92	253.49	81.00	8.00	89.00	43.00	58.00	69.00
P2SubgSubsMax	4513	3041	73.10	.30	78.00	20.32	412.98	91.00	8.00	99.00	56.00	78.00	89.00
P2SubgSubsMin	2106	5448	23.64	.33	20.00	15.15	229.43	85.00	4.00	89.00	13.00	20.00	28.00

Table C23. General Statistics of Predicted Distress Scores According to Very Good (90-100) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	5611	0	75.47	.26	82.94	19.67	386.91	99.97	.03	100.00	62.00	82.94	89.00
Mean Nearby Points	4501	1110	77.34	.28	86.09	19.12	365.54	98.15	.85	99.00	66.08	86.09	91.00
Med. Nearby Pts.	4599	1012	76.66	.29	86.29	19.95	397.88	98.15	.85	99.00	64.95	86.29	91.00
Linear Interpolation	4599	1012	76.66	.29	86.29	19.95	397.88	98.15	.85	99.00	64.95	86.29	91.00
Linear Trend Pts.	4281	1330	77.01	.29	85.18	19.19	368.14	96.06	2.94	99.00	66.20	85.18	90.70
Moving Average	4705	906	76.55	.29	85.42	19.77	390.95	98.15	.85	99.00	64.95	85.42	90.99
Cubic Spline Fitting	4629	982	76.44	.28	85.03	19.37	375.29	91.33	7.67	99.00	62.21	85.03	91.00
Cubic Spline4 D. Pts.	4600	1011	76.80	.29	86.51	19.60	384.06	98.15	.85	99.00	65.73	86.51	90.95
Sub. Subs. Mean	4695	916	76.13	.29	85.13	20.08	403.24	98.15	.85	99.00	64.21	85.13	91.00
Sub. Subs. Med.	4694	917	75.61	.30	84.93	20.34	413.64	98.15	.85	99.00	64.20	84.93	91.00
Sub. Subs. Max.	4795	816	75.73	.29	84.23	20.10	404.10	98.15	.85	99.00	64.21	84.23	90.97
Sub. Subs. Min.	4602	1009	76.90	.29	86.62	19.69	387.63	98.15	.85	99.00	66.57	86.62	91.00
P2LinearTrendatPts	3113	2498	89.70	.20	91.81	11.01	121.32	87.40	12.36	99.76	87.94	91.81	97.03
P2MovingAverage	3261	2350	83.21	.29	90.00	16.63	276.59	79.00	20.00	99.00	78.00	90.00	92.00
P2CubicSplineFitting	3905	1706	82.83	.25	87.79	15.74	247.68	86.77	12.56	99.33	76.44	87.79	91.85
P2CubicSpline4DPts	2863	2748	76.49	.43	86.67	23.12	534.55	96.50	3.50	100.00	67.00	86.67	94.00
P2SubgSubsMean	2654	2957	57.42	.23	61.14	12.02	144.52	80.00	9.00	89.00	53.29	61.14	65.62
P2SubgSubsMed	2731	2880	61.54	.27	68.00	13.91	193.40	80.00	9.00	89.00	52.50	68.00	72.00
P2SubgSubsMax	3321	2290	78.24	.31	86.00	17.99	323.77	83.00	16.00	99.00	73.00	86.00	89.00
P2SubgSubsMin	1457	4154	22.56	.44	14.00	16.86	284.29	85.00	4.00	89.00	13.00	14.00	28.00

Table C24. General Statistics of Predicted Distress Scores According to Good (80-89) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	6	0	64.47	9.58	68.06	23.47	550.61	52.99	35.97	88.96	37.67	68.06	87.90
Mean Nearby Points	3	3	75.69	7.93	76.49	13.73	188.62	27.43	61.57	89.00	61.57	76.49	.
Med. Nearby Pts.	4	2	78.95	6.50	82.55	12.99	168.82	27.28	61.72	89.00	65.32	82.55	88.99
Linear Interpolation	4	2	78.95	6.50	82.55	12.99	168.82	27.28	61.72	89.00	65.32	82.55	88.99
Linear Trend Pts.	4	2	65.83	11.21	68.75	22.41	502.36	52.17	36.83	89.00	42.94	68.75	85.81
Moving Average	3	3	75.62	7.89	76.18	13.66	186.69	27.31	61.69	89.00	61.69	76.18	.
Cubic Spline Fitting	3	3	75.27	8.01	75.54	13.87	192.38	27.74	61.26	89.00	61.26	75.54	.
Cubic Spline4 D. Pts.	4	2	78.70	6.68	82.46	13.36	178.38	28.10	60.90	89.00	64.67	82.46	88.98
Sub. Subs. Mean	4	2	78.81	6.69	82.71	13.38	178.94	28.19	60.81	89.00	64.72	82.71	89.00
Sub. Subs. Med.	4	2	79.00	6.61	82.97	13.23	175.00	27.93	61.07	89.00	65.04	82.97	88.99
Sub. Subs. Max.	4	2	79.61	6.28	83.50	12.56	157.66	26.54	62.46	89.00	66.35	83.50	89.00
Sub. Subs. Min.	3	3	75.36	8.10	76.09	14.03	196.80	28.03	60.97	89.00	60.97	76.09	.
P2LinearTrendatPts	3	3	75.24	7.57	75.82	13.12	172.13	26.22	61.85	88.07	61.85	75.82	.
P2MovingAverage	3	3	77.33	6.94	78.00	12.01	144.33	24.00	65.00	89.00	65.00	78.00	.
P2CubicSplineFitting	3	3	77.43	7.35	78.72	12.73	162.14	25.37	64.09	89.46	64.09	78.72	.
P2CubicSpline4DPts	3	3	76.63	7.24	77.28	12.54	157.26	25.06	63.78	88.83	63.78	77.28	.
P2SubgSubsMean	4	2	56.57	7.46	57.65	14.92	222.51	31.00	40.00	71.00	42.02	57.65	70.05
P2SubgSubsMed	4	2	60.00	8.60	61.00	17.20	296.00	38.00	40.00	78.00	43.00	61.00	76.00
P2SubgSubsMax	3	3	77.33	6.94	78.00	12.01	144.33	24.00	65.00	89.00	65.00	78.00	.
P2SubgSubsMin	1	5	32.00		32.00			.00	32.00	32.00	32.00	32.00	32.00

Table C25. General Statistics of Predicted Distress Scores According to Fair (70-79) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1	0	53.35		53.35			.00	53.35	53.35	53.35	53.35	53.35
Mean Nearby Points	1	0	53.41		53.41			.00	53.41	53.41	53.41	53.41	53.41
Med. Nearby Pts.	1	0	53.73		53.73			.00	53.73	53.73	53.73	53.73	53.73
Linear Interpolation	1	0	53.73		53.73			.00	53.73	53.73	53.73	53.73	53.73
Linear Trend Pts.	1	0	52.91		52.91			.00	52.91	52.91	52.91	52.91	52.91
Moving Average	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
Cubic Spline Fitting	1	0	52.81		52.81			.00	52.81	52.81	52.81	52.81	52.81
Cubic Spline4 D. Pts.	1	0	54.73		54.73			.00	54.73	54.73	54.73	54.73	54.73
Sub. Subs. Mean	1	0	53.93		53.93			.00	53.93	53.93	53.93	53.93	53.93
Sub. Subs. Med.	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
Sub. Subs. Max.	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
Sub. Subs. Min.	1	0	55.21		55.21			.00	55.21	55.21	55.21	55.21	55.21
P2LinearTrendatPts	1	0	57.77		57.77			.00	57.77	57.77	57.77	57.77	57.77
P2MovingAverage	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
P2CubicSplineFitting	1	0	52.78		52.78			.00	52.78	52.78	52.78	52.78	52.78
P2CubicSpline4DPts	1	0	57.81		57.81			.00	57.81	57.81	57.81	57.81	57.81
P2SubgSubsMean	1	0	38.40		38.40			.00	38.40	38.40	38.40	38.40	38.40
P2SubgSubsMed	1	0	40.00		40.00			.00	40.00	40.00	40.00	40.00	40.00
P2SubgSubsMax	1	0	45.00		45.00			.00	45.00	45.00	45.00	45.00	45.00
P2SubgSubsMin	1	0	32.00		32.00			.00	32.00	32.00	32.00	32.00	32.00

Table C26. General Statistics of Predicted Distress Scores According to Poor (60-69) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	2	0	69.85	4.86	69.85	6.87	47.26	9.72	64.99	74.71	64.99	69.85	.
Mean Nearby Points	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Med. Nearby Pts.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Linear Interpolation	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Linear Trend Pts.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Moving Average	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Cubic Spline Fitting	2	0	64.41	.59	64.41	.83	.70	1.18	63.82	65.00	63.82	64.41	.
Cubic Spline4 D. Pts.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Mean	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Med.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Max.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Min.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
P2LinearTrendatPts	1	1	57.52		57.52			.00	57.52	57.52	57.52	57.52	57.52
P2MovingAverage	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
P2CubicSplineFitting	1	1	65.92		65.92			.00	65.92	65.92	65.92	65.92	65.92
P2CubicSpline4DPts	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
P2SubgSubsMean	0	2											
P2SubgSubsMed	0	2											
P2SubgSubsMax	1	1	50.00		50.00			.00	50.00	50.00	50.00	50.00	50.00
P2SubgSubsMin	0	2											

Table C27. General Statistics of Predicted Distress Scores According to Very Poor (1-59) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	38	0	29.68	1.19	31.33	7.33	53.70	42.78	7.22	50.00	26.46	31.33	34.38
Mean Nearby Points	29	9	23.79	.94	27.00	5.06	25.60	20.95	6.05	27.00	19.00	27.00	27.00
Med. Nearby Pts.	29	9	23.87	.89	27.00	4.80	23.08	18.83	8.17	27.00	19.00	27.00	27.00
Linear Interpolation	29	9	23.87	.89	27.00	4.80	23.08	18.83	8.17	27.00	19.00	27.00	27.00
Linear Trend Pts.	29	9	23.85	.91	27.00	4.88	23.80	19.47	7.53	27.00	19.00	27.00	27.00
Moving Average	35	3	24.50	.98	27.00	5.78	33.43	31.00	19.00	50.00	19.00	27.00	27.00
Cubic Spline Fitting	29	9	23.83	.91	27.00	4.92	24.23	19.83	7.17	27.00	19.00	27.00	27.00
Cubic Spline4 D. Pts.	29	9	24.27	.71	27.00	3.83	14.70	8.00	19.00	27.00	19.00	27.00	27.00
Sub. Subs. Mean	31	7	23.64	.84	27.00	4.66	21.69	18.03	8.97	27.00	19.00	27.00	27.00
Sub. Subs. Med.	32	6	23.87	.68	27.00	3.85	14.85	8.00	19.00	27.00	19.00	27.00	27.00
Sub. Subs. Max.	30	8	24.13	.70	27.00	3.84	14.76	8.00	19.00	27.00	19.00	27.00	27.00
Sub. Subs. Min.	31	7	24.00	.69	27.00	3.85	14.81	8.00	19.00	27.00	19.00	27.00	27.00
P2LinearTrendatPts	28	10	17.79	.54	19.17	2.87	8.25	8.57	12.80	21.37	14.74	19.17	20.15
P2MovingAverage	28	10	24.43	.72	27.00	3.80	14.48	8.00	19.00	27.00	19.00	27.00	27.00
P2CubicSplineFitting	30	8	25.34	.80	27.40	4.40	19.38	17.73	12.28	30.01	21.05	27.40	28.69
P2CubicSpline4DPts	28	10	11.20	1.32	10.48	6.98	48.70	22.00	1.00	23.00	7.00	10.48	15.26
P2SubgSubsMean	29	9	16.37	.56	18.40	2.99	8.95	10.40	8.00	18.40	13.00	18.40	18.40
P2SubgSubsMed	29	9	18.72	.87	22.00	4.68	21.92	14.00	8.00	22.00	13.00	22.00	22.00
P2SubgSubsMax	29	9	20.69	1.14	25.00	6.11	37.36	17.00	8.00	25.00	13.00	25.00	25.00
P2SubgSubsMin	29	9	8.90	.52	7.00	2.81	7.88	6.00	7.00	13.00	7.00	7.00	13.00

Table C28. General Statistics of Predicted Distress Scores According Age (1993-2010) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	7554	0	71.17	.24	77.99	21.28	453.03	99.97	.03	100.00	53.99	77.99	88.96
Mean Nearby Points	5877	1677	73.05	.27	78.34	20.64	426.08	98.15	.85	99.00	54.75	78.34	88.99
Med. Nearby Pts.	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Interpolation	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Trend Pts.	5625	1929	72.67	.28	78.00	20.64	425.89	96.06	2.94	99.00	53.99	78.00	88.99
Moving Average	6327	1227	72.47	.26	78.00	21.02	441.98	98.15	.85	99.00	54.00	78.00	88.99
Cubic Spline Fitting	6054	1500	72.29	.27	78.00	20.71	428.98	91.83	7.17	99.00	53.99	78.00	88.98
Cubic Spline4 D. Pts.	5988	1566	72.75	.27	77.99	20.83	433.75	98.15	.85	99.00	54.12	77.99	88.98
Sub. Subs. Mean	6196	1358	72.15	.27	77.99	21.11	445.52	98.15	.85	99.00	54.00	77.99	88.99
Sub. Subs. Med.	6226	1328	71.31	.28	77.99	21.72	471.78	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Max.	6451	1103	71.43	.27	77.99	21.44	459.84	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Min.	6121	1433	72.83	.27	78.00	21.02	441.82	98.15	.85	99.00	55.12	78.00	88.99
P2LinearTrendatPts	3936	3618	85.86	.25	90.93	15.45	238.63	90.98	8.77	99.76	83.32	90.93	94.43
P2MovingAverage	4351	3203	77.37	.30	87.00	19.75	390.21	85.00	14.00	99.00	59.00	87.00	92.00
P2CubicSplineFitting	5187	2367	77.32	.27	84.72	19.30	372.47	89.31	10.02	99.33	68.72	84.72	90.96
P2CubicSpline4DPts	3679	3875	73.32	.41	83.00	24.80	615.05	99.00	1.00	100.00	57.81	83.00	93.33
P2SubgSubsMean	3616	3938	53.48	.23	55.12	14.01	196.27	81.00	8.00	89.00	40.57	55.12	64.05
P2SubgSubsMed	3661	3893	57.08	.26	58.00	15.92	253.49	81.00	8.00	89.00	43.00	58.00	69.00
P2SubgSubsMax	4513	3041	73.10	.30	78.00	20.32	412.98	91.00	8.00	99.00	56.00	78.00	89.00
P2SubgSubsMin	2106	5448	23.64	.33	20.00	15.15	229.43	85.00	4.00	89.00	13.00	20.00	28.00

Table C29. General Statistics of Predicted Distress Scores According to Early Age (1993-1998) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	182	0	64.43	1.99	69.94	26.85	721.12	90.54	8.35	98.89	41.98	69.94	89.00
Mean Nearby Points	162	20	66.71	2.03	70.97	25.89	670.25	89.46	9.43	98.89	45.64	70.97	90.66
Med. Nearby Pts.	166	16	65.73	2.06	69.94	26.52	703.36	87.94	10.95	98.89	45.32	69.94	90.66
Linear Interpolation	166	16	65.73	2.06	69.94	26.52	703.36	87.94	10.95	98.89	45.32	69.94	90.66
Linear Trend Pts.	158	24	66.86	2.03	69.94	25.53	651.59	89.07	9.82	98.89	45.41	69.94	90.66
Moving Average	164	18	66.43	2.03	70.30	25.96	673.80	80.79	18.10	98.89	48.05	70.30	90.66
Cubic Spline Fitting	166	16	65.36	2.05	69.74	26.46	700.27	90.45	8.44	98.89	43.59	69.74	90.66
Cubic Spline4 D. Pts.	164	18	66.72	2.01	72.00	25.79	665.29	86.24	12.65	98.89	48.69	72.00	90.66
Sub. Subs. Mean	166	16	65.70	2.06	69.94	26.50	702.18	90.23	8.66	98.89	45.32	69.94	90.66
Sub. Subs. Med.	165	17	66.04	2.04	69.94	26.25	688.93	90.09	8.80	98.89	46.63	69.94	90.66
Sub. Subs. Max.	165	17	66.06	2.04	69.94	26.21	686.75	87.17	11.72	98.89	46.63	69.94	90.66
Sub. Subs. Min.	167	15	65.64	2.05	69.94	26.46	700.05	89.89	9.00	98.89	45.43	69.94	90.66
P2LinearTrendatPts	93	89	79.48	2.67	91.87	25.76	663.59	87.40	12.36	99.76	63.79	91.87	98.98
P2MovingAverage	117	65	72.22	2.26	82.00	24.43	596.76	79.00	20.00	99.00	50.00	82.00	92.00
P2CubicSplineFitting	131	51	72.16	2.20	84.40	25.12	631.19	86.75	12.56	99.31	50.95	84.40	91.06
P2CubicSpline4DPts	86	96	69.62	2.97	86.00	27.53	757.85	88.00	11.00	99.00	40.00	86.00	94.50
P2SubgSubsMean	87	95	49.88	2.02	55.12	18.82	354.26	68.59	9.00	77.59	35.00	55.12	66.20
P2SubgSubsMed	89	93	54.61	2.29	56.00	21.59	466.08	80.00	9.00	89.00	41.00	56.00	70.50
P2SubgSubsMax	115	67	68.58	2.25	73.00	24.13	582.26	83.00	16.00	99.00	47.00	73.00	89.00
P2SubgSubsMin	51	131	21.49	1.41	20.00	10.05	101.05	58.00	4.00	62.00	15.00	20.00	25.00

Table C30. General Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1372	0	72.14	.53	77.96	19.72	388.82	99.91	.09	100.00	53.99	77.96	88.93
Mean Nearby Points	1033	339	74.07	.62	80.05	20.07	402.99	98.15	.85	99.00	57.85	80.05	89.00
Med. Nearby Pts.	1064	308	73.27	.64	78.00	20.95	438.73	98.15	.85	99.00	56.83	78.00	89.00
Linear Interpolation	1064	308	73.27	.64	78.00	20.95	438.73	98.15	.85	99.00	56.83	78.00	89.00
Linear Trend Pts.	963	409	74.39	.64	80.94	19.97	398.73	91.03	7.97	99.00	57.68	80.94	89.59
Moving Average	1116	256	72.87	.63	77.99	20.93	438.02	98.15	.85	99.00	55.99	77.99	88.99
Cubic Spline Fitting	1084	288	73.45	.60	78.00	19.80	391.96	86.05	12.95	99.00	55.71	78.00	88.96
Cubic Spline4 D. Pts.	1091	281	73.94	.60	78.00	19.75	390.19	98.15	.85	99.00	57.17	78.00	88.97
Sub. Subs. Mean	1106	266	72.87	.63	77.99	20.81	433.14	98.15	.85	99.00	55.55	77.99	88.96
Sub. Subs. Med.	1121	251	72.42	.63	77.99	21.08	444.45	98.15	.85	99.00	53.99	77.99	88.96
Sub. Subs. Max.	1154	218	72.55	.61	77.99	20.70	428.49	98.15	.85	99.00	54.02	77.99	88.96
Sub. Subs. Min.	1082	290	73.24	.63	78.00	20.85	434.66	98.15	.85	99.00	56.90	78.00	88.99
P2LinearTrendatPts	788	584	85.16	.57	90.91	16.14	260.42	90.98	8.77	99.76	79.27	90.91	95.08
P2MovingAverage	796	576	79.76	.67	89.00	18.95	359.22	80.00	19.00	99.00	69.00	89.00	92.00
P2CubicSplineFitting	954	418	78.76	.61	84.94	18.83	354.52	79.69	19.64	99.33	70.87	84.94	91.57
P2CubicSpline4DPts	748	624	73.29	.86	80.50	23.49	551.63	99.00	1.00	100.00	62.00	80.50	92.00
P2SubgSubsMean	657	715	56.26	.52	60.40	13.40	179.64	76.00	13.00	89.00	48.46	60.40	65.55
P2SubgSubsMed	690	682	60.98	.57	68.00	15.10	228.08	76.00	13.00	89.00	48.00	68.00	73.00
P2SubgSubsMax	846	526	76.30	.67	83.00	19.35	374.42	86.00	13.00	99.00	69.00	83.00	90.00
P2SubgSubsMin	367	1005	25.69	1.00	20.00	19.15	366.60	84.00	5.00	89.00	13.00	20.00	32.00

Table C31. General Statistics of Predicted Distress Scores According to Late Age (2005-2010) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	28	0	74.73	3.69	78.78	19.51	380.71	87.16	12.09	99.25	61.79	78.78	88.44
Mean Nearby Points	20	8	78.72	3.71	78.67	16.60	275.71	73.91	25.09	99.00	75.14	78.67	88.96
Med. Nearby Pts.	21	7	78.82	3.37	82.41	15.46	239.04	66.27	32.73	99.00	73.78	82.41	89.00
Linear Interpolation	21	7	78.82	3.37	82.41	15.46	239.04	66.27	32.73	99.00	73.78	82.41	89.00
Linear Trend Pts.	20	8	78.23	3.95	78.00	17.66	311.89	79.76	19.24	99.00	75.36	78.00	88.30
Moving Average	27	1	77.30	3.15	77.99	16.38	268.43	66.00	33.00	99.00	72.99	77.99	88.99
Cubic Spline Fitting	21	7	76.07	3.93	78.00	18.00	324.01	78.67	20.33	99.00	69.92	78.00	88.18
Cubic Spline4 D. Pts.	23	5	78.60	3.35	82.94	16.08	258.58	66.56	32.44	99.00	76.88	82.94	88.98
Sub. Subs. Mean	23	5	76.88	3.53	78.48	16.94	287.04	77.93	21.07	99.00	65.57	78.48	88.75
Sub. Subs. Med.	23	5	77.35	3.51	78.85	16.82	282.75	78.83	20.17	99.00	67.45	78.85	88.94
Sub. Subs. Max.	24	4	76.00	3.80	78.42	18.64	347.44	93.60	5.40	99.00	69.25	78.42	86.52
Sub. Subs. Min.	23	5	79.58	2.97	82.40	14.26	203.41	66.00	33.00	99.00	72.04	82.40	88.99
P2LinearTrendatPts	20	8	86.47	2.34	86.46	10.45	109.18	48.93	50.66	99.59	84.76	86.46	92.28
P2MovingAverage	19	9	80.21	3.46	78.00	15.09	227.62	66.00	33.00	99.00	78.00	78.00	89.00
P2CubicSplineFitting	22	6	79.78	3.40	80.59	15.93	253.79	73.04	26.24	99.28	75.22	80.59	88.86
P2CubicSpline4DPts	19	9	74.06	4.31	76.78	18.80	353.39	69.22	27.80	97.02	53.56	76.78	88.39
P2SubgSubsMean	13	15	54.76	3.53	54.98	12.72	161.78	51.27	21.40	72.67	54.54	54.98	61.11
P2SubgSubsMed	9	19	57.56	5.75	53.50	17.25	297.40	54.00	24.00	78.00	48.25	53.50	72.25
P2SubgSubsMax	15	13	76.87	4.42	83.00	17.13	293.27	65.00	24.00	89.00	78.00	83.00	89.00
P2SubgSubsMin	3	25	12.33	.67	13.00	1.15	1.33	2.00	11.00	13.00	11.00	13.00	.

Appendix D

Accuracy Improvement and Statistical Significance of Missing Data Techniques in Predicting Distress Scores:

Nonparametric Test: Mann-Whitney Test

Missing Data Points of CRCP 1993-2010

Table D1. Abbreviations Used for Accuracy Improvement and Statistical Significance of Missing Data Techniques in Predicting Distress Scores.

Abbreviation	**Explanation**	**Note**
Imp.	Improvement	
Eff.	Efficiency	
Sig.	Significance	
Obs.	Observation	
Mean	Mean	
Med.	Median	
Min.	Minimum	
Max.	Maximum	
%	Percentage	
Missing Data Techniques Brief	**Missing Data Techniques Explanation**	**Predicting By**
Do Nothing	Do Nothing	**Pavement Performance Model**
Mean Nearby Points	Mean of Nearby Points Using	
Med. Nearby Pts.	Median of Nearby Points	
Linear Interpolation	Linear Interpolation	
Linear Trend Pts.	Linear Trend at Points	
Moving Average	Moving Average	
Cubic Spline Fitting	Cubic Spline Fitting	
Cubic Spline4 D. Pts.	Cubic Spline 4 Data Points	
Sub. Subs. Mean	Subgroup Substitutions Mean	
Sub. Subs. Med.	Subgroup Substitutions Median	
Sub. Subs. Max.	Subgroup Substitutions Maximum	
Sub. Subs. Min.	Subgroup Substitutions Minimum	
P2LinearTrendatPts	Linear Trend at Points	**Missing Data Techniques**
P2MovingAverage	Moving Average Using	
P2CubicSplineFitting	Cubic Spline Fitting Using	
P2CubicSpline4DPts	Cubic Spline 4 Data Points	
P2SubgSubsMean	Subgroup Substitutions	
P2SubgSubsMed	Subgroup Substitutions	
P2SubgSubsMax	Subgroup Substitutions Maximum	
P2SubgSubsMin	Subgroup Substitutions Minimum	

Table D2. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases with 1, 2, and 3 Missing Data Points.

Predicting By	Case	One Data Point Missing			Two Data Points Missing			Three Data Points Missing		
	Technique	Median	P-Value	(%)	Median	P-Value	(%)	Median	P-Value	(%)
Pavement Performance Model	PMS Method	6.07	-	0.00	4.56	-	0.00	6.22	-	0.00
	Mean Nearby Points	5.12	0.04	15.70	4.52	0.08	0.93	6.51	0.23	-4.60
	Med. Nearby Pts.	5.32	0.03	12.33	4.00	0.01	12.35	6.37	0.19	-2.46
	Linear Interpolation	5.32	0.03	12.33	4.00	0.01	12.35	6.37	0.19	-2.46
	Linear Trend Pts.	5.14	0.11	15.40	5.00	0.49	-9.56	6.74	0.00	-8.37
	Moving Average	5.39	0.01	11.16	4.00	0.00	12.35	6.40	0.00	-2.95
	Cubic Spline Fitting	5.39	0.07	11.19	4.46	0.42	2.27	6.39	0.03	-2.76
	Cubic Spline4 D. Pts.	5.32	0.03	12.29	4.33	0.01	5.19	6.58	0.39	-5.86
	Sub. Subs. Mean	5.64	0.03	7.06	4.28	0.00	6.15	6.94	0.52	-11.67
	Sub. Subs. Med.	5.59	0.03	7.97	4.06	0.00	11.11	7.05	0.17	-13.40
	Sub. Subs. Max.	5.75	0.03	5.23	4.26	0.00	6.62	6.72	0.14	-8.09
	Sub. Subs. Min.	5.25	0.02	13.46	4.00	0.00	12.35	6.00	0.00	3.52
Missing Data Techniques	P2LinearTrendatPts	12.12	0.00	-99.61	10.76	0.00	-135.69	13.23	0.00	-112.71
	P2MovingAverage	4.00	0.00	34.10	4.00	0.00	12.35	5.00	0.00	19.60
	P2CubicSplineFitting	6.15	0.00	-1.28	5.40	0.00	-18.32	6.48	0.00	-4.18
	P2CubicSpline4DPts	13.00	0.00	-114.16	12.00	0.00	-162.94	13.33	0.00	-114.39
	P2SubgSubsMean	16.88	0.00	-178.00	18.15	0.00	-297.77	14.17	0.00	-127.79
	P2SubgSubsMed	15.00	0.00	-147.11	16.00	0.00	-250.58	14.00	0.00	-125.11
	P2SubgSubsMax	4.00	0.00	34.10	4.00	0.00	12.35	5.00	0.00	19.60
	P2SubgSubsMin	43.00	0.00	-608.38	49.00	0.00	-973.65	47.00	0.00	-655.73

Totally tested cases: 1232, 4144, and 7554 respectively

D-3

Table D3. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases with One Missing Data Point.

Predicting	Technique	Absolute Discrepancy							Accuracy Improvement				Mann-Whitney Test	
		Median	Mean	Max.	Min.	1st Quart	2nd Quart	3rd Quart	+	=	-	(%)	p-value	Null Hypothesis
Pavement Performance Model	PMS Method	6.07	12.00	74.00	0.00	0.94	6.07	15.72	0	1232	0	0.00	-	-
	Mean Nearby Points	5.12	11.76	78.14	0.00	0.55	5.12	15.17	689	49	494	15.70	0.04	Reject
	Med. Nearby Pts.	5.32	11.77	78.14	0.00	0.56	5.32	15.15	678	54	500	12.33	0.03	Reject
	Linear Interpolation	5.32	11.77	78.14	0.00	0.56	5.32	15.15	678	54	500	12.33	0.03	Reject
	Linear Trend Pts.	5.14	11.84	84.81	0.00	0.76	5.14	15.95	683	36	513	15.40	0.11	Accept
	Moving Average	5.39	11.77	78.14	0.00	0.12	5.39	15.04	656	52	524	11.16	0.01	Reject
	Cubic Spline Fitting	5.39	11.91	88.13	0.00	0.55	5.39	16.59	692	36	504	11.19	0.07	Reject
	Cubic Spline4 D. Pts.	5.32	11.81	78.14	0.00	0.41	5.32	15.16	680	52	500	12.29	0.03	Reject
	Sub. Subs. Mean	5.64	11.78	78.14	0.00	0.39	5.64	15.00	667	54	511	7.06	0.03	Reject
	Sub. Subs. Med.	5.59	11.77	78.14	0.00	0.18	5.59	15.00	662	53	517	7.97	0.03	Reject
	Sub. Subs. Max.	5.75	11.79	78.14	0.00	0.20	5.75	14.97	667	53	512	5.23	0.03	Reject
	Sub. Subs. Min.	5.25	11.77	78.14	0.00	0.18	5.25	15.00	656	51	525	13.46	0.02	Reject
Missing Data Techniques	P2LinearTrendatPts	12.12	17.24	84.49	0.00	4.76	12.12	25.28	164	0	1068	-99.61	0.00	Reject
	P2MovingAverage	4.00	11.75	82.00	0.00	0.00	4.00	15.00	650	6	576	34.10	0.00	Reject
	P2CubicSplineFitting	6.15	12.46	82.57	0.00	1.93	6.15	16.52	528	0	704	-1.28	0.00	Reject
	P2CubicSpline4DPts	13.00	19.14	90.00	0.00	5.50	13.00	28.71	433	0	799	-114.16	0.00	Reject
	P2SubgSubsMean	16.88	17.25	55.38	0.00	8.97	16.88	24.44	478	0	754	-178.00	0.00	Reject
	P2SubgSubsMed	15.00	16.41	66.50	0.00	7.00	15.00	22.00	491	0	741	-147.11	0.00	Reject
	P2SubgSubsMax	4.00	11.26	82.00	0.00	0.00	4.00	15.00	738	0	494	34.10	0.00	Reject
	P2SubgSubsMin	43.00	41.38	83.00	0.00	21.00	43.00	61.00	226	0	1006	-608.38	0.00	Reject

Totally tested cases: 1232

D-4

Table D4. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases of One Missing Data Point According to Distress Score Categories.

Predicting By	Category	Very Good (90 - 100)			Good (80 - 99)			Fair (70 - 79)			Poor (60 - 69)			Very Poor (1 - 59)		
	Technique	**Med**	**Sig.**	**(%)**	**Med**	**Sig.**	**(%)**	**Med**	**Sig.**	**(%)**	**Med**	**Sig.**	**(%)**	**Med**	**Sig.**	**(%)**
Pavement Performance Model	**PMS Method**	6.87	-	0.00	2.06	-	0	3.25	-	0.00	2.66	-	0	4.67	-	0.00
	Mean Nearby Points	6.48	0.21	5.79	1.68	0.08	18	3.03	0.63	6.75	1.83	0.27	31	3.91	0.08	16.43
	Med. Nearby Pts.	6.95	0.20	-1.16	1.38	0.07	33	2.64	0.53	18.73	1.00	0.24	62	4.00	0.09	14.40
	Linear Interpolation	6.95	0.20	-1.16	1.38	0.07	33	2.64	0.53	18.73	1.00	0.24	62	4.00	0.09	14.40
	Linear Trend Pts.	6.80	0.42	1.06	1.48	0.07	28	3.74	0.66	-15.09	1.87	0.30	30	3.79	0.06	18.82
	Moving Average	6.97	0.10	-1.41	1.91	0.11	8	3.17	0.46	2.38	2.00	0.38	25	3.85	0.08	17.68
	Cubic Spline Fitting	6.66	0.29	3.13	1.63	0.07	21	2.76	0.62	15.12	2.10	0.36	21	3.37	0.11	27.95
	Cubic Spline4 D. Pts.	6.97	0.16	-1.36	1.34	0.06	35	2.74	0.60	15.60	1.00	0.24	62	4.00	0.19	14.40
	Sub. Subs. Mean	6.97	0.17	-1.41	1.50	0.09	27	3.35	0.64	-3.11	1.00	0.28	62	4.00	0.07	14.40
	Sub. Subs. Med.	6.97	0.13	-1.41	1.91	0.22	8	3.62	0.74	-11.44	0.96	0.15	64	4.00	0.09	14.40
	Sub. Subs. Max.	6.97	0.14	-1.41	1.91	0.26	8	3.92	0.71	-20.66	1.00	0.27	62	4.00	0.11	14.40
	Sub. Subs. Min.	6.97	0.12	-1.41	1.91	0.12	8	3.53	0.52	-8.49	1.74	0.37	35	4.00	0.09	14.40
Missing Data Techniques	**P2LinearTrendatPts**	13.50	0.00	-96.47	4.91	0.00	-138	7.72	0.00	-137.31	7.51	0.00	-182	8.39	0.02	-79.58
	P2MovingAverage	5.00	0.00	27.26	0.00	0.00	100	2.00	0.04	38.48	2.00	0.10	25	2.00	0.01	57.20
	P2CubicSplineFitting	7.14	0.00	-3.89	1.34	0.93	35	3.35	0.41	-3.12	1.70	0.94	36	5.23	0.62	-11.95
	P2CubicSpline4DPts	13.00	0.00	-89.13	11.00	0.00	-434	10.00	0.00	-207.58	7.00	0.01	-163	13.33	0.00	-185.33
	P2SubgSubsMean	17.74	0.00	-158.08	17.71	0.00	-759	16.00	0.00	-392.14	15.83	0.00	-495	2.60	0.37	44.36
	P2SubgSubsMed	16.00	0.00	-132.77	16.00	0.00	-676	14.50	0.00	-346.00	12.50	0.00	-370	4.00	0.56	14.40
	P2SubgSubsMax	4.00	0.00	41.81	2.00	0.09	3	3.00	0.13	7.72	3.00	0.89	-13	2.00	0.07	57.20
	P2SubgSubsMin	48.00	0.00	-598.32	48.50	0.00	-2253	32.00	0.00	-884.27	32.00	0.00	-1103	9.00	0.47	-92.60

Totally tested cases: 1025 Very Good,70 Good, 59Fair, 25 Poor, and 53 Very Poor

D-5

Table D5. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases of One Missing Data Point with Very Good Distress Score Category (90-100).

Predicting	Technique	Absolute Discrepancy							Accuracy Improvement				Mann-Whitney Test	
		Median	Mean	Max.	Min.	1st Quart.	2nd Quart.	3rd Quart.	+	=	-	(%)	p-value	Null Hypothesis
Pavement Performance Model	**PMS Method**	6.87	12.97	74.00	0.00	1.12	6.87	19.28	0	1025	0	0.00	-	Accept
	Mean Nearby Points	6.48	12.89	78.14	0.00	0.66	6.48	19.40	549	49	427	5.79	0.21	Accept
	Med. Nearby Pts.	6.95	12.91	78.14	0.00	0.66	6.95	19.40	543	54	428	-1.16	0.20	Accept
	Linear Interpolation	6.95	12.91	78.14	0.00	0.66	6.95	19.40	543	54	428	-1.16	0.20	Accept
	Linear Trend Pts.	6.80	12.99	84.81	0.00	1.00	6.80	19.43	543	36	446	1.06	0.42	Accept
	Moving Average	6.97	12.86	78.14	0.00	0.50	6.97	18.82	539	51	435	-1.41	0.10	Accept
	Cubic Spline Fitting	6.66	13.07	88.13	0.00	0.78	6.66	19.74	554	36	435	3.13	0.29	Accept
	Cubic Spline4 D. Pts.	6.97	12.94	78.14	0.00	0.56	6.97	19.40	546	52	427	-1.36	0.16	Accept
	Sub. Subs. Mean	6.97	12.90	78.14	0.00	0.63	6.97	18.84	537	54	434	-1.41	0.17	Accept
	Sub. Subs. Med.	6.97	12.88	78.14	0.00	0.56	6.97	19.40	538	53	434	-1.41	0.13	Accept
	Sub. Subs. Max.	6.97	12.88	78.14	0.00	0.56	6.97	19.40	538	53	434	-1.41	0.14	Accept
	Sub. Subs. Min.	6.97	12.87	78.14	0.00	0.56	6.97	19.40	536	51	438	-1.41	0.12	Reject
Missing Data Techniques	**P2LinearTrendatPts**	13.50	18.32	84.49	0.00	5.32	13.50	26.39	126	0	899	-96.47	0.00	Reject
	P2MovingAverage	5.00	12.83	82.00	0.00	0.00	5.00	20.00	516	5	504	27.26	0.00	Reject
	P2CubicSplineFitting	7.14	13.55	82.57	0.00	2.14	7.14	18.09	421	0	604	-3.89	0.00	Reject
	P2CubicSpline4DPts	13.00	19.59	90.00	0.00	6.00	13.00	29.00	373	0	652	-89.13	0.00	Reject
	P2SubgSubsMean	17.74	17.84	55.38	0.00	9.20	17.74	24.80	406	0	619	-158.08	0.00	Reject
	P2SubgSubsMed	16.00	16.89	66.50	0.00	8.00	16.00	22.00	420	0	605	-132.77	0.00	Reject
	P2SubgSubsMax	4.00	12.16	82.00	0.00	0.00	4.00	18.00	603	0	422	41.81	0.00	Reject
	P2SubgSubsMin	48.00	43.57	83.00	0.00	24.00	48.00	64.00	178	0	847	-598.32	0.00	Reject

Totally tested cases: 1025

D-6

Table D6. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases of One Missing Data Point with Good Distress Score Category (80-89).

Predicting	Technique	Absolute Discrepancy							Accuracy Improvement				Mann-Whitney Test	
		Median	Mean	Max.	Min.	1st Quart.	2nd Quart.	3rd Quart.	+	=	-	(%)	p-value	Null Hypothesis
Pavement Performance Model	PMS Method	2.06	6.54	61.51	0.00	0.72	2.06	7.75	0	70	0	0	-	-
	Mean Nearby Points	1.68	5.88	63.01	0.00	0.00	1.68	7.83	44	0	26	18	0.08	Accept
	Med. Nearby Pts.	1.38	5.89	63.01	0.00	0.01	1.38	7.78	43	0	27	33	0.07	Accept
	Linear Interpolation	1.38	5.89	63.01	0.00	0.01	1.38	7.78	43	0	27	33	0.07	Accept
	Linear Trend Pts.	1.48	5.81	63.07	0.00	0.02	1.48	6.94	45	0	25	28	0.07	Accept
	Moving Average	1.91	6.30	65.97	0.00	0.00	1.91	9.28	39	0	31	8	0.11	Accept
	Cubic Spline Fitting	1.63	5.81	62.03	0.00	0.00	1.63	6.75	44	0	26	21	0.07	Accept
	Cubic Spline4 D. Pts.	1.34	5.81	63.01	0.00	0.01	1.34	7.11	46	0	24	35	0.06	Accept
	Sub. Subs. Mean	1.50	6.08	69.58	0.00	0.03	1.50	8.03	44	0	26	27	0.09	Accept
	Sub. Subs. Med.	1.91	6.20	65.97	0.00	0.03	1.91	8.02	45	0	25	8	0.22	Accept
	Sub. Subs. Max.	1.91	6.11	41.58	0.00	0.01	1.91	8.39	41	0	29	8	0.26	Accept
	Sub. Subs. Min.	1.91	6.18	65.97	0.00	0.00	1.91	8.36	42	0	28	8	0.12	Accept
Missing Data Techniques	P2LinearTrendatPts	4.91	11.61	73.36	0.30	2.69	4.91	16.25	8	0	62	-138	0.00	Reject
	P2MovingAverage	0.00	6.73	70.00	0.00	0.00	0.00	10.00	46	0	24	100	0.00	Reject
	P2CubicSplineFitting	1.34	7.16	68.53	0.07	0.84	1.34	9.21	35	0	35	35	0.93	Accept
	P2CubicSpline4DPts	11.00	15.19	80.00	0.00	2.50	11.00	19.67	19	0	51	-434	0.00	Reject
	P2SubgSubsMean	17.71	18.67	43.55	0.00	10.90	17.71	28.86	16	0	54	-759	0.00	Reject
	P2SubgSubsMed	16.00	18.21	40.00	0.00	7.00	16.00	29.75	15	0	55	-676	0.00	Reject
	P2SubgSubsMax	2.00	7.39	70.00	0.00	0.00	2.00	10.00	43	0	27	3	0.09	Reject
	P2SubgSubsMin	48.50	44.06	79.00	0.00	29.50	48.50	64.50	7	0	63	-2253	0.00	Reject

Totally tested cases: 70

Table D7. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases of One Missing Data Point with Fair Distress Score Category (70-79).

Predicting	Technique	Absolute Discrepancy							Accuracy Improvement				Mann-Whitney Test	
		Median	Mean	Max.	Min.	1st Quart.	2nd Quart.	3rd Quart.	+	=	-	(%)	p-value	Null Hypothesis
Pavement Performance Model	PMS Method	3.25	8.93	63.01	0.00	0.93	3.25	12.80	0	59	0	0.00	-	-
	Mean Nearby Points	3.03	8.49	62.71	0.00	0.42	3.03	10.19	36	0	23	6.75	0.63	Accept
	Med. Nearby Pts.	2.64	8.27	62.71	0.00	0.64	2.64	9.34	36	0	23	18.73	0.53	Accept
	Linear Interpolation	2.64	8.27	62.71	0.00	0.64	2.64	9.34	36	0	23	18.73	0.53	Accept
	Linear Trend Pts.	3.74	8.64	62.56	0.00	0.53	3.74	11.06	37	0	22	-15.09	0.66	Accept
	Moving Average	3.17	8.62	61.92	0.00	0.05	3.17	11.49	29	0	30	2.38	0.46	Accept
	Cubic Spline Fitting	2.76	8.66	62.74	0.00	0.59	2.76	12.68	39	0	20	15.12	0.62	Accept
	Cubic Spline4 D. Pts.	2.74	8.60	62.71	0.00	0.45	2.74	11.60	36	0	23	15.60	0.60	Accept
	Sub. Subs. Mean	3.35	8.74	62.82	0.00	0.11	3.35	12.54	33	0	26	-3.11	0.64	Accept
	Sub. Subs. Med.	3.62	8.82	62.19	0.00	0.08	3.62	13.20	27	0	32	-11.44	0.74	Accept
	Sub. Subs. Max.	3.92	8.93	62.91	0.00	0.39	3.92	13.20	32	0	27	-20.66	0.71	Accept
	Sub. Subs. Min.	3.53	8.67	61.92	0.00	0.03	3.53	12.14	29	0	30	-8.49	0.52	Accept
Missing Data Techniques	P2LinearTrendatPts	7.72	14.52	67.51	1.28	3.69	7.72	21.18	8	0	51	-137.31	0.00	Reject
	P2MovingAverage	2.00	8.63	65.00	0.00	0.00	2.00	13.00	34	0	25	38.48	0.04	Reject
	P2CubicSplineFitting	3.35	8.93	62.17	0.20	1.30	3.35	10.06	29	0	30	-3.12	0.41	Accept
	P2CubicSpline4DPts	10.00	16.40	84.00	0.00	5.00	10.00	21.17	17	0	42	-207.58	0.00	Reject
	P2SubgSubsMean	16.00	16.13	42.33	1.00	9.86	16.00	19.26	18	0	41	-392.14	0.00	Reject
	P2SubgSubsMed	14.50	16.03	52.00	0.00	9.50	14.50	19.00	19	0	40	-346.00	0.00	Reject
	P2SubgSubsMax	3.00	8.32	61.00	0.00	0.00	3.00	10.00	41	0	18	7.72	0.13	Accept
	P2SubgSubsMin	32.00	33.53	70.00	0.00	13.50	32.00	52.00	12	0	47	-884.27	0.00	Reject

Totally tested cases: 59

D-8

Table D8. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases of One Missing Data Point with Poor Distress Score Category (60-69).

Predicting	Technique	Absolute Discrepancy							Accuracy Improvement				Mann-Whitney Test	
		Median	Mean	Max.	Min.	1st Quart	2nd Quart	3rd Quart	+	=	-	(%)	p-value	Null Hypothesis
Pavement Performance Model	PMS Method	2.66	5.31	34.65	0.00	0.66	2.66	7.68	0	25	0	0.00	-	-
	Mean Nearby Points	1.83	4.26	31.00	0.00	0.21	1.83	6.00	21	0	4	31.08	0.27	Accept
	Med. Nearby Pts.	1.00	4.22	31.00	0.00	0.30	1.00	6.67	19	0	6	62.42	0.24	Accept
	Linear Interpolation	1.00	4.22	31.00	0.00	0.30	1.00	6.67	19	0	6	62.42	0.24	Accept
	Linear Trend Pts.	1.87	4.29	31.00	0.00	0.36	1.87	6.00	18	0	7	29.64	0.30	Accept
	Moving Average	2.00	4.67	31.00	0.00	0.27	2.00	6.00	15	0	10	24.83	0.38	Accept
	Cubic Spline Fitting	2.10	4.25	31.00	0.00	0.20	2.10	6.62	19	0	6	21.02	0.36	Accept
	Cubic Spline4 D. Pts.	1.00	4.18	31.00	0.00	0.25	1.00	6.00	19	0	6	62.42	0.24	Accept
	Sub. Subs. Mean	1.00	4.08	30.43	0.00	0.09	1.00	5.70	17	0	8	62.42	0.28	Accept
	Sub. Subs. Med.	0.96	3.94	31.00	0.00	0.06	0.96	6.00	18	0	7	63.85	0.15	Accept
	Sub. Subs. Max.	1.00	4.19	31.00	0.00	0.08	1.00	6.00	18	0	7	62.42	0.27	Accept
	Sub. Subs. Min.	1.74	4.49	31.00	0.00	0.08	1.74	6.00	16	0	9	34.72	0.37	Accept
Missing Data Techniques	P2LinearTrendatPts	7.51	10.69	40.40	1.34	4.63	7.51	11.74	6	0	19	-182.38	0.00	Reject
	P2MovingAverage	2.00	4.12	31.00	0.00	0.00	2.00	4.00	16	0	9	24.83	0.10	Accept
	P2CubicSplineFitting	1.70	4.61	30.83	0.01	1.21	1.70	6.16	13	0	12	36.13	0.94	Accept
	P2CubicSpline4DPts	7.00	17.32	64.00	0.00	2.00	7.00	27.17	5	0	20	-163.09	0.01	Reject
	P2SubgSubsMean	15.83	15.14	30.25	0.00	8.25	15.83	21.25	5	0	20	-495.09	0.00	Reject
	P2SubgSubsMed	12.50	13.46	28.00	0.00	5.50	12.50	24.50	6	0	19	-369.81	0.00	Reject
	P2SubgSubsMax	3.00	6.64	31.00	0.00	0.00	3.00	14.00	13	0	12	-12.75	0.89	Accept
	P2SubgSubsMin	32.00	28.48	54.00	0.00	12.00	32.00	40.00	4	0	21	-1102.7	0.00	Reject

Totally tested cases: 25

Table D9. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases of One Missing Data Point with Very Poor Distress Score Category (1-59).

Predicting	Technique	Absolute Discrepancy							Accuracy Improvement				Mann-Whitney Test	
		Median	Mean	Max.	Min.	1st Quart.	2nd Quart.	3rd Quart.	+	=	-	(%)	p-value	Null Hypothesis
Pavement Performance Model	PMS Method	4.67	6.99	24.53	0.00	0.54	4.67	12.96	0	53	0	0.00	-	-
	Mean Nearby Points	3.91	4.96	24.00	0.00	0.00	3.91	7.65	39	0	14	16.43	0.08	Accept
	Med. Nearby Pts.	4.00	4.98	24.00	0.00	0.00	4.00	7.59	37	0	16	14.40	0.09	Accept
	Linear Interpolation	4.00	4.98	24.00	0.00	0.00	4.00	7.59	37	0	16	14.40	0.09	Accept
	Linear Trend Pts.	3.79	4.87	24.00	0.00	0.00	3.79	6.98	40	0	13	18.82	0.06	Accept
	Moving Average	3.85	4.81	24.00	0.00	0.00	3.85	7.63	34	1	18	17.68	0.08	Accept
	Cubic Spline Fitting	3.37	4.78	23.98	0.00	0.05	3.37	7.67	36	0	17	27.95	0.11	Accept
	Cubic Spline4 D. Pts.	4.00	5.15	24.00	0.00	0.27	4.00	8.15	33	0	20	14.40	0.19	Accept
	Sub. Subs. Mean	4.00	4.60	24.00	0.00	0.01	4.00	7.13	36	0	17	14.40	0.07	Accept
	Sub. Subs. Med.	4.00	4.66	24.00	0.00	0.01	4.00	7.13	34	0	19	14.40	0.09	Accept
	Sub. Subs. Max.	4.00	4.91	24.00	0.00	0.00	4.00	7.13	38	0	15	14.40	0.11	Accept
	Sub. Subs. Min.	4.00	4.73	24.00	0.00	0.00	4.00	7.63	33	0	20	14.40	0.09	Accept
Missing Data Techniques	P2LinearTrendatPts	8.39	10.09	36.40	0.07	3.66	8.39	14.55	16	0	37	-79.58	0.02	Reject
	P2MovingAverage	2.00	4.53	24.00	0.00	0.00	2.00	7.00	38	1	14	57.20	0.01	Reject
	P2CubicSplineFitting	5.23	6.05	25.88	0.20	2.30	5.23	8.92	30	0	23	-11.95	0.62	Accept
	P2CubicSpline4DPts	13.33	19.39	69.67	0.00	7.00	13.33	24.00	19	0	34	-185.33	0.00	Reject
	P2SubgSubsMean	2.60	6.05	21.25	0.00	1.80	2.60	9.67	33	0	20	44.36	0.37	Accept
	P2SubgSubsMed	4.00	6.43	26.00	0.00	1.00	4.00	9.00	31	0	22	14.40	0.56	Accept
	P2SubgSubsMax	2.00	4.51	24.00	0.00	0.00	2.00	9.00	38	0	15	57.20	0.07	Accept
	P2SubgSubsMin	9.00	10.40	40.00	0.00	1.00	9.00	11.00	25	0	28	-92.60	0.47	Accept

Totally tested cases: 53

D-10

Table D10. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases of One Missing Data Point of Distress Score within Early, Middle, and Late Age Period of Time.

Predicting By	Case Technique	Early Age (1993-1998)			Middle Age (1999-2004)			Late Age (2005-2010)		
		Median	P-Value	(%)	Median	P-Value	(%)	Median	P-Value	(%)
Pavement Performance Model	PMS Method	5.97	-	0.00	6.47	-	0.00	4.75	-	0.00
	Mean Nearby Points	3.94	0.04	34.06	6.00	0.33	7.24	4.97	0.67	-4.47
	Med. Nearby Pts.	3.94	0.04	34.06	6.00	0.23	7.24	5.43	0.85	-14.28
	Linear Interpolation	3.94	0.04	34.06	6.00	0.23	7.24	5.43	0.85	-14.28
	Linear Trend Pts.	3.97	0.08	33.43	6.26	0.56	3.21	4.00	0.64	15.86
	Moving Average	3.91	0.04	34.48	6.00	0.14	7.24	5.23	0.54	-10.00
	Cubic Spline Fitting	4.10	0.04	31.26	6.00	0.29	7.24	6.45	0.72	-35.73
	Cubic Spline4 D. Pts.	3.94	0.04	34.06	6.00	0.19	7.24	6.30	0.97	-32.43
	Sub. Subs. Mean	3.98	0.04	33.37	6.00	0.16	7.24	7.05	0.96	-48.35
	Sub. Subs. Med.	3.99	0.05	33.19	6.00	0.13	7.24	7.05	0.89	-48.35
	Sub. Subs. Max.	3.98	0.05	33.37	6.27	0.18	3.11	6.72	0.91	-41.40
	Sub. Subs. Min.	3.91	0.04	34.48	6.00	0.15	7.24	5.54	0.62	-16.56
Missing Data Techniques	P2LinearTrendatPts	13.47	0.00	-125.65	12.10	0.00	-87.10	8.20	0.00	-72.45
	P2MovingAverage	4.00	0.00	33.01	5.00	0.00	22.70	3.00	0.00	36.90
	P2CubicSplineFitting	6.07	0.06	-1.61	6.39	0.01	1.24	4.41	0.49	7.34
	P2CubicSpline4DPts	12.00	0.00	-100.97	13.00	0.00	-100.99	13.00	0.00	-173.45
	P2SubgSubsMean	16.88	0.00	-182.61	16.80	0.00	-159.74	18.02	0.00	-279.07
	P2SubgSubsMed	14.50	0.00	-142.83	14.50	0.00	-124.18	16.00	0.00	-236.56
	P2SubgSubsMax	4.00	0.00	33.01	4.00	0.00	38.16	4.00	0.03	15.86
	P2SubgSubsMin	38.00	0.00	-536.39	46.00	0.00	-611.19	52.00	0.00	-993.81

Totally tested cases: 406, 4144, and 139 respectively

D-11

Table D11. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases of One Missing Data Point of Distress Score within Early Age Period (1993-1998).

Predicting	Technique	Absolute Discrepancy							Accuracy Improvement				Mann-Whitney Test	
		Median	Mean	Max.	Min.	1st Quart	2nd Quart	3rd Quart	+	=	-	(%)	p-value	Null Hypothesis
Pavement Performance Model	PMS Method	5.97	11.69	63.61	0.00	1.07	5.97	14.33	0	406	0	0.00	-	-
	Mean Nearby Points	3.94	11.12	65.97	0.00	0.06	3.94	14.36	225	43	138	34.06	0.04	Reject
	Med. Nearby Pts.	3.94	11.12	65.97	0.00	0.06	3.94	14.36	223	45	138	34.06	0.04	Reject
	Linear Interpolation	3.94	11.12	65.97	0.00	0.06	3.94	14.36	223	45	138	34.06	0.04	Reject
	Linear Trend Pts.	3.97	11.28	65.97	0.00	0.18	3.97	14.43	225	32	149	33.43	0.08	Accept
	Moving Average	3.91	11.15	65.97	0.00	0.06	3.91	14.36	217	44	145	34.48	0.04	Reject
	Cubic Spline Fitting	4.10	11.21	65.97	0.00	0.04	4.10	14.36	229	31	146	31.26	0.04	Reject
	Cubic Spline4 D. Pts.	3.94	11.13	65.97	0.00	0.06	3.94	14.36	218	44	144	34.06	0.04	Reject
	Sub. Subs. Mean	3.98	11.14	65.97	0.00	0.07	3.98	14.36	217	45	144	33.37	0.04	Reject
	Sub. Subs. Med.	3.99	11.17	65.97	0.00	0.07	3.99	14.36	214	45	147	33.19	0.05	Reject
	Sub. Subs. Max.	3.98	11.17	65.97	0.00	0.09	3.98	14.36	212	45	149	33.37	0.05	Reject
	Sub. Subs. Min.	3.91	11.14	65.97	0.00	0.09	3.91	14.36	215	44	147	34.48	0.04	Reject
Missing Data Techniques	P2LinearTrendatPts	13.47	17.74	84.49	0.00	4.64	13.47	26.40	55	0	351	-125.65	0.00	Reject
	P2MovingAverage	4.00	11.73	82.00	0.00	0.00	4.00	15.00	219	4	183	33.01	0.00	Reject
	P2CubicSplineFitting	6.07	12.57	82.57	0.01	1.86	6.07	15.77	170	0	236	-1.61	0.06	Accept
	P2CubicSpline4DPts	12.00	19.73	90.00	0.00	5.00	12.00	30.00	128	0	278	-100.97	0.00	Reject
	P2SubgSubsMean	16.88	17.02	51.43	0.00	8.98	16.88	24.44	165	0	241	-182.61	0.00	Reject
	P2SubgSubsMed	14.50	16.31	60.00	0.00	7.00	14.50	24.00	165	0	241	-142.83	0.00	Reject
	P2SubgSubsMax	4.00	11.02	82.00	0.00	0.00	4.00	13.00	257	0	149	33.01	0.00	Reject
	P2SubgSubsMin	38.00	38.45	83.00	0.00	16.00	38.00	59.00	88	0	318	-536.39	0.00	Reject

Totally tested cases: 406

D-12

Table D12. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases of One Missing Data Point of Distress Score within Middle Age Period (1999-2004).

Predicting	Technique	Absolute Discrepancy							Accuracy Improvement				Mann-Whitney Test	
		Median	Mean	Max.	Min.	1st Quart	2nd Quart	3rd Quart	+	=	-	(%)	p-value	Null Hypothesis
Pavement Performance Model	PMS Method	6.47	12.45	74.00	0.00	0.96	6.47	18.74	0	687	0	0.00	-	-
	Mean Nearby Points	6.00	12.45	78.14	0.00	0.76	6.00	18.52	385	6	296	7.24	0.33	Accept
	Med. Nearby Pts.	6.00	12.30	78.14	0.00	0.71	6.00	16.08	382	9	296	7.24	0.23	Accept
	Linear Interpolation	6.00	12.30	78.14	0.00	0.71	6.00	16.08	382	9	296	7.24	0.23	Accept
	Linear Trend Pts.	6.26	12.50	84.81	0.00	1.00	6.26	18.90	379	4	304	3.21	0.56	Accept
	Moving Average	6.00	12.32	78.14	0.00	0.56	6.00	17.00	371	8	308	7.24	0.14	Accept
	Cubic Spline Fitting	6.00	12.37	79.61	0.00	0.80	6.00	18.42	394	5	288	7.24	0.29	Accept
	Cubic Spline4 D. Pts.	6.00	12.39	78.14	0.00	0.62	6.00	17.18	390	8	289	7.24	0.19	Accept
	Sub. Subs. Mean	6.00	12.28	78.14	0.00	0.60	6.00	16.03	385	9	293	7.24	0.16	Accept
	Sub. Subs. Med.	6.00	12.23	78.14	0.00	0.56	6.00	15.83	378	8	301	7.24	0.13	Accept
	Sub. Subs. Max.	6.27	12.24	78.14	0.00	0.66	6.27	15.88	381	8	298	3.11	0.18	Accept
	Sub. Subs. Min.	6.00	12.32	78.14	0.00	0.64	6.00	17.00	372	7	308	7.24	0.15	Accept
Missing Data Techniques	P2LinearTrendatPts	12.10	17.56	84.34	0.07	4.83	12.10	25.37	88	0	599	-87.10	0.00	Reject
	P2MovingAverage	5.00	12.21	82.00	0.00	0.00	5.00	17.50	347	2	338	22.70	0.00	Reject
	P2CubicSplineFitting	6.39	12.91	82.56	0.00	2.10	6.39	17.59	290	0	397	1.24	0.01	Reject
	P2CubicSpline4DPts	13.00	19.20	84.00	0.00	5.58	13.00	28.00	261	0	426	-100.99	0.00	Reject
	P2SubgSubsMean	16.80	17.12	55.38	0.00	9.00	16.80	24.37	265	0	422	-159.74	0.00	Reject
	P2SubgSubsMed	14.50	16.13	66.50	0.00	7.00	14.50	22.00	279	0	408	-124.18	0.00	Reject
	P2SubgSubsMax	4.00	11.59	82.00	0.00	0.00	4.00	16.00	398	0	289	38.16	0.00	Reject
	P2SubgSubsMin	46.00	41.99	83.00	0.00	22.00	46.00	61.00	117	0	570	-611.19	0.00	Reject

Totally tested cases: 687

D-13

Table D13. Median Accuracy and Statistical Significance of the Predicted Distress Scores: Cases of One Missing Data Point of Distress Score within Late Age Period (2005-2010).

Predicting	Technique	Absolute Discrepancy							Accuracy Improvement				Mann-Whitney Test	
		Median	Mean	Max.	Min.	1st Quart.	2nd Quart.	3rd Quart.	+	=	-	(%)	p-value	Null Hypothesis
Pavement Performance Model	PMS Method	4.75	10.70	52.14	0.00	0.69	4.75	14.30	0	139	0	0.00	-	-
	Mean Nearby Points	4.97	10.28	51.00	0.00	0.31	4.97	14.51	79	0	60	-4.47	0.67	Accept
	Med. Nearby Pts.	5.43	11.06	71.15	0.00	0.51	5.43	15.15	73	0	66	-14.28	0.85	Accept
	Linear Interpolation	5.43	11.06	71.15	0.00	0.51	5.43	15.15	73	0	66	-14.28	0.85	Accept
	Linear Trend Pts.	4.00	10.28	53.36	0.00	0.70	4.00	13.98	79	0	60	15.86	0.64	Accept
	Moving Average	5.23	10.88	71.15	0.00	0.04	5.23	14.52	68	0	71	-10.00	0.54	Accept
	Cubic Spline Fitting	6.45	11.72	88.13	0.00	0.72	6.45	17.87	69	0	70	-35.73	0.72	Accept
	Cubic Spline4 D. Pts.	6.30	10.99	51.00	0.00	0.57	6.30	15.57	72	0	67	-32.43	0.97	Accept
	Sub. Subs. Mean	7.05	11.15	71.15	0.00	0.53	7.05	14.57	65	0	74	-48.35	0.96	Accept
	Sub. Subs. Med.	7.05	11.24	71.15	0.00	0.10	7.05	14.51	70	0	69	-48.35	0.89	Accept
	Sub. Subs. Max.	6.72	11.35	71.15	0.00	0.27	6.72	14.69	74	0	65	-41.40	0.91	Accept
	Sub. Subs. Min.	5.54	10.87	71.15	0.00	0.04	5.54	13.75	69	0	70	-16.56	0.62	Accept
Missing Data Techniques	P2LinearTrendatPts	8.20	14.23	51.72	0.21	4.72	8.20	21.76	21	0	118	-72.45	0.00	Reject
	P2MovingAverage	3.00	9.50	51.00	0.00	0.00	3.00	13.00	84	0	55	36.90	0.00	Reject
	P2CubicSplineFitting	4.41	9.96	51.30	0.01	1.34	4.41	11.43	68	0	71	7.34	0.49	Accept
	P2CubicSpline4DPts	13.00	17.09	58.50	0.00	6.33	13.00	23.83	44	0	95	-173.45	0.00	Reject
	P2SubgSubsMean	18.02	18.51	55.38	0.00	8.66	18.02	25.69	48	0	91	-279.07	0.00	Reject
	P2SubgSubsMed	16.00	18.05	66.50	0.00	8.50	16.00	22.00	47	0	92	-236.56	0.00	Reject
	P2SubgSubsMax	4.00	10.38	50.00	0.00	0.00	4.00	16.50	83	0	56	15.86	0.03	Reject
	P2SubgSubsMin	52.00	46.94	82.00	0.00	31.50	52.00	65.00	21	0	118	-993.81	0.00	Reject

Totally tested cases: 139

D-14

Table D14. General Statistics of Predicted Distress Scores According to Good (80-89) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	70	0	67.79	2.43	75.92	20.30	412.0	77.20	12.39	89.59	60.98	75.92	78.89
Mean Nearby Points	63	7	67.24	2.51	75.75	19.92	396.8	77.03	11.97	89.00	62.00	75.75	78.00
Med. Nearby Pts.	64	6	66.71	2.53	74.05	20.26	410.6	76.99	12.01	89.00	59.19	74.05	78.00
Linear Interpolation	64	6	66.71	2.53	74.05	20.26	410.6	76.99	12.01	89.00	59.19	74.05	78.00
Linear Trend Pts.	61	9	66.66	2.46	72.00	19.20	368.5	76.18	12.82	89.00	57.88	72.00	78.00
Moving Average	61	9	67.77	2.54	75.54	19.86	394.6	75.78	13.22	89.00	62.00	75.54	78.00
Cubic Spline Fitting	63	7	65.81	2.53	72.00	20.11	404.5	76.86	12.14	89.00	55.48	72.00	78.00
Cubic Spline4 D. Pts.	64	6	66.20	2.52	72.00	20.17	406.7	77.09	11.91	89.00	57.60	72.00	78.00
Sub. Subs. Mean	60	10	67.00	2.54	73.91	19.69	387.7	75.78	13.22	89.00	59.44	73.91	78.00
Sub. Subs. Med.	59	11	66.98	2.59	75.81	19.86	394.4	75.78	13.22	89.00	59.00	75.81	78.00
Sub. Subs. Max.	62	8	66.56	2.60	73.91	20.45	418.0	75.78	13.22	89.00	60.18	73.91	78.00
Sub. Subs. Min.	63	7	67.76	2.50	75.52	19.82	392.9	76.49	12.51	89.00	60.59	75.52	78.00
P2LinearTrendatPts	30	40	73.87	3.07	75.45	16.82	283.0	84.32	9.05	93.37	71.55	75.45	80.77
P2MovingAverage	65	5	71.37	2.07	78.00	16.70	278.7	75.00	14.00	89.00	69.00	78.00	78.00
P2CubicSplineFitting	50	20	70.84	2.06	76.82	14.56	211.9	74.06	15.50	89.56	66.98	76.82	78.10
P2CubicSpline4DPts	30	40	67.38	4.86	78.00	26.62	708.5	96.33	3.67	100.00	54.00	78.00	87.50
P2SubgSubsMean	21	49	44.99	3.84	48.10	17.61	310.3	61.00	10.00	71.00	28.44	48.10	60.34
P2SubgSubsMed	22	48	45.14	3.94	44.50	18.49	342.0	68.00	10.00	78.00	31.00	44.50	60.63
P2SubgSubsMax	57	13	69.37	2.49	78.00	18.78	352.7	79.00	10.00	89.00	62.00	78.00	78.00
P2SubgSubsMin	12	58	25.67	4.63	22.50	16.05	257.5	48.00	9.00	57.00	9.25	22.50	35.75

Table D15. General Statistics of Predicted Distress Scores According to Fair (70-79) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	59	0	60.52	2.19	67.35	16.85	283.9	61.92	22.17	84.09	47.65	67.35	75.75
Mean Nearby Points	48	11	59.84	2.22	66.80	15.37	236.2	56.00	22.00	78.00	47.86	66.80	71.68
Med. Nearby Pts.	50	9	59.69	2.20	66.68	15.57	242.5	56.00	22.00	78.00	47.57	66.68	71.44
Linear Interpolation	50	9	59.69	2.20	66.68	15.57	242.5	56.00	22.00	78.00	47.57	66.68	71.44
Linear Trend Pts.	48	11	59.89	2.21	66.36	15.30	234.0	56.00	22.00	78.00	48.43	66.36	71.72
Moving Average	53	6	61.30	2.07	68.38	15.05	226.5	56.00	22.00	78.00	49.50	68.38	74.23
Cubic Spline Fitting	51	8	58.30	2.33	66.06	16.67	277.8	56.28	21.72	78.00	46.16	66.06	71.53
Cubic Spline4 D. Pts.	50	9	58.28	2.37	64.17	16.75	280.6	56.53	21.47	78.00	46.13	64.17	70.96
Sub. Subs. Mean	52	7	59.89	2.19	66.61	15.77	248.8	56.00	22.00	78.00	48.00	66.61	72.16
Sub. Subs. Med.	50	9	59.58	2.23	65.66	15.78	249.0	56.00	22.00	78.00	47.75	65.66	72.16
Sub. Subs. Max.	51	8	59.65	2.21	65.60	15.76	248.3	56.00	22.00	78.00	47.32	65.60	72.00
Sub. Subs. Min.	52	7	60.91	2.09	67.75	15.09	227.9	56.00	22.00	78.00	49.25	67.75	73.15
P2LinearTrendatPts	28	31	65.64	3.41	71.96	18.05	325.7	75.72	12.86	88.59	59.45	71.96	75.93
P2MovingAverage	56	3	62.46	2.01	69.00	15.04	226.1	57.00	22.00	79.00	49.25	69.00	75.00
P2CubicSplineFitting	43	16	59.79	2.37	63.76	15.56	242.1	57.19	21.80	78.99	44.35	63.76	71.23
P2CubicSpline4DPts	25	34	56.17	5.36	60.67	26.80	718.5	97.83	.50	98.33	30.50	60.67	78.00
P2SubgSubsMean	24	35	39.70	2.41	41.95	11.81	139.6	43.25	13.00	56.25	30.15	41.95	48.10
P2SubgSubsMed	26	33	41.71	2.59	44.00	13.22	174.7	59.00	13.00	72.00	33.50	44.00	50.00
P2SubgSubsMax	50	9	60.34	2.49	67.00	17.61	310.1	65.00	13.00	78.00	47.75	67.00	75.75
P2SubgSubsMin	17	42	22.29	2.21	20.00	9.12	83.2	28.00	11.00	39.00	13.00	20.00	30.00

Table D16. General Statistics of Predicted Distress Scores According to Poor (60-69) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	26	0	45.84	3.65	45.19	18.64	347.3	65.02	7.54	72.56	30.85	45.19	62.02
Mean Nearby Points	24	2	46.06	3.39	45.23	16.60	275.4	55.18	13.82	69.00	32.03	45.23	62.00
Med. Nearby Pts.	24	2	46.02	3.41	45.38	16.70	278.8	55.67	13.33	69.00	32.39	45.38	62.00
Linear Interpolation	24	2	46.02	3.41	45.38	16.70	278.8	55.67	13.33	69.00	32.39	45.38	62.00
Linear Trend Pts.	24	2	46.12	3.39	45.10	16.59	275.2	55.94	13.06	69.00	32.04	45.10	62.00
Moving Average	22	4	45.11	3.44	45.00	16.14	260.5	51.35	13.65	65.00	32.18	45.00	62.00
Cubic Spline Fitting	24	2	45.92	3.41	45.40	16.72	279.5	55.62	13.38	69.00	31.98	45.40	61.97
Cubic Spline4 D. Pts.	24	2	46.03	3.44	46.14	16.85	283.8	56.55	12.45	69.00	32.69	46.14	62.00
Sub. Subs. Mean	25	1	45.34	3.48	45.00	17.41	303.2	61.50	7.50	69.00	32.21	45.00	61.95
Sub. Subs. Med.	25	1	45.38	3.50	45.00	17.49	305.8	61.45	7.55	69.00	32.23	45.00	61.99
Sub. Subs. Max.	25	1	43.53	3.63	43.27	18.13	328.8	61.45	7.55	69.00	28.34	43.27	62.00
Sub. Subs. Min.	23	3	44.57	3.31	45.00	15.88	252.0	51.32	13.68	65.00	32.00	45.00	59.33
P2LinearTrendatPts	12	14	44.28	5.66	49.82	19.60	384.1	61.34	8.76	70.10	27.45	49.82	56.83
P2MovingAverage	24	2	46.08	3.62	48.00	17.71	313.8	61.00	8.00	69.00	33.25	48.00	62.00
P2CubicSplineFitting	18	8	45.01	3.51	46.71	14.87	221.2	47.64	18.06	65.70	33.57	46.71	57.57
P2CubicSpline4DPts	6	20	48.78	9.33	57.17	22.86	522.7	51.67	20.00	71.67	21.25	57.17	66.67
P2SubgSubsMean	8	18	32.41	5.77	28.88	16.32	266.5	49.00	13.00	62.00	20.00	28.88	45.38
P2SubgSubsMed	10	16	36.05	4.89	38.50	15.47	239.2	49.00	13.00	62.00	20.00	38.50	49.25
P2SubgSubsMax	20	6	41.70	2.88	43.00	12.88	165.9	49.00	13.00	62.00	35.00	43.00	50.00
P2SubgSubsMin	7	19	26.29	6.49	20.00	17.17	294.9	50.00	12.00	62.00	13.00	20.00	32.00

Table D17. General Statistics of Predicted Distress Scores According to Very Poor (1-59) One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	53	0	32.35	1.72	31.71	12.52	156.8	45.59	11.39	56.98	21.98	31.71	42.60
Mean Nearby Points	47	6	30.02	1.90	27.00	13.03	169.9	48.72	8.28	57.00	20.00	27.00	43.10
Med. Nearby Pts.	45	8	29.61	1.89	27.00	12.70	161.4	48.28	8.72	57.00	20.00	27.00	38.83
Linear Interpolation	45	8	29.61	1.89	27.00	12.70	161.4	48.28	8.72	57.00	20.00	27.00	38.83
Linear Trend Pts.	44	9	28.88	1.89	26.50	12.54	157.2	48.22	8.78	57.00	20.00	26.50	36.39
Moving Average	48	5	29.89	1.88	26.83	13.05	170.3	45.32	11.53	56.85	20.00	26.83	41.24
Cubic Spline Fitting	45	8	29.23	1.85	27.00	12.38	153.2	49.41	7.59	57.00	20.00	27.00	37.64
Cubic Spline4 D. Pts.	41	12	29.80	1.97	27.00	12.61	159.0	46.97	9.07	56.04	20.00	27.00	39.33
Sub. Subs. Mean	45	8	29.36	1.92	27.00	12.86	165.4	49.31	7.69	57.00	19.99	27.00	38.81
Sub. Subs. Med.	44	9	30.27	2.01	27.00	13.31	177.1	49.05	7.95	57.00	19.97	27.00	42.21
Sub. Subs. Max.	48	5	29.67	1.91	27.00	13.24	175.2	52.68	4.32	57.00	19.98	27.00	42.20
Sub. Subs. Min.	47	6	29.90	1.86	27.00	12.78	163.3	45.42	11.58	57.00	20.00	27.00	41.99
P2LinearTrendatPts	23	30	22.75	2.79	19.11	13.38	179.1	48.80	8.73	57.52	13.04	19.11	29.92
P2MovingAverage	50	3	30.18	1.81	26.50	12.78	163.2	44.00	13.00	57.00	20.00	26.50	39.75
P2CubicSplineFitting	36	17	28.58	1.86	26.62	11.18	124.9	40.70	13.86	54.56	19.71	26.62	33.44
P2CubicSpline4DPts	25	28	18.73	3.23	18.00	16.13	260.1	64.00	1.00	65.00	7.00	18.00	20.75
P2SubgSubsMean	37	16	20.67	1.25	20.00	7.58	57.4	30.50	8.50	39.00	17.87	20.00	20.75
P2SubgSubsMed	38	15	22.32	1.50	20.00	9.25	85.5	40.50	8.50	49.00	18.50	20.00	22.00
P2SubgSubsMax	42	11	26.07	1.79	22.50	11.63	135.1	43.00	9.00	52.00	20.00	22.50	35.00
P2SubgSubsMin	35	18	16.57	1.25	20.00	7.42	55.0	25.00	7.00	32.00	10.00	20.00	20.00

Table D18. General Statistics of Predicted Distress Scores According Age (1993-2010) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1232	0	69.21	.65	75.71	22.73	516.7	98.73	.92	99.65	53.99	75.71	88.75
Mean Nearby Points	1116	116	69.57	.69	76.00	23.17	537.0	98.31	.69	99.00	53.99	76.00	88.97
Med. Nearby Pts.	1124	108	69.47	.69	75.95	23.17	536.9	98.31	.69	99.00	54.25	75.95	88.97
Linear Interpolation	1124	108	69.47	.69	75.95	23.17	536.9	98.31	.69	99.00	54.25	75.95	88.97
Linear Trend Pts.	1086	146	69.86	.70	75.97	23.09	533.2	98.00	1.00	99.00	54.71	75.97	88.98
Moving Average	1143	89	69.58	.68	75.95	23.06	531.7	98.31	.69	99.00	55.12	75.95	88.98
Cubic Spline Fitting	1122	110	69.42	.69	75.51	23.08	532.9	98.13	.87	99.00	53.99	75.51	88.98
Cubic Spline4 D. Pts.	1122	110	69.60	.69	75.98	23.10	533.6	98.31	.69	99.00	55.47	75.98	88.97
Sub. Subs. Mean	1134	98	69.40	.69	75.89	23.10	533.7	98.31	.69	99.00	54.68	75.89	88.97
Sub. Subs. Med.	1133	99	69.46	.69	75.95	23.09	533.4	98.31	.69	99.00	54.07	75.95	88.98
Sub. Subs. Max.	1142	90	69.23	.69	75.88	23.25	540.8	98.31	.69	99.00	53.99	75.88	88.97
Sub. Subs. Min.	1136	96	69.67	.68	76.09	23.02	529.8	98.31	.69	99.00	56.00	76.09	88.98
P2LinearTrendatPts	652	580	82.45	.81	90.81	20.75	430.4	91.05	8.73	99.77	75.88	90.81	95.66
P2MovingAverage	1146	86	72.83	.66	78.00	22.37	500.3	91.00	8.00	99.00	59.00	78.00	89.00
P2CubicSplineFitting	883	349	74.87	.74	81.48	21.94	481.4	95.05	4.30	99.35	64.54	81.48	90.89
P2CubicSpline4DPts	681	551	69.05	1.03	78.00	26.97	727.4	99.50	.50	100.00	52.00	78.00	92.00
P2SubgSubsMean	566	666	51.14	.78	56.10	18.62	346.7	84.00	5.00	89.00	38.40	56.10	65.62
P2SubgSubsMed	632	600	55.12	.82	59.00	20.50	420.3	84.00	5.00	89.00	41.00	59.00	72.00
P2SubgSubsMax	1032	200	71.49	.71	78.00	22.73	516.6	94.00	5.00	99.00	62.00	78.00	89.00
P2SubgSubsMin	373	859	25.19	.97	20.00	18.68	349.0	85.00	4.00	89.00	13.00	20.00	30.50

Table D19. General Statistics of Predicted Distress Scores According to Early Age (1993-1998) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	406	0	66.17	1.22	73.00	24.53	601.6	98.36	.92	99.28	48.60	73.00	87.36
Mean Nearby Points	393	13	66.35	1.26	72.97	24.91	620.4	98.20	.69	98.89	49.41	72.97	88.97
Med. Nearby Pts.	392	14	66.33	1.26	72.99	24.95	622.7	98.20	.69	98.89	49.41	72.99	88.98
Linear Interpolation	392	14	66.33	1.26	72.99	24.95	622.7	98.20	.69	98.89	49.41	72.99	88.98
Linear Trend Pts.	383	23	66.64	1.26	72.67	24.64	607.1	98.00	1.00	99.00	49.02	72.67	88.98
Moving Average	390	16	66.28	1.26	72.99	24.98	623.8	98.20	.69	98.89	49.23	72.99	88.98
Cubic Spline Fitting	392	14	66.59	1.25	72.82	24.67	608.5	97.91	1.09	99.00	49.76	72.82	88.98
Cubic Spline4 D. Pts.	392	14	66.50	1.25	73.00	24.83	616.7	98.20	.69	98.89	49.41	73.00	88.98
Sub. Subs. Mean	391	15	66.42	1.26	73.00	24.83	616.4	98.20	.69	98.89	49.41	73.00	88.97
Sub. Subs. Med.	389	17	66.42	1.26	73.00	24.91	620.4	98.20	.69	98.89	49.41	73.00	88.98
Sub. Subs. Max.	389	17	66.44	1.26	73.00	24.91	620.4	98.20	.69	98.89	49.41	73.00	88.98
Sub. Subs. Min.	389	17	66.38	1.26	73.00	24.90	620.2	98.20	.69	98.89	49.41	73.00	88.97
P2LinearTrendatPts	210	196	80.18	1.51	89.49	21.95	481.9	90.73	9.05	99.77	71.93	89.49	95.52
P2MovingAverage	383	23	69.28	1.24	78.00	24.24	587.5	91.00	8.00	99.00	52.00	78.00	89.00
P2CubicSplineFitting	295	111	71.88	1.37	77.62	23.52	553.1	95.05	4.30	99.35	54.81	77.62	89.81
P2CubicSpline4DPts	223	183	64.88	1.92	74.00	28.67	821.8	96.00	3.00	99.00	39.00	74.00	92.00
P2SubgSubsMean	195	211	47.52	1.39	50.33	19.40	376.4	73.80	5.00	78.80	34.44	50.33	62.55
P2SubgSubsMed	217	189	51.40	1.48	54.00	21.80	475.3	84.00	5.00	89.00	38.50	54.00	69.00
P2SubgSubsMax	352	54	67.92	1.31	78.00	24.49	599.6	94.00	5.00	99.00	49.00	78.00	89.00
P2SubgSubsMin	144	262	24.06	1.27	20.00	15.22	231.7	74.00	4.00	78.00	15.25	20.00	29.00

Table D20. General Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	687	0	70.13	.84	75.51	21.93	480.9	92.11	7.54	99.65	56.04	75.51	88.96
Mean Nearby Points	608	79	70.78	.90	76.29	22.22	493.7	90.72	8.28	99.00	56.00	76.29	88.96
Med. Nearby Pts.	616	71	70.74	.89	76.17	22.20	492.8	90.28	8.72	99.00	56.48	76.17	88.96
Linear Interpolation	616	71	70.74	.89	76.17	22.20	492.8	90.28	8.72	99.00	56.48	76.17	88.96
Linear Trend Pts.	591	96	71.07	.91	76.29	22.24	494.6	96.96	2.04	99.00	56.05	76.29	88.98
Moving Average	631	56	70.58	.88	76.09	22.14	490.1	88.14	10.86	99.00	56.65	76.09	88.98
Cubic Spline Fitting	618	69	70.58	.89	75.68	22.03	485.5	91.41	7.59	99.00	56.00	75.68	88.97
Cubic Spline4 D. Pts.	617	70	70.80	.89	76.29	22.19	492.3	89.93	9.07	99.00	56.69	76.29	88.96
Sub. Subs. Mean	628	59	70.58	.89	76.09	22.25	495.2	91.50	7.50	99.00	56.51	76.09	88.96
Sub. Subs. Med.	628	59	70.66	.89	76.09	22.20	493.0	91.45	7.55	99.00	56.88	76.09	88.98
Sub. Subs. Max.	633	54	70.23	.90	76.09	22.57	509.5	94.68	4.32	99.00	56.05	76.09	88.97
Sub. Subs. Min.	626	61	70.81	.88	76.09	22.08	487.5	88.14	10.86	99.00	57.17	76.09	88.98
P2LinearTrendatPts	367	320	83.46	1.04	91.10	19.83	393.3	91.05	8.73	99.77	76.80	91.10	96.65
P2MovingAverage	635	52	73.92	.85	78.00	21.52	463.1	91.00	8.00	99.00	62.00	78.00	90.00
P2CubicSplineFitting	492	195	76.06	.94	82.08	20.92	437.5	87.34	12.02	99.35	67.98	82.08	91.13
P2CubicSpline4DPts	389	298	69.87	1.33	78.00	26.29	691.4	99.50	.50	100.00	57.00	78.00	92.00
P2SubgSubsMean	313	374	52.91	1.02	58.58	17.97	322.9	80.50	8.50	89.00	41.64	58.58	66.14
P2SubgSubsMed	354	333	57.00	1.04	62.00	19.53	381.4	80.50	8.50	89.00	42.00	62.00	73.00
P2SubgSubsMax	567	120	72.82	.91	78.00	21.65	468.8	90.00	9.00	99.00	65.00	78.00	89.00
P2SubgSubsMin	196	491	26.46	1.50	20.00	21.03	442.1	85.00	4.00	89.00	13.00	20.00	32.00

Table D21. General Statistics of Predicted Distress Scores According to Late Age (2005-2010) for One year Missing Data point Case (1).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	139	0	73.55	1.70	77.98	20.06	402.6	84.48	14.94	99.43	65.65	77.98	88.97
Mean Nearby Points	115	24	74.20	1.92	78.00	20.60	424.5	82.91	16.09	99.00	64.95	78.00	89.00
Med. Nearby Pts.	116	23	73.35	1.93	77.98	20.81	433.2	84.43	14.57	99.00	64.39	77.98	88.98
Linear Interpolation	116	23	73.35	1.93	77.98	20.81	433.2	84.43	14.57	99.00	64.39	77.98	88.98
Linear Trend Pts.	112	27	74.46	1.96	78.00	20.70	428.6	82.79	16.21	99.00	65.64	78.00	89.00
Moving Average	122	17	74.94	1.79	78.00	19.80	391.9	85.50	13.50	99.00	66.46	78.00	88.99
Cubic Spline Fitting	112	27	72.99	2.09	77.98	22.15	490.7	98.13	.87	99.00	62.03	77.98	89.00
Cubic Spline4 D. Pts.	113	26	73.87	1.93	77.98	20.50	420.3	85.30	13.70	99.00	64.79	77.98	88.99
Sub. Subs. Mean	115	24	73.10	1.91	77.91	20.49	419.9	85.58	13.42	99.00	64.95	77.91	88.98
Sub. Subs. Med.	116	23	73.13	1.90	77.97	20.41	416.6	85.50	13.50	99.00	64.95	77.97	88.97
Sub. Subs. Max.	120	19	73.00	1.85	77.97	20.27	411.0	85.67	13.33	99.00	64.39	77.97	88.97
Sub. Subs. Min.	121	18	74.39	1.82	78.00	20.06	402.4	85.50	13.50	99.00	65.52	78.00	88.99
P2LinearTrendatPts	75	64	83.86	2.47	91.68	21.40	458.1	87.93	11.80	99.73	80.77	91.68	95.37
P2MovingAverage	128	11	78.07	1.68	87.00	18.98	360.3	80.00	19.00	99.00	73.00	87.00	89.00
P2CubicSplineFitting	96	43	77.89	2.17	87.41	21.26	451.8	83.66	15.65	99.31	71.43	87.41	91.08
P2CubicSpline4DPts	69	70	77.91	2.71	87.00	22.49	505.6	91.00	9.00	100.00	71.42	87.00	96.00
P2SubgSubsMean	58	81	53.75	2.34	61.14	17.85	318.5	67.83	13.00	80.83	42.92	61.14	66.79
P2SubgSubsMed	61	78	57.48	2.53	69.00	19.72	389.0	70.50	13.00	83.50	44.50	69.00	75.00
P2SubgSubsMax	113	26	75.88	1.97	87.00	20.95	439.0	86.00	13.00	99.00	73.00	87.00	89.00
P2SubgSubsMin	33	106	22.58	3.04	13.00	17.45	304.4	66.00	7.00	73.00	13.00	13.00	28.00

Table D22. General Statistics of Predicted Distress Scores for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	4144	0	71.10	.33	77.60	21.44	459.47	97.77	2.23	100.00	56.00	77.60	88.95
Mean Nearby Points	3236	908	72.22	.38	77.36	21.38	457.23	98.15	.85	99.00	56.28	77.36	88.99
Med. Nearby Pts.	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Interpolation	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Trend Pts.	3085	1059	72.11	.38	76.95	21.24	451.11	98.58	.42	99.00	55.98	76.95	88.98
Moving Average	3385	759	72.12	.37	77.96	21.43	459.24	98.15	.85	99.00	57.17	77.96	88.99
Cubic Spline Fitting	3298	846	71.73	.37	76.82	21.42	458.68	98.13	.87	99.00	55.94	76.82	88.98
Cubic Spline4 D. Pts.	3310	834	71.93	.37	76.95	21.54	464.04	98.15	.85	99.00	56.45	76.95	88.98
Sub. Subs. Mean	3383	761	71.65	.37	76.79	21.62	467.22	98.15	.85	99.00	56.30	76.79	88.99
Sub. Subs. Med.	3399	745	71.42	.37	76.71	21.76	473.57	98.15	.85	99.00	56.05	76.71	88.98
Sub. Subs. Max.	3442	702	71.45	.37	76.79	21.67	469.50	98.15	.85	99.00	56.05	76.79	88.98
Sub. Subs. Min.	3349	795	72.21	.37	77.97	21.44	459.75	98.15	.85	99.00	57.77	77.97	88.99
P2LinearTrendatPts	2124	2020	84.80	.37	90.86	17.02	289.65	99.70	.07	99.77	78.97	90.86	95.69
P2MovingAverage	2220	1924	77.51	.44	87.00	20.71	428.99	85.00	14.00	99.00	62.00	87.00	92.00
P2CubicSplineFitting	2853	1291	76.89	.37	82.18	19.65	386.19	93.17	6.18	99.35	69.30	82.18	90.98
P2CubicSpline4DPts	1895	2249	72.92	.58	83.00	25.22	635.94	99.50	.50	100.00	59.67	83.00	93.50
P2SubgSubsMean	1698	2446	54.08	.37	57.33	15.32	234.58	84.00	5.00	89.00	42.00	57.33	65.62
P2SubgSubsMed	1793	2351	58.27	.40	62.00	17.09	291.97	84.00	5.00	89.00	44.00	62.00	72.00
P2SubgSubsMax	2206	1938	73.52	.46	78.00	21.50	462.32	94.00	5.00	99.00	57.00	78.00	89.00
P2SubgSubsMin	1029	3115	24.62	.54	20.00	17.40	302.72	85.00	4.00	89.00	13.00	20.00	32.00

Table D23. General Statistics of Predicted Distress Scores According to Very Good (90-100) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	3111	1	74.61	.37	78.84	20.37	414.82	97.77	2.23	100.00	64.87	78.84	89.00
Mean Nearby Points	2562	550	75.72	.40	81.91	20.32	413.07	98.15	.85	99.00	64.73	81.91	90.79
Med. Nearby Pts.	2609	503	75.27	.40	80.46	20.67	427.41	98.15	.85	99.00	64.73	80.46	90.68
Linear Interpolation	2609	503	75.27	.40	80.46	20.67	427.41	98.15	.85	99.00	64.73	80.46	90.68
Linear Trend Pts.	2428	684	75.77	.41	82.32	20.09	403.68	98.58	.42	99.00	64.11	82.32	90.70
Moving Average	2644	468	75.50	.40	80.98	20.39	415.64	98.15	.85	99.00	64.95	80.98	90.13
Cubic Spline Fitting	2601	511	75.20	.40	80.94	20.43	417.58	98.13	.87	99.00	62.94	80.94	90.63
Cubic Spline4 D. Pts.	2634	478	75.32	.40	80.05	20.55	422.28	98.15	.85	99.00	64.95	80.05	90.29
Sub. Subs. Mean	2664	448	74.98	.40	79.09	20.66	427.04	98.15	.85	99.00	64.63	79.09	90.66
Sub. Subs. Med.	2674	438	74.83	.40	78.27	20.72	429.44	98.15	.85	99.00	64.21	78.27	90.28
Sub. Subs. Max.	2698	414	74.88	.40	78.00	20.59	423.96	98.15	.85	99.00	64.21	78.00	89.41
Sub. Subs. Min.	2619	493	75.67	.40	80.98	20.31	412.57	98.15	.85	99.00	66.34	80.98	90.66
P2LinearTrendatPts	1688	1424	89.09	.31	91.95	12.85	165.12	84.08	15.69	99.77	87.15	91.95	97.72
P2MovingAverage	1799	1313	82.42	.42	89.00	17.79	316.41	81.00	18.00	99.00	78.00	89.00	93.00
P2CubicSplineFitting	2136	976	81.89	.37	87.48	17.01	289.26	89.93	9.42	99.35	74.52	87.48	92.65
P2CubicSpline4DPts	1568	1544	76.10	.59	86.00	23.19	537.82	97.00	3.00	100.00	63.33	86.00	94.17
P2SubgSubsMean	1348	1764	57.66	.36	61.14	13.19	174.06	81.00	8.00	89.00	50.62	61.14	66.55
P2SubgSubsMed	1450	1662	62.22	.39	68.00	14.80	219.15	81.00	8.00	89.00	53.50	68.00	73.00
P2SubgSubsMax	1781	1331	78.11	.45	86.00	18.96	359.31	83.00	16.00	99.00	72.00	86.00	91.00
P2SubgSubsMin	797	2315	24.66	.67	17.00	18.79	353.22	85.00	4.00	89.00	13.00	17.00	28.00

Table D24. General Statistics of Predicted Distress Scores According to Good (80-89) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	74	0	73.93	1.49	76.89	12.79	163.57	75.52	14.21	89.72	75.40	76.89	78.58
Mean Nearby Points	46	28	71.95	1.97	76.21	13.35	178.15	74.12	14.88	89.00	71.21	76.21	76.82
Med. Nearby Pts.	47	27	71.82	2.09	76.09	14.33	205.48	71.70	17.30	89.00	71.19	76.09	76.78
Linear Interpolation	47	27	71.82	2.09	76.09	14.33	205.48	71.70	17.30	89.00	71.19	76.09	76.78
Linear Trend Pts.	50	24	72.52	1.92	76.41	13.60	185.07	69.57	19.43	89.00	71.40	76.41	77.11
Moving Average	42	32	73.40	2.07	76.09	13.38	179.10	75.78	13.22	89.00	71.32	76.09	76.76
Cubic Spline Fitting	50	24	71.73	1.88	76.08	13.29	176.63	65.90	23.10	89.00	70.82	76.08	76.99
Cubic Spline4 D. Pts.	41	33	71.05	2.28	76.19	14.58	212.67	67.07	21.93	89.00	70.89	76.19	76.69
Sub. Subs. Mean	45	29	74.10	1.88	76.38	12.64	159.79	68.23	20.77	89.00	71.19	76.38	77.23
Sub. Subs. Med.	42	32	73.71	2.03	76.09	13.13	172.32	69.17	19.83	89.00	71.19	76.09	76.61
Sub. Subs. Max.	44	30	71.94	2.28	76.02	15.10	227.95	61.17	27.83	89.00	71.19	76.02	76.61
Sub. Subs. Min.	41	33	73.53	2.13	76.09	13.65	186.20	73.06	15.94	89.00	71.28	76.09	76.31
P2LinearTrendatPts	32	42	77.74	1.01	75.62	5.70	32.50	25.42	64.01	89.43	75.31	75.62	79.42
P2MovingAverage	9	65	71.78	5.96	78.00	17.88	319.69	53.00	36.00	89.00	61.00	78.00	89.00
P2CubicSplineFitting	61	13	76.30	1.02	77.40	7.99	63.87	57.64	31.93	89.56	76.91	77.40	77.89
P2CubicSpline4DPts	13	61	73.89	6.10	79.28	22.00	484.19	76.11	12.39	88.50	72.33	79.28	87.58
P2SubgSubsMean	13	61	52.64	4.21	48.10	15.19	230.71	42.56	28.44	71.00	40.00	48.10	67.20
P2SubgSubsMed	14	60	53.75	4.80	52.00	17.95	322.03	53.00	25.00	78.00	40.00	52.00	70.00
P2SubgSubsMax	10	64	69.50	5.72	71.50	18.08	326.72	47.00	42.00	89.00	53.50	71.50	89.00
P2SubgSubsMin	5	69	27.40	5.10	32.00	11.41	130.30	30.00	9.00	39.00	17.00	32.00	35.50

Table D25. General Statistics of Predicted Distress Scores According to Fair (70-79) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	19	0	65.79	3.82	68.15	16.65	277.24	62.14	23.16	85.30	52.80	68.15	76.85
Mean Nearby Points	15	4	63.89	3.11	67.60	12.04	144.93	42.03	35.00	77.03	52.85	67.60	76.02
Med. Nearby Pts.	15	4	64.00	3.12	67.80	12.09	146.21	41.82	35.00	76.82	53.21	67.80	76.09
Linear Interpolation	15	4	64.00	3.12	67.80	12.09	146.21	41.82	35.00	76.82	53.21	67.80	76.09
Linear Trend Pts.	13	6	62.65	3.44	66.82	12.40	153.77	42.45	35.00	77.45	52.12	66.82	72.79
Moving Average	15	4	64.35	3.04	68.38	11.77	138.60	42.97	35.00	77.97	54.37	68.38	73.00
Cubic Spline Fitting	14	5	63.01	3.23	67.21	12.07	145.66	42.41	35.00	77.41	52.15	67.21	70.45
Cubic Spline4 D. Pts.	15	4	64.05	3.14	68.09	12.16	147.76	42.30	35.00	77.30	53.54	68.09	76.03
Sub. Subs. Mean	14	5	63.50	3.37	67.09	12.59	158.62	42.89	35.00	77.89	53.07	67.09	76.14
Sub. Subs. Med.	13	6	63.07	3.62	66.09	13.04	170.01	42.97	35.00	77.97	52.70	66.09	76.30
Sub. Subs. Max.	14	5	63.67	3.39	66.31	12.70	161.36	41.60	35.00	76.60	53.07	66.31	76.22
Sub. Subs. Min.	13	6	62.79	3.50	67.98	12.63	159.50	42.97	35.00	77.97	52.70	67.98	72.45
P2LinearTrendatPts	13	6	63.87	3.40	65.93	12.25	150.14	47.05	29.33	76.38	59.49	65.93	73.58
P2MovingAverage	6	13	54.50	4.08	56.00	9.99	99.90	27.00	35.00	62.00	50.75	56.00	62.00
P2CubicSplineFitting	16	3	64.96	2.83	69.24	11.30	127.73	39.97	37.20	77.17	54.72	69.24	72.82
P2CubicSpline4DPts	14	5	61.51	5.35	73.25	20.02	400.94	58.39	20.00	78.39	46.92	73.25	77.11
P2SubgSubsMean	9	10	43.91	3.04	47.00	9.11	83.06	26.50	26.50	53.00	38.40	47.00	53.00
P2SubgSubsMed	9	10	45.11	2.78	48.00	8.34	69.61	24.00	29.00	53.00	40.00	48.00	53.00
P2SubgSubsMax	6	13	49.00	4.40	45.00	10.79	116.40	27.00	35.00	62.00	42.50	45.00	62.00
P2SubgSubsMin	6	13	30.50	1.91	32.00	4.68	21.90	12.00	25.00	37.00	25.00	32.00	33.25

Table D26. General Statistics of Predicted Distress Scores According to Poor (60-69) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	8	0	53.97	4.05	51.15	11.46	131.32	29.72	43.78	73.50	43.93	51.15	62.10
Mean Nearby Points	5	3	46.62	4.61	42.52	10.30	106.07	23.90	41.10	65.00	41.33	42.52	53.97
Med. Nearby Pts.	5	3	47.43	4.40	43.09	9.83	96.59	22.54	42.46	65.00	42.76	43.09	54.27
Linear Interpolation	5	3	47.43	4.40	43.09	9.83	96.59	22.54	42.46	65.00	42.76	43.09	54.27
Linear Trend Pts.	5	3	47.13	4.48	42.99	10.02	100.33	23.04	41.96	65.00	41.98	42.99	54.35
Moving Average	7	1	51.60	4.05	44.01	10.72	114.99	23.13	41.87	65.00	42.95	44.01	62.00
Cubic Spline Fitting	5	3	47.40	4.43	43.52	9.90	97.98	23.33	41.67	65.00	42.00	43.52	54.74
Cubic Spline4 D. Pts.	6	2	50.15	4.21	43.96	10.31	106.32	22.33	42.67	65.00	43.33	43.96	62.58
Sub. Subs. Mean	6	2	49.20	4.53	42.57	11.10	123.16	23.86	41.14	65.00	41.81	42.57	62.68
Sub. Subs. Med.	6	2	49.27	4.52	42.67	11.06	122.32	23.89	41.11	65.00	41.94	42.67	62.70
Sub. Subs. Max.	5	3	46.73	4.58	42.63	10.23	104.69	23.89	41.11	65.00	41.66	42.63	53.85
Sub. Subs. Min.	7	1	51.41	4.12	43.72	10.90	118.89	23.47	41.53	65.00	42.71	43.72	62.00
P2LinearTrendatPts	2	6	57.64	1.12	57.64	1.58	2.49	2.23	56.52	58.76	56.52	57.64	
P2MovingAverage	3	5	51.67	6.67	45.00	11.55	133.33	20.00	45.00	65.00	45.00	45.00	
P2CubicSplineFitting	5	3	52.55	5.00	44.80	11.19	125.22	21.83	44.20	66.03	44.20	44.80	64.76
P2CubicSpline4DPts	2	6	61.31	3.69	61.31	5.22	27.30	7.39	57.61	65.00	57.61	61.31	
P2SubgSubsMean	0	8											
P2SubgSubsMed	0	8											
P2SubgSubsMax	1	7	50.00		50.00			.00	50.00	50.00	50.00	50.00	50.00
P2SubgSubsMin	0	8											

Table D27. General Statistics of Predicted Distress Scores According to Very Poor (1-59) Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	46	0	28.54	1.65	28.88	11.21	125.62	46.88	5.12	51.99	19.98	28.88	35.59
Mean Nearby Points	29	17	24.39	1.61	27.00	8.70	75.60	45.27	5.69	50.96	19.00	27.00	27.00
Med. Nearby Pts.	30	16	23.91	1.63	27.00	8.95	80.10	45.48	5.52	51.00	19.00	27.00	27.00
Linear Interpolation	30	16	23.91	1.63	27.00	8.95	80.10	45.48	5.52	51.00	19.00	27.00	27.00
Linear Trend Pts.	28	18	24.05	1.42	27.00	7.52	56.57	38.34	12.64	50.98	19.00	27.00	27.00
Moving Average	36	10	25.06	1.73	26.50	10.38	107.83	45.20	6.80	52.00	19.00	26.50	27.00
Cubic Spline Fitting	28	18	24.95	1.57	27.00	8.29	68.79	39.28	11.72	51.00	19.00	27.00	27.00
Cubic Spline4 D. Pts.	29	17	23.20	1.55	27.00	8.32	69.23	45.47	5.53	51.00	19.00	27.00	27.00
Sub. Subs. Mean	32	14	22.60	1.48	22.99	8.37	69.98	44.90	6.10	51.00	19.00	22.99	27.00
Sub. Subs. Med.	35	11	23.13	1.63	19.99	9.65	93.04	46.72	5.27	52.00	19.00	19.99	27.00
Sub. Subs. Max.	32	14	24.89	1.81	27.00	10.26	105.28	46.01	5.98	51.99	19.00	27.00	27.00
Sub. Subs. Min.	34	12	24.49	1.66	26.50	9.69	93.89	44.50	7.50	52.00	19.00	26.50	27.00
P2LinearTrendatPts	28	18	19.06	1.84	19.14	9.72	94.50	51.96	.07	52.03	13.55	19.14	20.32
P2MovingAverage	24	22	25.58	1.43	27.00	6.98	48.78	33.00	18.00	51.00	19.00	27.00	27.00
P2CubicSplineFitting	33	13	26.03	1.44	26.86	8.28	68.49	35.28	13.50	48.78	20.15	26.86	28.29
P2CubicSpline4DPts	28	18	13.25	2.14	10.10	11.34	128.64	54.61	1.00	55.61	7.00	10.10	21.76
P2SubgSubsMean	26	20	16.93	1.20	18.40	6.13	37.52	30.20	8.00	38.20	13.00	18.40	18.40
P2SubgSubsMed	26	20	18.94	1.43	22.00	7.27	52.89	33.00	8.00	41.00	13.00	22.00	22.00
P2SubgSubsMax	26	20	22.42	1.89	25.00	9.64	92.89	39.00	8.00	47.00	13.00	25.00	25.00
P2SubgSubsMin	25	21	9.92	.97	7.00	4.85	23.49	22.00	6.00	28.00	7.00	7.00	13.00

Table D28. General Statistics of Predicted Distress Scores According Age (1993-2010) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	4144	0	71.10	.33	77.60	21.44	459.47	97.77	2.23	100.00	56.00	77.60	88.95
Mean Nearby Points	3236	908	72.22	.38	77.36	21.38	457.23	98.15	.85	99.00	56.28	77.36	88.99
Med. Nearby Pts.	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Interpolation	3315	829	71.88	.37	76.95	21.57	465.36	98.15	.85	99.00	56.17	76.95	88.98
Linear Trend Pts.	3085	1059	72.11	.38	76.95	21.24	451.11	98.58	.42	99.00	55.98	76.95	88.98
Moving Average	3385	759	72.12	.37	77.96	21.43	459.24	98.15	.85	99.00	57.17	77.96	88.99
Cubic Spline Fitting	3298	846	71.73	.37	76.82	21.42	458.68	98.13	.87	99.00	55.94	76.82	88.98
Cubic Spline4 D. Pts.	3310	834	71.93	.37	76.95	21.54	464.04	98.15	.85	99.00	56.45	76.95	88.98
Sub. Subs. Mean	3383	761	71.65	.37	76.79	21.62	467.22	98.15	.85	99.00	56.30	76.79	88.99
Sub. Subs. Med.	3399	745	71.42	.37	76.71	21.76	473.57	98.15	.85	99.00	56.05	76.71	88.98
Sub. Subs. Max.	3442	702	71.45	.37	76.79	21.67	469.50	98.15	.85	99.00	56.05	76.79	88.98
Sub. Subs. Min.	3349	795	72.21	.37	77.97	21.44	459.75	98.15	.85	99.00	57.77	77.97	88.99
P2LinearTrendatPts	2124	2020	84.80	.37	90.86	17.02	289.65	99.70	.07	99.77	78.97	90.86	95.69
P2MovingAverage	2220	1924	77.51	.44	87.00	20.71	428.99	85.00	14.00	99.00	62.00	87.00	92.00
P2CubicSplineFitting	2853	1291	76.89	.37	82.18	19.65	386.19	93.17	6.18	99.35	69.30	82.18	90.98
P2CubicSpline4DPts	1895	2249	72.92	.58	83.00	25.22	635.94	99.50	.50	100.00	59.67	83.00	93.50
P2SubgSubsMean	1698	2446	54.08	.37	57.33	15.32	234.58	84.00	5.00	89.00	42.00	57.33	65.62
P2SubgSubsMed	1793	2351	58.27	.40	62.00	17.09	291.97	84.00	5.00	89.00	44.00	62.00	72.00
P2SubgSubsMax	2206	1938	73.52	.46	78.00	21.50	462.32	94.00	5.00	99.00	57.00	78.00	89.00
P2SubgSubsMin	1029	3115	24.62	.54	20.00	17.40	302.72	85.00	4.00	89.00	13.00	20.00	32.00

Table D29. General Statistics of Predicted Distress Scores According to Early Age (1993-1998) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	449	0	66.42	1.16	73.50	24.67	608.48	87.30	11.47	98.77	48.69	73.50	88.93
Mean Nearby Points	390	59	67.01	1.26	73.79	24.92	621.13	89.56	9.33	98.89	49.30	73.79	88.99
Med. Nearby Pts.	395	54	66.90	1.25	72.00	24.83	616.36	85.95	12.94	98.89	49.41	72.00	88.99
Linear Interpolation	395	54	66.90	1.25	72.00	24.83	616.36	85.95	12.94	98.89	49.41	72.00	88.99
Linear Trend Pts.	367	82	67.80	1.27	74.74	24.28	589.58	89.80	9.09	98.89	48.97	74.74	88.99
Moving Average	387	62	67.11	1.26	72.97	24.75	612.76	85.74	13.15	98.89	49.41	72.97	88.99
Cubic Spline Fitting	382	67	67.01	1.26	72.00	24.69	609.73	85.44	13.49	98.93	48.69	72.00	88.99
Cubic Spline4 D. Pts.	392	57	67.10	1.25	72.98	24.73	611.68	85.95	12.94	98.89	49.41	72.98	88.98
Sub. Subs. Mean	391	58	67.49	1.23	73.00	24.42	596.12	86.34	12.55	98.89	50.00	73.00	88.99
Sub. Subs. Med.	391	58	67.52	1.23	73.00	24.41	595.81	86.38	12.51	98.89	50.00	73.00	88.99
Sub. Subs. Max.	391	58	67.52	1.23	73.00	24.40	595.49	86.38	12.51	98.89	50.00	73.00	88.99
Sub. Subs. Min.	392	57	67.15	1.24	72.22	24.62	606.30	88.55	10.34	98.89	49.41	72.22	88.99
P2LinearTrendatPts	217	232	79.81	1.54	90.80	22.75	517.74	89.96	9.81	99.77	67.91	90.80	95.67
P2MovingAverage	248	201	72.60	1.50	79.00	23.67	560.25	85.00	14.00	99.00	51.75	79.00	92.00
P2CubicSplineFitting	314	135	72.07	1.31	77.49	23.27	541.44	89.93	9.42	99.35	52.94	77.49	89.83
P2CubicSpline4DPts	190	259	67.70	2.03	78.50	28.04	786.32	96.00	3.00	99.00	40.00	78.50	92.00
P2SubgSubsMean	177	272	50.29	1.32	54.98	17.60	309.83	70.00	8.00	78.00	38.40	54.98	64.05
P2SubgSubsMed	197	252	55.68	1.42	56.00	19.99	399.50	81.00	8.00	89.00	41.00	56.00	71.00
P2SubgSubsMax	253	196	68.62	1.49	73.00	23.67	560.29	89.00	10.00	99.00	47.00	73.00	89.00
P2SubgSubsMin	119	330	23.18	1.18	20.00	12.83	164.69	74.00	4.00	78.00	15.00	20.00	29.00

Table D30. General Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1288	0	71.78	.57	76.92	20.58	423.67	97.49	2.23	99.72	56.99	76.92	88.94
Mean Nearby Points	1014	274	73.05	.65	77.79	20.66	426.96	93.31	5.69	99.00	58.75	77.79	88.96
Med. Nearby Pts.	1039	249	72.62	.65	76.97	21.08	444.55	93.48	5.52	99.00	57.99	76.97	88.97
Linear Interpolation	1039	249	72.62	.65	76.97	21.08	444.55	93.48	5.52	99.00	57.99	76.97	88.97
Linear Trend Pts.	963	325	72.95	.66	77.50	20.53	421.45	95.59	3.41	99.00	57.17	77.50	88.98
Moving Average	1056	232	72.51	.65	77.63	21.15	447.16	92.20	6.80	99.00	58.00	77.63	88.98
Cubic Spline Fitting	1049	239	72.80	.63	76.88	20.27	411.06	96.40	2.60	99.00	57.17	76.88	88.96
Cubic Spline4 D. Pts.	1053	235	72.93	.63	76.93	20.52	421.14	94.23	4.77	99.00	59.19	76.93	88.96
Sub. Subs. Mean	1052	236	72.41	.65	76.71	21.00	440.95	92.90	6.10	99.00	57.91	76.71	88.98
Sub. Subs. Med.	1080	208	72.20	.64	76.71	21.16	447.72	93.73	5.27	99.00	57.99	76.71	88.97
Sub. Subs. Max.	1078	210	72.38	.64	76.71	20.90	436.77	93.02	5.98	99.00	58.00	76.71	88.98
Sub. Subs. Min.	1044	244	72.76	.65	77.11	20.98	440.02	91.50	7.50	99.00	59.00	77.11	88.98
P2LinearTrendatPts	694	594	85.42	.65	91.26	17.09	292.21	99.70	.07	99.77	78.99	91.26	96.82
P2MovingAverage	720	568	79.01	.75	89.00	20.20	408.04	81.00	18.00	99.00	69.00	89.00	92.00
P2CubicSplineFitting	902	386	78.28	.63	84.58	18.96	359.34	85.85	13.50	99.35	70.62	84.58	91.52
P2CubicSpline4DPts	655	633	73.46	.94	80.50	24.09	580.36	99.00	1.00	100.00	62.00	80.50	93.00
P2SubgSubsMean	560	728	55.92	.63	60.40	14.94	223.13	81.00	8.00	89.00	48.10	60.40	66.41
P2SubgSubsMed	605	683	60.35	.67	68.00	16.49	272.06	81.00	8.00	89.00	48.00	68.00	73.00
P2SubgSubsMax	725	563	75.70	.77	83.00	20.69	428.03	91.00	8.00	99.00	69.00	83.00	90.00
P2SubgSubsMin	337	951	26.31	1.12	17.00	20.61	424.81	85.00	4.00	89.00	13.00	17.00	32.00

Table D31. General Statistics of Predicted Distress Scores According to Late Age (2005-2010) for Two Years Missing Data points Case (2).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	90	0	77.86	1.62	78.00	15.38	236.60	90.59	8.84	99.43	74.49	78.00	88.81
Mean Nearby Points	60	30	79.36	2.06	81.45	15.99	255.77	86.97	12.03	99.00	74.69	81.45	88.99
Med. Nearby Pts.	63	27	79.59	1.87	80.46	14.85	220.44	81.64	17.36	99.00	76.24	80.46	88.99
Linear Interpolation	63	27	79.59	1.87	80.46	14.85	220.44	81.64	17.36	99.00	76.24	80.46	88.99
Linear Trend Pts.	54	36	80.28	2.20	83.56	16.18	261.95	88.78	10.22	99.00	74.17	83.56	89.00
Moving Average	73	17	79.55	1.61	78.00	13.78	189.83	66.00	33.00	99.00	75.00	78.00	88.99
Cubic Spline Fitting	58	32	78.07	2.20	80.98	16.77	281.38	88.71	10.29	99.00	68.66	80.98	88.80
Cubic Spline4 D. Pts.	61	29	79.88	1.90	81.56	14.85	220.45	71.21	27.79	99.00	74.87	81.56	89.00
Sub. Subs. Mean	66	24	79.09	1.73	78.00	14.09	198.39	71.96	27.04	99.00	76.02	78.00	89.00
Sub. Subs. Med.	68	22	78.50	1.71	77.98	14.06	197.74	72.83	26.17	99.00	74.99	77.98	88.99
Sub. Subs. Max.	68	22	77.83	1.90	78.00	15.69	246.09	94.57	4.43	99.00	73.67	78.00	88.99
Sub. Subs. Min.	69	21	80.01	1.63	80.13	13.51	182.46	66.00	33.00	99.00	76.17	80.13	88.99
P2LinearTrendatPts	46	44	89.20	1.24	90.57	8.43	71.08	44.57	55.10	99.68	86.38	90.57	94.70
P2MovingAverage	44	46	84.50	1.96	89.00	13.02	169.60	66.00	33.00	99.00	78.00	89.00	92.00
P2CubicSplineFitting	59	31	81.85	1.90	85.53	14.58	212.60	73.13	26.17	99.30	75.78	85.53	90.11
P2CubicSpline4DPts	42	48	82.92	2.21	87.50	14.32	205.10	59.89	39.28	99.17	76.46	87.50	94.00
P2SubgSubsMean	31	59	60.06	2.15	61.30	11.99	143.85	59.43	21.40	80.83	54.98	61.30	66.79
P2SubgSubsMed	28	62	64.59	2.69	69.00	14.25	203.11	59.50	24.00	83.50	52.75	69.00	75.50
P2SubgSubsMax	35	55	81.29	2.30	85.00	13.59	184.62	75.00	24.00	99.00	78.00	85.00	89.00
P2SubgSubsMin	14	76	19.64	4.80	13.00	17.97	322.86	52.00	10.00	62.00	13.00	13.00	13.00

Table D32. General Statistics of Predicted Distress Scores for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	7554	0	71.17	.24	77.99	21.28	453.03	99.97	.03	100.00	53.99	77.99	88.96
Mean Nearby Points	5877	1677	73.05	.27	78.34	20.64	426.08	98.15	.85	99.00	54.75	78.34	88.99
Med. Nearby Pts.	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Interpolation	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Trend Pts.	5625	1929	72.67	.28	78.00	20.64	425.89	96.06	2.94	99.00	53.99	78.00	88.99
Moving Average	6327	1227	72.47	.26	78.00	21.02	441.98	98.15	.85	99.00	54.00	78.00	88.99
Cubic Spline Fitting	6054	1500	72.29	.27	78.00	20.71	428.98	91.83	7.17	99.00	53.99	78.00	88.98
Cubic Spline4 D. Pts.	5988	1566	72.75	.27	77.99	20.83	433.75	98.15	.85	99.00	54.12	77.99	88.98
Sub. Subs. Mean	6196	1358	72.15	.27	77.99	21.11	445.52	98.15	.85	99.00	54.00	77.99	88.99
Sub. Subs. Med.	6226	1328	71.31	.28	77.99	21.72	471.78	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Max.	6451	1103	71.43	.27	77.99	21.44	459.84	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Min.	6121	1433	72.83	.27	78.00	21.02	441.82	98.15	.85	99.00	55.12	78.00	88.99
P2LinearTrendatPts	3936	3618	85.86	.25	90.93	15.45	238.63	90.98	8.77	99.76	83.32	90.93	94.43
P2MovingAverage	4351	3203	77.37	.30	87.00	19.75	390.21	85.00	14.00	99.00	59.00	87.00	92.00
P2CubicSplineFitting	5187	2367	77.32	.27	84.72	19.30	372.47	89.31	10.02	99.33	68.72	84.72	90.96
P2CubicSpline4DPts	3679	3875	73.32	.41	83.00	24.80	615.05	99.00	1.00	100.00	57.81	83.00	93.33
P2SubgSubsMean	3616	3938	53.48	.23	55.12	14.01	196.27	81.00	8.00	89.00	40.57	55.12	64.05
P2SubgSubsMed	3661	3893	57.08	.26	58.00	15.92	253.49	81.00	8.00	89.00	43.00	58.00	69.00
P2SubgSubsMax	4513	3041	73.10	.30	78.00	20.32	412.98	91.00	8.00	99.00	56.00	78.00	89.00
P2SubgSubsMin	2106	5448	23.64	.33	20.00	15.15	229.43	85.00	4.00	89.00	13.00	20.00	28.00

Table D33. General Statistics of Predicted Distress Scores According to Very Good (90-100) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	5611	0	75.47	.26	82.94	19.67	386.91	99.97	.03	100.00	62.00	82.94	89.00
Mean Nearby Points	4501	1110	77.34	.28	86.09	19.12	365.54	98.15	.85	99.00	66.08	86.09	91.00
Med. Nearby Pts.	4599	1012	76.66	.29	86.29	19.95	397.88	98.15	.85	99.00	64.95	86.29	91.00
Linear Interpolation	4599	1012	76.66	.29	86.29	19.95	397.88	98.15	.85	99.00	64.95	86.29	91.00
Linear Trend Pts.	4281	1330	77.01	.29	85.18	19.19	368.14	96.06	2.94	99.00	66.20	85.18	90.70
Moving Average	4705	906	76.55	.29	85.42	19.77	390.95	98.15	.85	99.00	64.95	85.42	90.99
Cubic Spline Fitting	4629	982	76.44	.28	85.03	19.37	375.29	91.33	7.67	99.00	62.21	85.03	91.00
Cubic Spline4 D. Pts.	4600	1011	76.80	.29	86.51	19.60	384.06	98.15	.85	99.00	65.73	86.51	90.95
Sub. Subs. Mean	4695	916	76.13	.29	85.13	20.08	403.24	98.15	.85	99.00	64.21	85.13	91.00
Sub. Subs. Med.	4694	917	75.61	.30	84.93	20.34	413.64	98.15	.85	99.00	64.20	84.93	91.00
Sub. Subs. Max.	4795	816	75.73	.29	84.23	20.10	404.10	98.15	.85	99.00	64.21	84.23	90.97
Sub. Subs. Min.	4602	1009	76.90	.29	86.62	19.69	387.63	98.15	.85	99.00	66.57	86.62	91.00
P2LinearTrendatPts	3113	2498	89.70	.20	91.81	11.01	121.32	87.40	12.36	99.76	87.94	91.81	97.03
P2MovingAverage	3261	2350	83.21	.29	90.00	16.63	276.59	79.00	20.00	99.00	78.00	90.00	92.00
P2CubicSplineFitting	3905	1706	82.83	.25	87.79	15.74	247.68	86.77	12.56	99.33	76.44	87.79	91.85
P2CubicSpline4DPts	2863	2748	76.49	.43	86.67	23.12	534.55	96.50	3.50	100.00	67.00	86.67	94.00
P2SubgSubsMean	2654	2957	57.42	.23	61.14	12.02	144.52	80.00	9.00	89.00	53.29	61.14	65.62
P2SubgSubsMed	2731	2880	61.54	.27	68.00	13.91	193.40	80.00	9.00	89.00	52.50	68.00	72.00
P2SubgSubsMax	3321	2290	78.24	.31	86.00	17.99	323.77	83.00	16.00	99.00	73.00	86.00	89.00
P2SubgSubsMin	1457	4154	22.56	.44	14.00	16.86	284.29	85.00	4.00	89.00	13.00	14.00	28.00

Table D34. General Statistics of Predicted Distress Scores According to Good (80-89) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	6	0	64.47	9.58	68.06	23.47	550.61	52.99	35.97	88.96	37.67	68.06	87.90
Mean Nearby Points	3	3	75.69	7.93	76.49	13.73	188.62	27.43	61.57	89.00	61.57	76.49	.
Med. Nearby Pts.	4	2	78.95	6.50	82.55	12.99	168.82	27.28	61.72	89.00	65.32	82.55	88.99
Linear Interpolation	4	2	78.95	6.50	82.55	12.99	168.82	27.28	61.72	89.00	65.32	82.55	88.99
Linear Trend Pts.	4	2	65.83	11.21	68.75	22.41	502.36	52.17	36.83	89.00	42.94	68.75	85.81
Moving Average	3	3	75.62	7.89	76.18	13.66	186.69	27.31	61.69	89.00	61.69	76.18	.
Cubic Spline Fitting	3	3	75.27	8.01	75.54	13.87	192.38	27.74	61.26	89.00	61.26	75.54	.
Cubic Spline4 D. Pts.	4	2	78.70	6.68	82.46	13.36	178.38	28.10	60.90	89.00	64.67	82.46	88.98
Sub. Subs. Mean	4	2	78.81	6.69	82.71	13.38	178.94	28.19	60.81	89.00	64.72	82.71	89.00
Sub. Subs. Med.	4	2	79.00	6.61	82.97	13.23	175.00	27.93	61.07	89.00	65.04	82.97	88.99
Sub. Subs. Max.	4	2	79.61	6.28	83.50	12.56	157.66	26.54	62.46	89.00	66.35	83.50	89.00
Sub. Subs. Min.	3	3	75.36	8.10	76.09	14.03	196.80	28.03	60.97	89.00	60.97	76.09	.
P2LinearTrendatPts	3	3	75.24	7.57	75.82	13.12	172.13	26.22	61.85	88.07	61.85	75.82	.
P2MovingAverage	3	3	77.33	6.94	78.00	12.01	144.33	24.00	65.00	89.00	65.00	78.00	.
P2CubicSplineFitting	3	3	77.43	7.35	78.72	12.73	162.14	25.37	64.09	89.46	64.09	78.72	.
P2CubicSpline4DPts	3	3	76.63	7.24	77.28	12.54	157.26	25.06	63.78	88.83	63.78	77.28	.
P2SubgSubsMean	4	2	56.57	7.46	57.65	14.92	222.51	31.00	40.00	71.00	42.02	57.65	70.05
P2SubgSubsMed	4	2	60.00	8.60	61.00	17.20	296.00	38.00	40.00	78.00	43.00	61.00	76.00
P2SubgSubsMax	3	3	77.33	6.94	78.00	12.01	144.33	24.00	65.00	89.00	65.00	78.00	.
P2SubgSubsMin	1	5	32.00		32.00			.00	32.00	32.00	32.00	32.00	32.00

Table D35. General Statistics of Predicted Distress Scores According to Fair (70-79) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1	0	53.35		53.35			.00	53.35	53.35	53.35	53.35	53.35
Mean Nearby Points	1	0	53.41		53.41			.00	53.41	53.41	53.41	53.41	53.41
Med. Nearby Pts.	1	0	53.73		53.73			.00	53.73	53.73	53.73	53.73	53.73
Linear Interpolation	1	0	53.73		53.73			.00	53.73	53.73	53.73	53.73	53.73
Linear Trend Pts.	1	0	52.91		52.91			.00	52.91	52.91	52.91	52.91	52.91
Moving Average	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
Cubic Spline Fitting	1	0	52.81		52.81			.00	52.81	52.81	52.81	52.81	52.81
Cubic Spline4 D. Pts.	1	0	54.73		54.73			.00	54.73	54.73	54.73	54.73	54.73
Sub. Subs. Mean	1	0	53.93		53.93			.00	53.93	53.93	53.93	53.93	53.93
Sub. Subs. Med.	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
Sub. Subs. Max.	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
Sub. Subs. Min.	1	0	55.21		55.21			.00	55.21	55.21	55.21	55.21	55.21
P2LinearTrendatPts	1	0	57.77		57.77			.00	57.77	57.77	57.77	57.77	57.77
P2MovingAverage	1	0	56.00		56.00			.00	56.00	56.00	56.00	56.00	56.00
P2CubicSplineFitting	1	0	52.78		52.78			.00	52.78	52.78	52.78	52.78	52.78
P2CubicSpline4DPts	1	0	57.81		57.81			.00	57.81	57.81	57.81	57.81	57.81
P2SubgSubsMean	1	0	38.40		38.40			.00	38.40	38.40	38.40	38.40	38.40
P2SubgSubsMed	1	0	40.00		40.00			.00	40.00	40.00	40.00	40.00	40.00
P2SubgSubsMax	1	0	45.00		45.00			.00	45.00	45.00	45.00	45.00	45.00
P2SubgSubsMin	1	0	32.00		32.00			.00	32.00	32.00	32.00	32.00	32.00

Table D36. General Statistics of Predicted Distress Scores According to Poor (60-69) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	2	0	69.85	4.86	69.85	6.87	47.26	9.72	64.99	74.71	64.99	69.85	.
Mean Nearby Points	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Med. Nearby Pts.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Linear Interpolation	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Linear Trend Pts.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Moving Average	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Cubic Spline Fitting	2	0	64.41	.59	64.41	.83	.70	1.18	63.82	65.00	63.82	64.41	.
Cubic Spline4 D. Pts.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Mean	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Med.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Max.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
Sub. Subs. Min.	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
P2LinearTrendatPts	1	1	57.52		57.52			.00	57.52	57.52	57.52	57.52	57.52
P2MovingAverage	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
P2CubicSplineFitting	1	1	65.92		65.92			.00	65.92	65.92	65.92	65.92	65.92
P2CubicSpline4DPts	2	0	65.00	.00	65.00	.00	.00	.00	65.00	65.00	65.00	65.00	65.00
P2SubgSubsMean	0	2											
P2SubgSubsMed	0	2											
P2SubgSubsMax	1	1	50.00		50.00			.00	50.00	50.00	50.00	50.00	50.00
P2SubgSubsMin	0	2											

Table D37. General Statistics of Predicted Distress Scores According to Very Poor (1-59) Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	38	0	29.68	1.19	31.33	7.33	53.70	42.78	7.22	50.00	26.46	31.33	34.38
Mean Nearby Points	29	9	23.79	.94	27.00	5.06	25.60	20.95	6.05	27.00	19.00	27.00	27.00
Med. Nearby Pts.	29	9	23.87	.89	27.00	4.80	23.08	18.83	8.17	27.00	19.00	27.00	27.00
Linear Interpolation	29	9	23.87	.89	27.00	4.80	23.08	18.83	8.17	27.00	19.00	27.00	27.00
Linear Trend Pts.	29	9	23.85	.91	27.00	4.88	23.80	19.47	7.53	27.00	19.00	27.00	27.00
Moving Average	35	3	24.50	.98	27.00	5.78	33.43	31.00	19.00	50.00	19.00	27.00	27.00
Cubic Spline Fitting	29	9	23.83	.91	27.00	4.92	24.23	19.83	7.17	27.00	19.00	27.00	27.00
Cubic Spline4 D. Pts.	29	9	24.27	.71	27.00	3.83	14.70	8.00	19.00	27.00	19.00	27.00	27.00
Sub. Subs. Mean	31	7	23.64	.84	27.00	4.66	21.69	18.03	8.97	27.00	19.00	27.00	27.00
Sub. Subs. Med.	32	6	23.87	.68	27.00	3.85	14.85	8.00	19.00	27.00	19.00	27.00	27.00
Sub. Subs. Max.	30	8	24.13	.70	27.00	3.84	14.76	8.00	19.00	27.00	19.00	27.00	27.00
Sub. Subs. Min.	31	7	24.00	.69	27.00	3.85	14.81	8.00	19.00	27.00	19.00	27.00	27.00
P2LinearTrendatPts	28	10	17.79	.54	19.17	2.87	8.25	8.57	12.80	21.37	14.74	19.17	20.15
P2MovingAverage	28	10	24.43	.72	27.00	3.80	14.48	8.00	19.00	27.00	19.00	27.00	27.00
P2CubicSplineFitting	30	8	25.34	.80	27.40	4.40	19.38	17.73	12.28	30.01	21.05	27.40	28.69
P2CubicSpline4DPts	28	10	11.20	1.32	10.48	6.98	48.70	22.00	1.00	23.00	7.00	10.48	15.26
P2SubgSubsMean	29	9	16.37	.56	18.40	2.99	8.95	10.40	8.00	18.40	13.00	18.40	18.40
P2SubgSubsMed	29	9	18.72	.87	22.00	4.68	21.92	14.00	8.00	22.00	13.00	22.00	22.00
P2SubgSubsMax	29	9	20.69	1.14	25.00	6.11	37.36	17.00	8.00	25.00	13.00	25.00	25.00
P2SubgSubsMin	29	9	8.90	.52	7.00	2.81	7.88	6.00	7.00	13.00	7.00	7.00	13.00

Table D38. General Statistics of Predicted Distress Scores According Age (1993-2010) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	7554	0	71.17	.24	77.99	21.28	453.03	99.97	.03	100.00	53.99	77.99	88.96
Mean Nearby Points	5877	1677	73.05	.27	78.34	20.64	426.08	98.15	.85	99.00	54.75	78.34	88.99
Med. Nearby Pts.	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Interpolation	6029	1525	72.54	.27	78.00	21.10	445.33	98.15	.85	99.00	53.99	78.00	88.99
Linear Trend Pts.	5625	1929	72.67	.28	78.00	20.64	425.89	96.06	2.94	99.00	53.99	78.00	88.99
Moving Average	6327	1227	72.47	.26	78.00	21.02	441.98	98.15	.85	99.00	54.00	78.00	88.99
Cubic Spline Fitting	6054	1500	72.29	.27	78.00	20.71	428.98	91.83	7.17	99.00	53.99	78.00	88.98
Cubic Spline4 D. Pts.	5988	1566	72.75	.27	77.99	20.83	433.75	98.15	.85	99.00	54.12	77.99	88.98
Sub. Subs. Mean	6196	1358	72.15	.27	77.99	21.11	445.52	98.15	.85	99.00	54.00	77.99	88.99
Sub. Subs. Med.	6226	1328	71.31	.28	77.99	21.72	471.78	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Max.	6451	1103	71.43	.27	77.99	21.44	459.84	98.15	.85	99.00	53.99	77.99	88.98
Sub. Subs. Min.	6121	1433	72.83	.27	78.00	21.02	441.82	98.15	.85	99.00	55.12	78.00	88.99
P2LinearTrendatPts	3936	3618	85.86	.25	90.93	15.45	238.63	90.98	8.77	99.76	83.32	90.93	94.43
P2MovingAverage	4351	3203	77.37	.30	87.00	19.75	390.21	85.00	14.00	99.00	59.00	87.00	92.00
P2CubicSplineFitting	5187	2367	77.32	.27	84.72	19.30	372.47	89.31	10.02	99.33	68.72	84.72	90.96
P2CubicSpline4DPts	3679	3875	73.32	.41	83.00	24.80	615.05	99.00	1.00	100.00	57.81	83.00	93.33
P2SubgSubsMean	3616	3938	53.48	.23	55.12	14.01	196.27	81.00	8.00	89.00	40.57	55.12	64.05
P2SubgSubsMed	3661	3893	57.08	.26	58.00	15.92	253.49	81.00	8.00	89.00	43.00	58.00	69.00
P2SubgSubsMax	4513	3041	73.10	.30	78.00	20.32	412.98	91.00	8.00	99.00	56.00	78.00	89.00
P2SubgSubsMin	2106	5448	23.64	.33	20.00	15.15	229.43	85.00	4.00	89.00	13.00	20.00	28.00

Figure A39. General Statistics of Predicted Distress Scores According to Early Age (1993-1998) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	182	0	64.43	1.99	69.94	26.85	721.12	90.54	8.35	98.89	41.98	69.94	89.00
Mean Nearby Points	162	20	66.71	2.03	70.97	25.89	670.25	89.46	9.43	98.89	45.64	70.97	90.66
Med. Nearby Pts.	166	16	65.73	2.06	69.94	26.52	703.36	87.94	10.95	98.89	45.32	69.94	90.66
Linear Interpolation	166	16	65.73	2.06	69.94	26.52	703.36	87.94	10.95	98.89	45.32	69.94	90.66
Linear Trend Pts.	158	24	66.86	2.03	69.94	25.53	651.59	89.07	9.82	98.89	45.41	69.94	90.66
Moving Average	164	18	66.43	2.03	70.30	25.96	673.80	80.79	18.10	98.89	48.05	70.30	90.66
Cubic Spline Fitting	166	16	65.36	2.05	69.74	26.46	700.27	90.45	8.44	98.89	43.59	69.74	90.66
Cubic Spline4 D. Pts.	164	18	66.72	2.01	72.00	25.79	665.29	86.24	12.65	98.89	48.69	72.00	90.66
Sub. Subs. Mean	166	16	65.70	2.06	69.94	26.50	702.18	90.23	8.66	98.89	45.32	69.94	90.66
Sub. Subs. Med.	165	17	66.04	2.04	69.94	26.25	688.93	90.09	8.80	98.89	46.63	69.94	90.66
Sub. Subs. Max.	165	17	66.06	2.04	69.94	26.21	686.75	87.17	11.72	98.89	46.63	69.94	90.66
Sub. Subs. Min.	167	15	65.64	2.05	69.94	26.46	700.05	89.89	9.00	98.89	45.43	69.94	90.66
P2LinearTrendatPts	93	89	79.48	2.67	91.87	25.76	663.59	87.40	12.36	99.76	63.79	91.87	98.98
P2MovingAverage	117	65	72.22	2.26	82.00	24.43	596.76	79.00	20.00	99.00	50.00	82.00	92.00
P2CubicSplineFitting	131	51	72.16	2.20	84.40	25.12	631.19	86.75	12.56	99.31	50.95	84.40	91.06
P2CubicSpline4DPts	86	96	69.62	2.97	86.00	27.53	757.85	88.00	11.00	99.00	40.00	86.00	94.50
P2SubgSubsMean	87	95	49.88	2.02	55.12	18.82	354.26	68.59	9.00	77.59	35.00	55.12	66.20
P2SubgSubsMed	89	93	54.61	2.29	56.00	21.59	466.08	80.00	9.00	89.00	41.00	56.00	70.50
P2SubgSubsMax	115	67	68.58	2.25	73.00	24.13	582.26	83.00	16.00	99.00	47.00	73.00	89.00
P2SubgSubsMin	51	131	21.49	1.41	20.00	10.05	101.05	58.00	4.00	62.00	15.00	20.00	25.00

Table D40. General Statistics of Predicted Distress Scores According to Middle Age (1999-2004) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	1372	0	72.14	.53	77.96	19.72	388.82	99.91	.09	100.00	53.99	77.96	88.93
Mean Nearby Points	1033	339	74.07	.62	80.05	20.07	402.99	98.15	.85	99.00	57.85	80.05	89.00
Med. Nearby Pts.	1064	308	73.27	.64	78.00	20.95	438.73	98.15	.85	99.00	56.83	78.00	89.00
Linear Interpolation	1064	308	73.27	.64	78.00	20.95	438.73	98.15	.85	99.00	56.83	78.00	89.00
Linear Trend Pts.	963	409	74.39	.64	80.94	19.97	398.73	91.03	7.97	99.00	57.68	80.94	89.59
Moving Average	1116	256	72.87	.63	77.99	20.93	438.02	98.15	.85	99.00	55.99	77.99	88.99
Cubic Spline Fitting	1084	288	73.45	.60	78.00	19.80	391.96	86.05	12.95	99.00	55.71	78.00	88.96
Cubic Spline4 D. Pts.	1091	281	73.94	.60	78.00	19.75	390.19	98.15	.85	99.00	57.17	78.00	88.97
Sub. Subs. Mean	1106	266	72.87	.63	77.99	20.81	433.14	98.15	.85	99.00	55.55	77.99	88.96
Sub. Subs. Med.	1121	251	72.42	.63	77.99	21.08	444.45	98.15	.85	99.00	53.99	77.99	88.96
Sub. Subs. Max.	1154	218	72.55	.61	77.99	20.70	428.49	98.15	.85	99.00	54.02	77.99	88.96
Sub. Subs. Min.	1082	290	73.24	.63	78.00	20.85	434.66	98.15	.85	99.00	56.90	78.00	88.99
P2LinearTrendatPts	788	584	85.16	.57	90.91	16.14	260.42	90.98	8.77	99.76	79.27	90.91	95.08
P2MovingAverage	796	576	79.76	.67	89.00	18.95	359.22	80.00	19.00	99.00	69.00	89.00	92.00
P2CubicSplineFitting	954	418	78.76	.61	84.94	18.83	354.52	79.69	19.64	99.33	70.87	84.94	91.57
P2CubicSpline4DPts	748	624	73.29	.86	80.50	23.49	551.63	99.00	1.00	100.00	62.00	80.50	92.00
P2SubgSubsMean	657	715	56.26	.52	60.40	13.40	179.64	76.00	13.00	89.00	48.46	60.40	65.55
P2SubgSubsMed	690	682	60.98	.57	68.00	15.10	228.08	76.00	13.00	89.00	48.00	68.00	73.00
P2SubgSubsMax	846	526	76.30	.67	83.00	19.35	374.42	86.00	13.00	99.00	69.00	83.00	90.00
P2SubgSubsMin	367	1005	25.69	1.00	20.00	19.15	366.60	84.00	5.00	89.00	13.00	20.00	32.00

Table D41. General Statistics of Predicted Distress Scores According to Late Age (2005-2010) for Three Years Missing Data points Case (3).

Missing Data Techniques Brief	Valid	Not Valid	Mean	Std. Err. Mean	Med.	Std. Dev.	Var.	Range	Min.	Max.	50%	50%	75%
Do Nothing	28	0	74.73	3.69	78.78	19.51	380.71	87.16	12.09	99.25	61.79	78.78	88.44
Mean Nearby Points	20	8	78.72	3.71	78.67	16.60	275.71	73.91	25.09	99.00	75.14	78.67	88.96
Med. Nearby Pts.	21	7	78.82	3.37	82.41	15.46	239.04	66.27	32.73	99.00	73.78	82.41	89.00
Linear Interpolation	21	7	78.82	3.37	82.41	15.46	239.04	66.27	32.73	99.00	73.78	82.41	89.00
Linear Trend Pts.	20	8	78.23	3.95	78.00	17.66	311.89	79.76	19.24	99.00	75.36	78.00	88.30
Moving Average	27	1	77.30	3.15	77.99	16.38	268.43	66.00	33.00	99.00	72.99	77.99	88.99
Cubic Spline Fitting	21	7	76.07	3.93	78.00	18.00	324.01	78.67	20.33	99.00	69.92	78.00	88.18
Cubic Spline4 D. Pts.	23	5	78.60	3.35	82.94	16.08	258.58	66.56	32.44	99.00	76.88	82.94	88.98
Sub. Subs. Mean	23	5	76.88	3.53	78.48	16.94	287.04	77.93	21.07	99.00	65.57	78.48	88.75
Sub. Subs. Med.	23	5	77.35	3.51	78.85	16.82	282.75	78.83	20.17	99.00	67.45	78.85	88.94
Sub. Subs. Max.	24	4	76.00	3.80	78.42	18.64	347.44	93.60	5.40	99.00	69.25	78.42	86.52
Sub. Subs. Min.	23	5	79.58	2.97	82.40	14.26	203.41	66.00	33.00	99.00	72.04	82.40	88.99
P2LinearTrendatPts	20	8	86.47	2.34	86.46	10.45	109.18	48.93	50.66	99.59	84.76	86.46	92.28
P2MovingAverage	19	9	80.21	3.46	78.00	15.09	227.62	66.00	33.00	99.00	78.00	78.00	89.00
P2CubicSplineFitting	22	6	79.78	3.40	80.59	15.93	253.79	73.04	26.24	99.28	75.22	80.59	88.86
P2CubicSpline4DPts	19	9	74.06	4.31	76.78	18.80	353.39	69.22	27.80	97.02	53.56	76.78	88.39
P2SubgSubsMean	13	15	54.76	3.53	54.98	12.72	161.78	51.27	21.40	72.67	54.54	54.98	61.11
P2SubgSubsMed	9	19	57.56	5.75	53.50	17.25	297.40	54.00	24.00	78.00	48.25	53.50	72.25
P2SubgSubsMax	15	13	76.87	4.42	83.00	17.13	293.27	65.00	24.00	89.00	78.00	83.00	89.00
P2SubgSubsMin	3	25	12.33	.67	13.00	1.15	1.33	2.00	11.00	13.00	11.00	13.00	.

Appendix E

Appendix E1

Function for one year missing data point to obtain:

Predicted score, Discrepancy, Efficiency and Average Efficiency

```
function mazin_main_1yearsK(variablename,foldername)

% Create empty matrices to store the data
Secs_Disc=[];
Secs_Eff=[];
Secs_pred_values=[];
Secs_Avg_Eff=[];

for i=1:25
  if i==7||i==11||i==21||i==23||i==16   % Except Districts 7,11,21,23
    continue;
  else
    fname=['District_',num2str(i)];
    %------------------------------------------
    % For One District
    load ([variablename,'\',foldername,'\',fname],'sec_filt');

    if ~isempty(sec_filt)
      j=1;
      while j<=length(sec_filt) % Check All rows of sec_filt
        %------------------------------------------
        % One Section in a district
        secID=sec_filt(j,1);
        SecStart=j;
        SecLen=0; % Initial Value

        DismissData=[];

        % Routine to find the section length
        while sec_filt(j,1)==secID
          SecLen=SecLen+1; % To find the section length
          j=j+1; % Update j
          if j>length(sec_filt)
```

```
        break;
    end
end

%----------------------------------------
%Dismiss the last data point in the pavement section
%Test: Dismiss Last year of section

% Save the Actual Value of the last year
ObservedValue=sec_filt(SecStart+SecLen-1,3);
% Save the last year
DismissYear=sec_filt(SecStart+SecLen-1,2);
% Store the date for each section without the last year
% (year, Score)
DismissData=sec_filt(SecStart:SecStart+SecLen-2,2:3);
% The length of section data without the last year
DissLen=length(DismissData);
%----------------------------------------

% Missing one data point from the pavement section history
pred_values=[];
Disc=[];
Eff=[];
MissingData=DismissData(:,2)';


for missID = 3:DissLen-2
    %----------------------------------------
    %Rebuild the missing data point using statisticl
    %techniques
    RebuildData = zeros(11,DissLen); % 11 for 11 methods

    %Method#1: Mean of Nearby
    Rebuild_Val = mean([MissingData(missID-2:missID-1),...
        MissingData(missID+1:missID+2)]);
    RebuildData(1,:) = MissingData;
    RebuildData(1,missID) = Rebuild_Val;

    %Method#2: Median of Nearby
   Rebuild_Val = median([MissingData(missID-2:missID-1),...
        MissingData(missID+1:missID+2)]);
    RebuildData(2,:) = MissingData;
    RebuildData(2,missID) = Rebuild_Val;

    %Method#3: Linear Interoplation
```

```
Rebuild_Val = interp1([1,3],[MissingData(missID-1),...
   MissingData(missID+1)],2);
RebuildData(3,:) = MissingData;
RebuildData(3,missID) = Rebuild_Val;

%Method#4: Linear Trend at point
Rebuild_Val = polyval(polyfit([1:missID-1,...
   missID+1:DissLen],[MissingData(1:missID-1),...
   MissingData(missID+1:DissLen)],1),missID);
RebuildData(4,:) = MissingData;
RebuildData(4,missID) = Rebuild_Val;

%Method#5: Moving Average
Rebuild_Val = MissingData(missID+1);
RebuildData(5,:) = MissingData;
RebuildData(5,missID) = Rebuild_Val;

%Method#6: Cubic Spline at all points (Fitting)
Rebuild_Val = polyval(polyfit([1:missID-1,missID+1:...
   DissLen],[MissingData(1:missID-1),...
   MissingData(missID+1:DissLen)],3),missID);
RebuildData(6,:) = MissingData;
RebuildData(6,missID) = Rebuild_Val;

%Method#7: Cubic Spline at 4 points
Rebuild_Val = polyval(polyfit([1,2,4,5],...
   [MissingData(missID-2:missID-1),...
   MissingData(missID+1:missID+2)],3),3);
RebuildData(7,:) = MissingData;
RebuildData(7,missID) = Rebuild_Val;

%Method#8: SubGroup
temp=[];
k=0;
MissingYear=DismissData(missID,1);
for z=1:length(sec_filt)
   if (sec_filt(z,2)== MissingYear && ...
         (z<SecStart || z>=(SecStart+SecLen)))
      x=sec_filt(z,3);
      if x <= MissingData(missID-1) && x >=...
            MissingData(missID+1)
         k=k+1;
         temp(k)=x;
      end
   end
```

```
end

if k~=0  % temp array is not empty
   Rebuild_Val=mean(temp);
   RebuildData(8,:)=MissingData;
   RebuildData(8,missID)=Rebuild_Val;

   Rebuild_Val=median(temp);
   RebuildData(9,:)=MissingData;
   RebuildData(9,missID)=Rebuild_Val;

   Rebuild_Val=max(temp);
   RebuildData(10,:)=MissingData;
   RebuildData(10,missID)=Rebuild_Val;

   Rebuild_Val=min(temp);
   RebuildData(11,:)=MissingData;
   RebuildData(11,missID)=Rebuild_Val;
else
   RebuildData(8,:)=MissingData;
   RebuildData(8,missID)=-1;
   RebuildData(9,:)=MissingData;
   RebuildData(9,missID)=-1;
   RebuildData(10,:)=MissingData;
   RebuildData(10,missID)=-1;
   RebuildData(11,:)=MissingData;
   RebuildData(11,missID)=-1;
end
%-----------------------------------------

%Predict the future scores (i.e. Dismissed value) using
%nonlinear regression
pred_values(missID,1:6)=[i,secID,DismissYear,...
   ObservedValue,MissingYear, DismissData(missID,2)];

%Tech#1
%Predict without Rebuild
indata = single([DismissData(1:missID-1,:);...
   DismissData(missID+1:DissLen,:)]);
if strcmp(variablename,'RS') == 1    % String Compare
 pred_values(missID,7) = check3(nlr_mazin_rs(indata));
else
   y = nlr_mazin(indata, variablename);
   pred_values(missID,7) = check2(y);
```

```
end

%Tech#2
%Predict with Rebuild
for k=1:11
  indata=single([DismissData(:,1),RebuildData(k,:)']);
    if strcmp(variablename,'RS') == 1
        pred_values(missID,k+7) = ...
            check4(nlr_mazin_rs(indata), ...
            sec_filt(SecStart+SecLen-2,3));
    else
        x = nlr_mazin(indata, variablename);
        pred_values(missID,k+7) = ...
            check(x, sec_filt(SecStart+SecLen-2,3));
    end
end
%-----------------------------------------------------
% Predict 2 using statistical techniques directly (i.e.
% without using the pavement performance model)

% Linear Trend at point
Estimated_Val = polyval(polyfit([1:DissLen ],...
    [RebuildData(4,:)],1),DissLen);
if strcmp(variablename,'RS') == 1
    pred_values(missID, 19) = check3(Estimated_Val);
else
    pred_values(missID, 19) = check2(Estimated_Val);
end

% Moving Average
Estimated_Val = RebuildData(5,end);
if strcmp(variablename,'RS') == 1
    pred_values(missID, 20) = check3(Estimated_Val);
else
    pred_values(missID, 20) = check2(Estimated_Val);
end

% Cubic Spline
Estimated_Val = polyval(polyfit([1:DissLen ],...
    [RebuildData(6,:)],3),DissLen);
if strcmp(variablename,'RS') == 1
    pred_values(missID, 21) = check3(Estimated_Val);
else
    pred_values(missID, 21) = check2(Estimated_Val);
end
```

```
% Cubic Spline at 4 points
Estimated_Val = polyval(polyfit([1,2,3,4],...
   [RebuildData(7,end-3:end)],3),5);
if strcmp(variablename,'RS') == 1
   pred_values(missID, 22) = check3(Estimated_Val);
else
   pred_values(missID, 22) = check2(Estimated_Val);
end

% Populate the missing data points using the available
% subgroup data point (no prediction of the future
% score)
% SubGrouping
temp1=[];
k=0;
a=DismissData(end,1);
for z=1:length(sec_filt)
   if (sec_filt(z,2)== a+1 && (z<SecStart || ...
         z>=(SecStart+SecLen)))
      x=sec_filt(z,3);
      if x <= MissingData(end)
         k=k+1;
         temp1(k)=x;
      end
   end
end


if k~=0  % temp array is not empty
   Estimated_Val=mean(temp1);
   if strcmp(variablename,'RS') == 1
     pred_values(missID, 23) = check3(Estimated_Val);
   else
     pred_values(missID, 23) = check2(Estimated_Val);
   end

   Estimated_Val=median(temp1);
   if strcmp(variablename,'RS') == 1
     pred_values(missID, 24) = check3(Estimated_Val);
   else
     pred_values(missID, 24) = check2(Estimated_Val);
   end

   Estimated_Val=max(temp1);
```

```
    if strcmp(variablename,'RS') == 1
      pred_values(missID, 25) = check3(Estimated_Val);
    else
      pred_values(missID, 25) = check2(Estimated_Val);
    end

    Estimated_Val=min(temp1);
    if strcmp(variablename,'RS') == 1
      pred_values(missID, 26) = check3(Estimated_Val);
    else
      pred_values(missID, 26) = check2(Estimated_Val);
    end

else
    pred_values(missID, 23)=-1;
    pred_values(missID, 24)=-1;
    pred_values(missID, 25)=-1;
    pred_values(missID, 26)=-1;
end

indata1 = single([DismissData(1:missID-1,:);...
    DismissData(missID+1:DissLen,:)]);


% Predict 2 using statistical techniques directly (i.e.
% without using the pavement performance model) WITHOUT
% REBUILDING missing data point

% Predict using Linear Trend at 1 point
Estimated_Val = polyval(polyfit([1:DissLen-1 ],...
    [indata1(:,2)'],1),DissLen);
if strcmp(variablename,'RS') == 1
    pred_values(missID, 27) = check3(Estimated_Val);
else
    pred_values(missID, 27) = check2(Estimated_Val);
end

% Predict using moving Average
Estimated_Val = indata1(end,2)';
if strcmp(variablename,'RS') == 1
    pred_values(missID, 28) = check3(Estimated_Val);
else
    pred_values(missID, 28) = check2(Estimated_Val);
end
```

```
% Predict using Cubic Spline
Estimated_Val = polyval(polyfit([1:DissLen-1 ],...
   [indata1(:,2)'],3),DissLen);
if strcmp(variablename,'RS') == 1
   pred_values(missID, 29) = check3(Estimated_Val);
else
   pred_values(missID, 29) = check2(Estimated_Val);
end

% Predict using Cubic Spline with 4 points
Estimated_Val = polyval(polyfit([1,2,3,4],...
   [indata1(end-3:end,2)'],3),5);
if strcmp(variablename,'RS') == 1
   pred_values(missID, 30) = check3(Estimated_Val);
else
   pred_values(missID, 30) = check2(Estimated_Val);
end
%---------------------------------------------------

%Scale of predicted values to Single value
pred_values = single(pred_values);

%----------------------------------------

%Discrepancy and Efficiency Test
Disc(missID,1:3) = [i,secID,MissingYear];
Eff(missID,1:3) = [i,secID,MissingYear];
%---------------------------------------------
% Efficiency Calculation
for k=4:27
   if pred_values(missID,k+3) == -1 || ...
         pred_values(missID,k+3)==-2
      Eff(missID,k)=-1000;
   elseif k>4 &&  Eff(missID,4)==-1000
      Eff(missID,k)=-1000;
   else
      if (pred_values(missID,4) == ...
            pred_values(missID, k+3)) || ...
            (pred_values(missID,4) == ...
            pred_values(missID, 7))
         Eff(missID,k) = 100;
      else
         Eff(missID,k) = (abs(pred_values...
            (missID,4) - pred_values(missID, 7))...
            - abs(pred_values(missID,4) - ...
```

```
                pred_values(missID, k+3))) / ...
                (abs(pred_values(missID,4) - ...
                pred_values(missID, 7))) *100;
            if abs(Eff(missID,k)) >= 100;
                Eff(missID,k) = -1000;
            end
        end
    end
end
%-------------------------------------------------------
% Dicepancy Calculation
for k=4:28
    if pred_values(missID,k+2) == -1 || ...
            pred_values(missID,k+2)==-2
        Disc(missID,k)=-1000;
    elseif k>4 && Disc(missID,4)==-1000
        Disc(missID,k)=-1000;
    else
        Disc(missID,k)=(pred_values(missID,k+2) ...
            - ObservedValue);
    end
end


end

%Calculate the the AVG Efficiency for all sections
Avg_Eff(1:4)=[i,secID,0,0];
for c=5:size(Eff,2)
    temp=[];
    k=0;
    for r=3:size(Eff,1)-2
        if Eff(r,c) >= Eff_thr && Eff(r,c) <= -Eff_thr
            k=k+1;
            temp(k)= Eff(r,c);
        end
    end
    % avg efficiency
    if k>0
        Avg_Eff(c)=mean(temp);
    else
        Avg_Eff(c)=-1000;
    end
end
```

```
            % Save the calculated data for each pavement section
            Secs_Disc=[Secs_Disc;Disc];
            Secs_Eff=[Secs_Eff;Eff];
            Secs_pred_values=[Secs_pred_values;pred_values];

            Secs_Avg_Eff=[Secs_Avg_Eff;[Avg_Eff(1:2),Avg_Eff(5:23)]];

            % % %        end  % Test case, Section

          end  % end of district
      end  % end of district
      % % % % end  % test case, District 24
   end  % if, Except Districts 7,11,21,23
end  % for, All Districts

% Calculate the overall average efficiency for each statistical technique
Overall_avg_Eff=[];
[r,c]=size(Secs_Avg_Eff);
x = [];
for i=3:c
   s=0;
   cnt=0;
   for j=1:r
      if Secs_Avg_Eff(j,i)~=-1000
         s=s+Secs_Avg_Eff(j,i);
         cnt=cnt+1;
      end
   end
   Overall_avg_Eff(i-2)=s/cnt;
   x = [x cnt];
end
% %-----------------------------------------

% Store all results in Excel format files
save([variablename,'\',foldername,'\1Years_results'],'Overall_avg_Eff',...
   'Secs_Avg_Eff','Secs_Disc','Secs_Eff','Secs_pred_values');
xlswrite([variablename,'\',foldername,...
   '\1Years_Overall_avg_Eff_NEW_K.xls...x'],Overall_avg_Eff);
xlswrite([variablename,'\',foldername,...
   '\1Years_Secs_Avg_Eff_NEW_K.xlsx'],Secs_Avg_Eff);
xlswrite([variablename,'\',foldername,...
   '\1Years_Overall_Avg_Eff_Section_Count_NEW_K.xlsx'],x);
xlswrite([variablename,'\',foldername,...
   '\1Years_Secs_Disc_NEW_K.xlsx'],Secs_Disc);
xlswrite([variablename,'\',foldername,...
```

```
    '\1Years_Secs_Eff_NEW_K.xlsx'],Secs_Eff);
xlswrite([variablename,'\',foldername,...
    '\1Years_Secs_pred_values_NEW_K.xlsx'],Secs_pred_values);

Data_New = [Secs_pred_values Secs_Disc Secs_Eff];
xlswrite([variablename,'\',foldername,...
    '\1Years_Secs_PredValues_Disc_Eff_NEW_K.xlsx'],Data_New);

end
```

End Appendix E1

Appendix E2

Function for two years missing data point to obtain:

predicted score, Discrepancy, Efficiency and Average Efficiency

```
function mazin_main_2yearsK(variablename,foldername)

% Create empty matrices to store the data
Secs_Disc=[];
Secs_Eff=[];
Secs_pred_values=[];
Secs_Avg_Eff=[];


for DisID=1:1
    % Except Districts 7,11,21,23 and 16
    if DisID==7||DisID==11||DisID==21||DisID==23||DisID==16
        continue;
    else
        fname=['District_',num2str(DisID)];
        %----------------------------------------
        % One Section in a district
        load ([variablename,'\',foldername,'\',fname],'sec_filt');

        if ~isempty(sec_filt)
            j=1;
            while j<=length(sec_filt)
                %----------------------------------------
                % One Section in a district
```

```
secID=sec_filt(j,1);
SecStart=j;
SecLen=0;

DismissData=[];

% Routine to find the section length
while sec_filt(j,1)==secID
   SecLen=SecLen+1; % To find the section length
   j=j+1; % Update j
   if j>length(sec_filt)
      break;
   end
end

%--------------------------------
%Dismiss the last data point in the pavement section
%Test: Dismiss Last year of section

% Save the Actual Value of the last year
ObservedValue=sec_filt(SecStart+SecLen-1,3);
% Save the last year
DismissYear=sec_filt(SecStart+SecLen-1,2);
% Store the date for each section without the last
% year (year, Score)
DismissData=sec_filt(SecStart:SecStart+SecLen-2,2:3);
% The length of section data without the last year
DissLen=size(DismissData,1);

% Missing two data points from the pavement section history
pred_values=[];
Disc=[];
Eff=[];
cntr=0;
MissingData=DismissData(:,2)';
for missID1=3:DissLen-3
   for missID2=missID1+1:DissLen-2
      MissingYear1=DismissData(missID1,1);
      MissingYear2=DismissData(missID2,1);
      cntr=cntr+1;
      %Rebuild
      RebuildData1=[];
      RebuildData2=[];
      RebuildData1(1:missID2,:)=DismissData(1:missID2,:);
      for t=missID2:DissLen-1
```

```
    RebuildData1(t,:)=DismissData(t+1,:);
end
%Method#1: Mean of Nearby
% Rebuild first point
RebuildData1(missID1,2)=...
    mean([RebuildData1(missID1-2:missID1-1,2)',...
    RebuildData1(missID1+1:missID1+2,2)']);
% Rebuild Second point
RebuildData2(1,:)=[RebuildData1(1:missID2-1,2)'...
    ,DismissData(missID2:DissLen,2)'];
RebuildData2(1,missID2)=...
    mean([RebuildData1(missID2-2:missID2-1,2)',...
    DismissData(missID2+1:missID2+2,2)']);

%Method#2: Median of Nearby
% Rebuild first point
RebuildData1(missID1,2)=...
  median([RebuildData1(missID1-2:missID1-1,2)',...
    RebuildData1(missID1+1:missID1+2,2)']);
% Rebuild Second point
RebuildData2(2,:)=[RebuildData1(1:missID2-1,2)',...
    DismissData(missID2:DissLen,2)'];
RebuildData2(2,missID2)=...
  median([RebuildData1(missID2-2:missID2-1,2)',...
    DismissData(missID2+1:missID2+2,2)']);

%Method#3: Linear Interoplation
% Rebuild first point
RebuildData1(missID1,2)=...
    interp1([1,3],[RebuildData1(missID1-1,2),...
    RebuildData1(missID1+1,2)],2);
% Rebuild Second point
RebuildData2(3,:)=[RebuildData1(1:missID2-1,2)',...
    DismissData(missID2:DissLen,2)'];
RebuildData2(3,missID2)=...
    interp1([1,3],[RebuildData1(missID2-1,2),...
    DismissData(missID2+1,2)],2);

%Method#4: Linear Trend at point
% Rebuild first point
RebuildData1(missID1,2)=polyval(polyfit(...
    [1:missID1-1,missID1+1:DissLen-1],...
    [RebuildData1(1:missID1-1,2)',...
RebuildData1(missID1+1:DissLen-1,2)'],1),missID1);
% Rebuild Second point
```

```
RebuildData2(4,:)=[RebuildData1(1:missID2-1,2)',...
   DismissData(missID2:DissLen,2)'];
RebuildData2(4,missID2)=polyval(polyfit(...
   [1:missID2-1,missID2+1:DissLen],...
   [RebuildData1(1:missID2-1,2)',...
   DismissData(missID2+1:DissLen,2)'],1),missID2);

%Method#5: Moving Average
% Rebuild first point
RebuildData1(missID1,2)=RebuildData1(missID1+1,2);
% Rebuild Second point
RebuildData2(5,:)=[RebuildData1(1:missID2-1,2)',...
   DismissData(missID2:DissLen,2)'];
RebuildData2(5,missID2)=DismissData(missID2+1,2);

%Method#6: Cubic Spline at all points (Fitting)
% Rebuild first point
RebuildData1(missID1,2)=polyval(polyfit([1:...
   missID1-1,missID1+1:DissLen-1],...
   [RebuildData1(1:missID1-1,2)',...
   RebuildData1(missID1+1:DissLen-1,2)'],3),...
   missID1);
% Rebuild Second point
RebuildData2(6,:)=[RebuildData1(1:missID2-1,2)',...
   DismissData(missID2:DissLen,2)'];
RebuildData2(6,missID2)=polyval(polyfit(...
   [1:missID2-1,missID2+1:DissLen],...
   [RebuildData1(1:missID2-1,2)',...
   DismissData(missID2+1:DissLen,2)'],3),missID2);

%Method#7: Cubic Spline at 4 points
% Rebuild first point
RebuildData1(missID1,2)=polyval(polyfit([1,2,4,...
   5],[RebuildData1(missID1-2:missID1-1,2)',...
   RebuildData1(missID1+1:missID1+2,2)'],3),3);
% Rebuild Second point
RebuildData2(7,:)=[RebuildData1(1:missID2-1,2)',...
   DismissData(missID2:DissLen,2)'];
RebuildData2(7,missID2)=polyval(polyfit([1,2,4,...
   5],[RebuildData1(missID2-2:missID2-1,2)',...
   DismissData(missID2+1:missID2+2,2)'],3),3);

%Method#8: SubGroup
% Rebuild first point
temp=[];
```

```
k=0;
for z=1:length(sec_filt)
   if (sec_filt(z,2)==MissingYear1 && ...
         (z<SecStart || z>=(SecStart+SecLen)))
      x=sec_filt(z,3);
      if x <= RebuildData1(missID1-1,2) && ...
            x >= RebuildData1(missID1+1,2)
         k=k+1;
         temp(k)=x;
      end
   end
end
if k~=0  % temp array is not empty
   RebuildData1(missID1,2)=mean(temp);
   RebuildData2(8,:)=[RebuildData1(1:missID2-1,...
      2)',DismissData(missID2:DissLen,2)'];
   RebuildData1(missID1,2)=median(temp);
   RebuildData2(9,:)=[RebuildData1(1:missID2-1,...
      2)',DismissData(missID2:DissLen,2)'];
   RebuildData1(missID1,2)=max(temp);
  RebuildData2(10,:)=[RebuildData1(1:missID2-1,...
      2)',DismissData(missID2:DissLen,2)'];
   RebuildData1(missID1,2)=min(temp);
  RebuildData2(11,:)=[RebuildData1(1:missID2-1,...
      2)',DismissData(missID2:DissLen,2)'];
else
   RebuildData1(missID1,2)=-1;
   RebuildData2(8,:)=[RebuildData1(1:missID2-1,...
      2)',DismissData(missID2:DissLen,2)'];
   RebuildData2(9,:)=[RebuildData1(1:missID2-1,...
      2)',DismissData(missID2:DissLen,2)'];
   RebuildData2(10,:)=[RebuildData1(1:missID2-...
      1,2)',DismissData(missID2:DissLen,2)'];
   RebuildData2(11,:)=[RebuildData1(1:missID2-...
      1,2)',DismissData(missID2:DissLen,2)'];
end
% Rebuild Second point
temp=[];
k=0;
for z=1:length(sec_filt)
   if (sec_filt(z,2)==MissingYear2 && ...
         (z<SecStart || z>=(SecStart+SecLen)))
      x=sec_filt(z,3);
      if x <= RebuildData1(missID2-1,2) && ...
            x >= DismissData(missID2+1,2) ...
```

```
            && RebuildData1(missID2-1,2)~=-1
          k=k+1;
          temp(k)=x;
        end
      end
    end
    if k~=0  % temp array is not empty
      RebuildData2(8,missID2)=mean(temp);
      RebuildData2(9,missID2)=median(temp);
      RebuildData2(10,missID2)=max(temp);
      RebuildData2(11,missID2)=min(temp);
    else
      RebuildData2(8,missID2)=-1;
      RebuildData2(9,missID2)=-1;
      RebuildData2(10,missID2)=-1;
      RebuildData2(11,missID2)=-1;
    end

    %------------------------------------------
    %Predict the future scores (i.e. Dismissed value)
    %using nonlinear regression
    pred_values(cntr,1:8)=[DisID,secID,DismissYear,...
      ObservedValue,MissingYear1,MissingYear2,...
      DismissData(missID1,2),DismissData(missID2,2)];

    %Tech#1:Prediction without rebuild
    indata1=single([RebuildData1(1:missID1-1,:);...
      RebuildData1(missID1+1:DissLen-1,:)]);
    if strcmp(variablename,'RS')==1
    pred_values(cntr,9)=check3(nlr_mazin_rs(indata1));
    else
      pred_values(cntr,9)=check2(nlr_mazin...
        (indata1, variablename));
    end

    %Tech#2: Prediction with rebuild
    for k=1:11
      indata2=single([DismissData(:,1),...
        RebuildData2(k,:)']);
      if strcmp(variablename,'RS')==1
        pred_values(cntr,k+9)= ...
          check4(nlr_mazin_rs(indata2), ...
          sec_filt(SecStart+SecLen-2,3));
      else
        pred_values(cntr,k+9)= check(nlr_mazin...
```

```
            (indata2, variablename), sec_filt...
            (SecStart+SecLen-2,3));
    end
end

%Scale of predicted values to Single value
pred_values=single(pred_values);
%-----------------------------------------
% Predict 2 using statistical techniques directly
%(i.e. without using the pavement performance model)

% Linear Trend at point
Estimated_Val = polyval(polyfit([1:DissLen ],...
    [RebuildData2(4,:)],1),DissLen);
if strcmp(variablename,'RS') == 1
    pred_values(cntr, 21) = check3(Estimated_Val);
else
    pred_values(cntr, 21) = check2(Estimated_Val);
end

% Moving Average
Estimated_Val = RebuildData2(5,end);
if strcmp(variablename,'RS') == 1
    pred_values(cntr, 22) = check3(Estimated_Val);
else
    pred_values(cntr, 22) = check2(Estimated_Val);
end

% Cubic Spline
Estimated_Val = polyval(polyfit([1:DissLen ],...
    [RebuildData2(6,:)],3),DissLen);
if strcmp(variablename,'RS') == 1
    pred_values(cntr, 23) = check3(Estimated_Val);
else
    pred_values(cntr, 23) = check2(Estimated_Val);
end

% Cubic Spline at 4 points
Estimated_Val = polyval(polyfit([1,2,3,4],...
    [RebuildData2(7,end-3:end)],3),5);
if strcmp(variablename,'RS') == 1
    pred_values(cntr, 24) = check3(Estimated_Val);
else
    pred_values(cntr, 24) = check2(Estimated_Val);
end
```

```
% Populate the missing data points using the
% available subgroup data point (no prediction of
% the future score)
% SubGrouping
temp1=[];
k=0;
a=DismissData(end,1);
for z=1:length(sec_filt)
   if (sec_filt(z,2)== a+1 && (z<SecStart || ...
         z>=(SecStart+SecLen)))
      x=sec_filt(z,3);
      if x <= MissingData(end)
         k=k+1;
         temp1(k)=x;
      end
   end
end

if k~=0  % temp array is not empty
   Estimated_Val=mean(temp1);
   if strcmp(variablename,'RS') == 1
   pred_values(cntr, 25) = check3(Estimated_Val);
   else
   pred_values(cntr, 25) = check2(Estimated_Val);
   end

   Estimated_Val=median(temp1);
   if strcmp(variablename,'RS') == 1
   pred_values(cntr, 26) = check3(Estimated_Val);
   else
   pred_values(cntr, 26) = check2(Estimated_Val);
   end

   Estimated_Val=max(temp1);
   if strcmp(variablename,'RS') == 1
   pred_values(cntr, 27) = check3(Estimated_Val);
   else
   pred_values(cntr, 27) = check2(Estimated_Val);
   end

   Estimated_Val=min(temp1);
   if strcmp(variablename,'RS') == 1
   pred_values(cntr, 28) = check3(Estimated_Val);
   else
```

```
        pred_values(cntr, 28) = check2(Estimated_Val);
        end

    else
        pred_values(cntr, 25)=-1;
        pred_values(cntr, 26)=-1;
        pred_values(cntr, 27)=-1;
        pred_values(cntr, 28)=-1;
    end

    indata1=single([RebuildData1(1:missID1-1,:);...
        RebuildData1(missID1+1:DissLen-1,:)]);


% Predict 2 using statistical techniques directly (i.e.
% without using the pavement performance model) WITHOUT
% REBUILDING missing data point

    % Predict using Linear Trend at 1 point
    Estimated_Val = polyval(polyfit([1:DissLen-2 ],...
        [indata1(:,2)'],1),DissLen);
    if strcmp(variablename,'RS') == 1
        pred_values(cntr, 29) = check3(Estimated_Val);
    else
        pred_values(cntr, 29) = check2(Estimated_Val);
    end

    % Predict using moving Average
    Estimated_Val = indata1(end,2)';
    if strcmp(variablename,'RS') == 1
        pred_values(cntr, 30) = check3(Estimated_Val);
    else
        pred_values(cntr, 30) = check2(Estimated_Val);
    end

    % Predict using Cubic Spline
    Estimated_Val = polyval(polyfit([1:DissLen-2 ],...
        [indata1(:,2)'],3),DissLen);
    if strcmp(variablename,'RS') == 1
        pred_values(cntr, 31) = check3(Estimated_Val);
    else
        pred_values(cntr, 31) = check2(Estimated_Val);
    end

    % Predict using Cubic Spline with 4 points
```

```
      Estimated_Val = polyval(polyfit([1,2,3,4],...
         [indata1(end-3:end,2)'],3),5);
      if strcmp(variablename,'RS') == 1
         pred_values(cntr, 32) = check3(Estimated_Val);
      else
         pred_values(cntr, 32) = check2(Estimated_Val);
      end

      %----------------------------------------

      %Discrepancy and Efficiency Test
  Disc(cntr,1:4)=[DisID,secID,MissingYear1,MissingYear2];
   Eff(cntr,1:4)=[DisID,secID,MissingYear1,MissingYear2];


      for k=5:28
 if pred_values(cntr,k+4)==-1 || pred_values(cntr,k+4)==-2
            Disc(cntr,k)=-1000;
            Eff(cntr,k)=-1000;
         elseif k>5 && Disc(cntr,5)==-1000
            Disc(cntr,k)=-1000;
            Eff(cntr,k)=-1000;
         else
            Disc(cntr,k)=(pred_values(cntr,k+4)-...
               ObservedValue);
            Eff(cntr,k)=(abs(Disc(cntr,5))-abs(Disc...
               (cntr,k)))/abs(Disc(cntr,5))* 100;
            if abs(Eff(cntr,k)) >= Eff_thr;
               Eff(cntr,k) = -1000;
            end
         end
         if (isnan(Eff(cntr,k)) || Eff(cntr,k) == inf)
            Eff(cntr,k) = -1000;
         end
      end

   end
end
%Calculate the the AVG Efficiency for all sections
Avg_Eff(1:5)=[DisID,secID,0,0,0];
for c=6:size(Eff,2)
   temp=[];
   k=0;
   for r=1:size(Eff,1)
      if abs(Eff(r,c))<=Eff_thr
```

```
                k=k+1;
                temp(k)= Eff(r,c);

              end
            end
            % avg efficiency
            if k>0
              Avg_Eff(c)=mean(temp);
            else
              Avg_Eff(c)=-1000;
            end
          end

          % Save the calculated data for each pavement section
          Secs_Disc=[Secs_Disc;Disc];
          Secs_Eff=[Secs_Eff;Eff];
          Secs_pred_values=[Secs_pred_values;pred_values];

          Secs_Avg_Eff=[Secs_Avg_Eff;[Avg_Eff(1:2),Avg_Eff...
            (6:size(Eff,2))]];

        end  % end of district
      end  % end of district
      % % % % end  % test case, District 24
    end  % if, Except Districts 7,11,21,23

end  % for, All Districts
% %-----------------------------------------
% Calculate the overall average efficiency for each statistical technique
[r,c]=size(Secs_Avg_Eff);
x = [];
for i=3:c
    s=0;
    cnt=0;
    for j=1:r
      if Secs_Avg_Eff(j,i)~=-1000
        s=s+Secs_Avg_Eff(j,i);
        cnt=cnt+1;
      end
    end
    Overall_avg_Eff(i-2)=s/cnt;
    x = [x cnt];
end
% %-----------------------------------------
```

```
% Store all results in Excel format files
save([variablename,'\',foldername,'\2Years_results'],'Overall_avg_Eff',...
   'Secs_Avg_Eff','Secs_Disc','Secs_Eff','Secs_pred_values');
xlswrite([variablename,'\',foldername,...
   '\2Years_Overall_avg_Eff_NEW_K.xlsx'],Overall_avg_Eff);
xlswrite([variablename,'\',foldername,...
   '\2Years_Secs_Avg_Eff_NEW_K.xlsx'],Secs_Avg_Eff);
xlswrite([variablename,'\',foldername,...
   '\2Years_Secs_Disc_NEW_K.xlsx'],Secs_Disc);
xlswrite([variablename,'\',foldername,...
   '\2Years_Secs_Eff_NEW_K.xlsx'],Secs_Eff);
xlswrite([variablename,'\',foldername,...
   '\2Years_Secs_pred_values_NEW_K.xlsx'],Secs_pred_values);
xlswrite([variablename,'\',foldername,...
   '\2Years_Overall_Avg_Eff_Section_Count_NEW_K.xlsx'],x);

Data_New = [Secs_pred_values Secs_Disc Secs_Eff];
xlswrite([variablename,'\',foldername,...
   '\2Years_Secs_PredValues_Disc_Eff_NEW_K.xlsx'],Data_New);
end
```

End Appendix E2

Appendix E3

Function for three years missing data points to obtain:

Predicted score, Discrepancy, Efficiency and Average Efficiency

```
function mazin_main_3yearsK(variablename,foldername)


% Create empty matrices to store the data
Secs_Disc=[];
Secs_Eff=[];
Secs_pred_values=[];
Secs_Avg_Eff=[];


for DisID=1:1
   % Except Districts 7,11,21,23 and 16
   if DisID==7||DisID==11||DisID==21||DisID==23||DisID==16
```

```
    continue;
  else
    fname=['District_',num2str(DisID)];
    %-----------------------------------------
    % For One District
    load ([variablename,'\',foldername,'\',fname],'sec_filt');
    if ~isempty(sec_filt)
      j=1;
      while j<=length(sec_filt) % Check All rows of sec_filt
        %-----------------------------------------
        % One Section in a district
        secID=sec_filt(j,1);
        SecStart=j;
        SecLen=0;

        DismissData=[];

        while sec_filt(j,1)==secID
          SecLen=SecLen+1;
          j=j+1;
          if j>length(sec_filt)
            break;
          end
        end

        %-----------------------------------------
        %Dismiss the last data point in the pavement section
        %Test: Dismiss Last year of section

        % Save the Actual Value of the last year
        ObservedValue=sec_filt(SecStart+SecLen-1,3);
        % Save the last year
        DismissYear=sec_filt(SecStart+SecLen-1,2);
        % Store the date for each section without the last
        % year (year, Score)
        DismissData=sec_filt(SecStart:SecStart+SecLen-2,2:3);
        % The length of section data without the last year
        DissLen=size(DismissData,1);

        %-----------------------------------------

       % Missing three data points from the pavement section history
        pred_values=[];
        Disc=[];
        Eff=[];
```

```
cntr=0;
MissingData=DismissData(:,2)';


for missID1=3:DissLen-4
    for missID2=missID1+1:DissLen-3
        for missID3=missID2+1:DissLen-2
            MissingYear1=DismissData(missID1,1);
            MissingYear2=DismissData(missID2,1);
            MissingYear3=DismissData(missID3,1);
            cntr=cntr+1;
            %Rebuild
            RebuildData1=[];
            RebuildData2=[];
            RebuildData3=[];
            t1=0;
            t2=0;
            for i=1:DissLen
                if i~=missID2 && i~=missID3
                    t1=t1+1;
                    RebuildData1(t1,:)=DismissData(i,:);
                end
                if i~=missID3
                    t2=t2+1;
                    RebuildData2(t2,:)=DismissData(i,:);
                end
            end

            %Method#1: Mean of Nearby
            % Rebuild First point
            x=mean([RebuildData1(missID1-2:missID1-1,2);...
                RebuildData1(missID1+1:missID1+2,2)]);
            RebuildData1(missID1,2)=x;
            % Rebuild Second point
            RebuildData2(missID1,2)=x;
            RebuildData2(missID2,2)=...
                mean([RebuildData2(missID2-2:...
                missID2-1,2);RebuildData2(missID2+1:...
                missID2+2,2)]);
            % Rebuild Third point
         RebuildData3(1,:)=[RebuildData2(1:missID3-1,2)',...
             DismissData(missID3:DissLen,2)'];
         RebuildData3(1,missID3)= ...
             mean([RebuildData2(missID3-2:missID3-1,2)',...
             DismissData(missID3+1:missID3+2,2)']);
```

```
%Method#2: Median of Nearby
% Rebuild First point
x=median([RebuildData1(missID1-2:missID1-1,2);...
 RebuildData1(missID1+1:missID1+2,2)]);
RebuildData1(missID1,2)=x;
% Rebuild Second point
RebuildData2(missID1,2)=x;
RebuildData2(missID2,2)=...
   median([RebuildData2(missID2-2:...
   missID2-1,2);RebuildData2(missID2+1:...
   missID2+2,2)]);
% Rebuild Third point
RebuildData3(2,:)=...
   [RebuildData2(1:missID3-1,2)',...
   DismissData(missID3:DissLen,2)'];
RebuildData3(2,missID3)=...
   median([RebuildData2(missID3-2:...
   missID3-1,2)',DismissData(missID3+1:...
   missID3+2,2)']);

%Method#3: Linear Interoplation
% Rebuild first point
x=interp1([1,3],[RebuildData1(missID1-1,2),...
   RebuildData1(missID1+1,2)],2);
RebuildData1(missID1,2)=x;
% Rebuild Second point
RebuildData2(missID1,2)=x;
RebuildData2(missID2,2)=interp1([1,3],...
   [RebuildData2(missID2-1,2),...
   RebuildData2(missID2+1,2)],2);
% Rebuild Third point
RebuildData3(3,:)=[RebuildData2(1:missID3-1,2)',...
   DismissData(missID3:DissLen,2)'];
RebuildData3(3,missID3)=interp1([1,3],...
   [RebuildData2(missID3-1,2),...
   DismissData(missID3+1,2)],2);

%Method#4: Linear Trend at point
% Rebuild first point
x=polyval(polyfit([1:missID1-1,...
   missID1+1:DissLen-2],...
   [RebuildData1(1:missID1-1,2)',...
  RebuildData1(missID1+1:DissLen-2,2)'],1),...
   missID1);
```

```
RebuildData1(missID1,2)=x;
% Rebuild Second point
RebuildData2(missID1,2)=x;
RebuildData2(missID2,2)=...
   polyval(polyfit([1:missID2-1,...
   missID2+1:DissLen-1],...
   [RebuildData2(1:missID2-1,2)',...
   RebuildData2(missID2+1:DissLen-1,2)'],1)...
   ,missID2);
% Rebuild Third point
RebuildData3(4,:)=...
   [RebuildData2(1:missID3-1,2)',...
   DismissData(missID3:DissLen,2)'];
RebuildData3(4,missID3)=...
   polyval(polyfit([1:missID3-1,...
   missID3+1:DissLen],...
   [RebuildData2(1:missID3-1,2)',...
   DismissData(missID3+1:DissLen,2)'],1),...
   missID3);

%Method#5: Moving Average
% Rebuild first point
x=RebuildData1(missID1+1,2);
RebuildData1(missID1,2)=x;
% Rebuild Second point
RebuildData2(missID1,2)=x;
RebuildData2(missID2,2)=...
   RebuildData2(missID2+1,2);
% Rebuild Third point
RebuildData3(5,:)=[RebuildData2(1:missID3-1,2)',...
   DismissData(missID3:DissLen,2)'];
RebuildData3(5,missID3)=DismissData(missID3+1,2);

%Method#6: Cubic Spline at all points (Fitting)
% Rebuild first point
x=polyval(polyfit([1:missID1-1,missID1+1:DissLen-2],...
   [RebuildData1(1:missID1-1,2)',...
   RebuildData1(missID1+1:DissLen-2,2)'],3),...
   missID1);
RebuildData1(missID1,2)=x;
% Rebuild Second point
RebuildData2(missID1,2)=x;
RebuildData2(missID2,2)=...
   polyval(polyfit([1:missID2-1,...
   missID2+1:DissLen-1],...
```

```
        [RebuildData2(1:missID2-1,2)',...
        RebuildData2(missID2+1:DissLen-1,2)'],3)...
        ,missID2);
    % Rebuild Third point
    RebuildData3(6,:)=...
        [RebuildData2(1:missID3-1,2)',...
        DismissData(missID3:DissLen,2)'];
    RebuildData3(6,missID3)=...
        polyval(polyfit([1:missID3-1,...
        missID3+1:DissLen],...
        [RebuildData2(1:missID3-1,2)',...
        DismissData(missID3+1:DissLen,2)'],3),...
        missID3);

    %Method#7: Cubic Spline at 4 points
    % Rebuild first point
    x=polyval(polyfit([1,2,4,5],...
        [RebuildData1(missID1-2:missID1-1,2)',...
       RebuildData1(missID1+1:missID1+2,2)'],3),3);
    RebuildData1(missID1,2)=x;
    % Rebuild Second point
    RebuildData2(missID1,2)=x;
    RebuildData2(missID2,2)=...
        polyval(polyfit([1,2,4,5],...
        [RebuildData2(missID2-2:missID2-1,2)',...
      RebuildData2(missID2+1:missID2+2,2)'],3),3);
    % Rebuild Third point
RebuildData3(7,:)=[RebuildData2(1:missID3-1,2)',...
      DismissData(missID3:DissLen,2)'];
    RebuildData3(7,missID3)=...
        polyval(polyfit([1,2,4,5],...
        [RebuildData2(missID3-2:missID3-1,2)',...
        DismissData(missID3+1:missID3+2,2)'],3),3);

    %Method#8: SubGroup
    RebuildData3(8,:)=DismissData(:,2)';
    RebuildData3(9,:)=DismissData(:,2)';
    RebuildData3(10,:)=DismissData(:,2)';
    RebuildData3(11,:)=DismissData(:,2)';
    % Rebuild first point
    temp=[];
    k=0;
    for z=1:length(sec_filt)
        if (sec_filt(z,2)==MissingYear1 &&...
            (z<SecStart || z>=(SecStart+SecLen)))
```

```
      x=sec_filt(z,3);
      if x <= RebuildData1(missID1-1,2)...
         && x >= RebuildData1(missID1+1,2)
        k=k+1;
        temp(k)=x;
      end
    end
  end
  if k~=0  % temp array is not empty
    RebuildData2(missID1,2)=mean(temp);
    RebuildData3(8,missID1)=mean(temp);
    RebuildData3(9,missID1)=median(temp);
    RebuildData3(10,missID1)=max(temp);
    RebuildData3(11,missID1)=min(temp);
  else
    RebuildData2(missID1,2)=-1;
    RebuildData3(8,missID1)=-1;
    RebuildData3(9,missID1)=-1;
    RebuildData3(10,missID1)=-1;
    RebuildData3(11,missID1)=-1;
  end
  % Rebuild Second point
  temp=[];
  k=0;
  for z=1:length(sec_filt)
    if (sec_filt(z,2)==MissingYear2 &&...
         (z<SecStart || z>=(SecStart+SecLen)))
      x=sec_filt(z,3);
      if x <= RebuildData2(missID2-1,2)...
        && x >= RebuildData2(missID2+1,...
       2) && RebuildData2(missID2-1,2)~=-1
        k=k+1;
        temp(k)=x;
      end
    end
  end
  if k~=0  % temp array is not empty
    RebuildData2(missID2,2)=mean(temp);
    RebuildData3(8,missID2)=mean(temp);
    RebuildData3(9,missID2)=median(temp);
    RebuildData3(10,missID2)=max(temp);
    RebuildData3(11,missID2)=min(temp);
  else
    RebuildData2(missID2,2)=-1;
    RebuildData3(8,missID2)=-1;
```

```
    RebuildData3(9,missID2)=-1;
    RebuildData3(10,missID2)=-1;
    RebuildData3(11,missID2)=-1;
end
% Rebuild Third point
temp=[];
k=0;
for z=1:length(sec_filt)
    if (sec_filt(z,2)==MissingYear3 &&...
        (z<SecStart || z>=(SecStart+SecLen)))
        x=sec_filt(z,3);
        if x <= RebuildData2(missID3-1,2)...
          && x >= DismissData(missID3+1,2)...
           && RebuildData2(missID3-1,2)~=-1
            k=k+1;
            temp(k)=x;
        end
    end
end
if k~=0  % temp array is not empty
    RebuildData3(8,missID3)=mean(temp);
    RebuildData3(9,missID3)=median(temp);
    RebuildData3(10,missID3)=max(temp);
    RebuildData3(11,missID3)=min(temp);
else
    RebuildData3(8,missID3)=-1;
    RebuildData3(9,missID3)=-1;
    RebuildData3(10,missID3)=-1;
    RebuildData3(11,missID3)=-1;
end
%-----------------------------------------

%Predict the future scores
%(i.e. Dismissed value) using
%nonlinear regression
pred_values(cntr,1:10)=[DisID,secID,...
    DismissYear,ObservedValue,MissingYear1,...
    MissingYear2,MissingYear3,...
    DismissData(missID1,2),...
    DismissData(missID2,2), ...
    DismissData(missID3,2)];

%Tech#1:Prediction without rebuild
indata1=single([RebuildData1(1:missID1-1,:);...
    RebuildData1(missID1+1:DissLen-2,:)]);
```

```
if strcmp(variablename,'RS')==1
   pred_values(cntr,11)=...
      check3(nlr_mazin_rs(indata1));
else
   pred_values(cntr,11)=...
    check2(nlr_mazin(indata1, variablename));
end

%Tech#2: Prediction with rebuild
for k=1:11
   indata2=single([DismissData(:,1),...
      RebuildData3(k,:)']);
   if strcmp(variablename,'RS')==1
      pred_values(cntr,k+11)=...
         check4(nlr_mazin_rs(indata2),...
         sec_filt(SecStart+SecLen-2,3));
   else
      pred_values(cntr,k+11)=...
         check(nlr_mazin(indata2,...
         variablename), ...
         sec_filt(SecStart+SecLen-2,3));
   end

end
%Scale of predicted values to Single value
pred_values=single(pred_values);
%----------------------------------------
% Predict 2 using statistical techniques
% directly (i.e. without using the pavement
% performance model)

% Linear Trend at point
Estimated_Val = ...
   polyval(polyfit([1:DissLen ],...
   [RebuildData3(4,:)],1),DissLen);
if strcmp(variablename,'RS')==1
   pred_values(cntr,23)=check3(Estimated_Val);
else
   pred_values(cntr,23)=check2(Estimated_Val);
end

% Moving Average
Estimated_Val = RebuildData3(5,end);
if strcmp(variablename,'RS')==1
   pred_values(cntr,24)=check3(Estimated_Val);
```

```
 else
    pred_values(cntr,24)=check2(Estimated_Val);
 end

 % Cubic Spline
Estimated_Val = polyval(polyfit([1:DissLen ],...
   [RebuildData3(6,:)],3),DissLen);
 if strcmp(variablename,'RS')==1
    pred_values(cntr,25)=check3(Estimated_Val);
 else
    pred_values(cntr,25)=check2(Estimated_Val);
 end

 % Cubic Spline at 4 points
 Estimated_Val = polyval(polyfit([1,2,3,4],...
    [RebuildData3(7,end-3:end)],3),5);
 if strcmp(variablename,'RS')==1
    pred_values(cntr,26)=check3(Estimated_Val);
 else
    pred_values(cntr,26)=check2(Estimated_Val);
 end

 % Populate the missing data points using the
 % available subgroup data point (no prediction
 % of the future score)
 % Subgrouping
 temp1=[];
 k=0;
 a=DismissData(end,1);
 for z=1:length(sec_filt)
  if (sec_filt(z,2)== a+1 && (z<SecStart ||...
          z>=(SecStart+SecLen)))
       x=sec_filt(z,3);
       if x <= MissingData(end)
          k=k+1;
          temp1(k)=x;
       end
    end
 end

 if k~=0  % temp array is not empty
    Estimated_Val=mean(temp1);
    if strcmp(variablename,'RS')==1
       pred_values(cntr,27)=...
          check3(Estimated_Val);
```

```
        else
            pred_values(cntr,27)=...
                check2(Estimated_Val);
        end

        Estimated_Val=median(temp1);
        if strcmp(variablename,'RS')==1
            pred_values(cntr,28)=...
                check3(Estimated_Val);
        else
            pred_values(cntr,28)=...
                check2(Estimated_Val);
        end

        Estimated_Val=max(temp1);
        if strcmp(variablename,'RS')==1
            pred_values(cntr,29)=...
                check3(Estimated_Val);
        else
            pred_values(cntr,29)=...
                check2(Estimated_Val);
        end

        Estimated_Val=min(temp1);
        if strcmp(variablename,'RS')==1
            pred_values(cntr,30)=...
                check3(Estimated_Val);
        else
            pred_values(cntr,30)=...
                check2(Estimated_Val);
        end

    else
        pred_values(cntr, 27)=-1;
        pred_values(cntr, 28)=-1;
        pred_values(cntr, 29)=-1;
        pred_values(cntr, 30)=-1;
    end


    indata1=single([RebuildData1(1:missID1-1,:);...
        RebuildData1(missID1+1:DissLen-2,:)]);

% Predict 2 using statistical techniques directly (i.e.
% without using the pavement performance model) WITHOUT
```

```
% REBUILDING missing data point

    % Predict using Linear Trend at 1 point
    Estimated_Val = ...
      polyval(polyfit([1:DissLen-3 ],...
      [indata1(:,2)'],1),DissLen);
    if strcmp(variablename,'RS') == 1
      pred_values(cntr, 31) = ...
        check3(Estimated_Val);
    else
      pred_values(cntr, 31) = ...
        check2(Estimated_Val);
    end

    % Predict using moving Average
    Estimated_Val = indata1(end,2)';
    if strcmp(variablename,'RS') == 1
      pred_values(cntr, 32) = ...
        check3(Estimated_Val);
    else
      pred_values(cntr, 32) = ...
        check2(Estimated_Val);
    end

    % Predict using Cubic Spline
    Estimated_Val = ...
      polyval(polyfit([1:DissLen-3 ],...
      [indata1(:,2)'],3),DissLen);
    if strcmp(variablename,'RS') == 1
      pred_values(cntr, 33) =...
        check3(Estimated_Val);
    else
      pred_values(cntr, 33) = ...
        check2(Estimated_Val);
    end

    % Predict using Cubic Spline with 4 points
    Estimated_Val = polyval(polyfit([1,2,3,4],...
      [indata1(end-3:end,2)'],3),5);
    if strcmp(variablename,'RS') == 1
      pred_values(cntr, 34) = ...
        check3(Estimated_Val);
    else
      pred_values(cntr, 34) = ...
        check2(Estimated_Val);
```

```
            end


            %----------------------------------------

            %Discrepancy and Efficiency Test
            Disc(cntr,1:5)=[DisID,secID,MissingYear1,...
               MissingYear2,MissingYear3];
            Eff(cntr,1:5)=[DisID,secID,MissingYear1,...
               MissingYear2,MissingYear3];

            for k=6:29
               if pred_values(cntr,k+5)==-1 ||...
                     pred_values(cntr,k+5)==-2
                  Disc(cntr,k)=-1000;
                  Eff(cntr,k)=-1000;
               elseif k>6 && Disc(cntr,6)==-1000
                  Disc(cntr,k)=-1000;
                  Eff(cntr,k)=-1000;
               else
                  Disc(cntr,k)=...
                  (pred_values(cntr,k+5)-ObservedValue);
                 Eff(cntr,k)=(abs(Disc(cntr,6))-...
                 abs(Disc(cntr,k)))/abs(Disc(cntr,6))* 100;

                  if abs(Eff(cntr,k)) >= Eff_thr;
                     Eff(cntr,k) = -1000;
                  end

               end
             if (isnan(Eff(cntr,k)) || Eff(cntr,k) == inf)
                  Eff(cntr,k) = -1000;
               end
            end
         end
      end
   end

   %Calculate the the AVG Efficiency for all sections
   Avg_Eff(1:6)=[DisID,secID,0,0,0,0];
   for c=7:size(Eff,2)
      temp=[];
      k=0;
      for r=1:size(Eff,1)
         if abs(Eff(r,c))<=Eff_thr
```

```
                k=k+1;
                temp(k)= Eff(r,c);

              end
            end
            % avg efficiency
            if k>0
              Avg_Eff(c)=mean(temp);
            else
              Avg_Eff(c)=-1000;
            end
          end

          % Save the calculated data for each pavement section
          Secs_Disc=[Secs_Disc;Disc];
          Secs_Eff=[Secs_Eff;Eff];
          Secs_pred_values=[Secs_pred_values;pred_values];

          Secs_Avg_Eff=[Secs_Avg_Eff;[Avg_Eff(1:2),...
            Avg_Eff(7:size(Eff,2))]];

        end  % end of district
      end  % end of district
      % % % % end  % test case, District 24
    end  % if, Except Districts 7,11,21,23
end  % for, All Districts
% %----------------------------------------
% Calculate the overall average efficiency for each statistical technique
Overall_avg_Eff=[];
[r,c]=size(Secs_Avg_Eff);
x = [];
for i=3:c
    s=0;
    cnt=0;
    for j=1:r
      if Secs_Avg_Eff(j,i)~=-1000
        s=s+Secs_Avg_Eff(j,i);
        cnt=cnt+1;
      end
    end
    Overall_avg_Eff(i-2)=s/cnt;
    x = [x cnt];
end
if ~isempty(Overall_avg_Eff)
    % %----------------------------------------
```

```
    % Store all results in Excel format files
    save([variablename,'\',foldername,'\3Years_results'],...
        'Overall_avg_Eff','Secs_Avg_Eff','Secs_Disc',...
        'Secs_Eff','Secs_pred_values');
    xlswrite([variablename,'\',foldername,...
        '\3Years_Overall_avg_Eff_NEW_K.xlsx'],Overall_avg_Eff);
    xlswrite([variablename,'\',foldername,...
        '\3Years_Secs_Avg_Eff_NEW_K.xlsx'],Secs_Avg_Eff);
    xlswrite([variablename,'\',foldername,...
        '\3Years_Secs_Disc_NEW_K.xlsx'],Secs_Disc);
    xlswrite([variablename,'\',foldername,...
        '\3Years_Secs_Eff_NEW_K.xlsx'],Secs_Eff);
    xlswrite([variablename,'\',foldername,...
        '\3Years_Secs_pred_values_NEW_K.xlsx'],Secs_pred_values);
    xlswrite([variablename,'\',foldername,...
        '\3Years_Overall_Avg_Eff_Section_Count_NEW_K.xlsx'],x);

    Data_New = [Secs_pred_values Secs_Disc Secs_Eff];
    xlswrite([variablename,'\',foldername,...
        '\3Years_Secs_PredValues_Disc_Eff_NEW_K.xlsx'],Data_New);
    % %----------------------------------------

end
end
```

End Appendix E3

Appendix E4

Prediction of CS and DS values using performance model formula

```
function [ypred]=nlr_mazin (indata, a)



if check_indata_nlr(indata(:,2))==0
    ypred=-1;
else

    % The Pavement performance model formula for CS and DS
    mdl = @(a,x)(100-a(1)*exp(-((a(2)./x).^a(3))));

    % Calculate the year (Estimated Age)
    x=indata(:,1)-1992 ;
    pyear=x(length(x))+1;
```

```
    % Store the scores in a vector
    y=indata(:,2);

    % To Initilise the alpha, beta and rho for DS and CS
    if strcmp(a,'DS')==1
        a0 = [54.485; 15; 3.228];
    else
        a0 = [53.137; 15; 3.005];
    end

    % Predict the DS and CS values using the Pavement performance model
    try
        [ahat,r,J,cov,mse] = nlinfit(x,y,mdl,a0); %See Help
        [ypred dlt] = nlpredci(mdl,pyear,ahat,r,'Covar',cov,'alpha',0.05);
    catch ME1
        ypred=-2;
    end
end
end
```

End Appendix E4

Appendix E5

Prediction of RS values using performance model formula

```
function [ypred]=nlr_mazin_rs (indata)


if check_indata_nlr(indata(:,2))==0
  ypred=-1;
else

  % The Pavement performance model formula for RS
  mdl = @(a,x)(5-a(1)*exp(-((a(2)./x).^a(3))));

  % Calculate the year (Estimated Age)
  x=indata(:,1)-1992;
  pyear=x(length(x))+1;

  % Store the scores in a vector
  y=indata(:,2);
```

```
    % To Initilise the alpha, beta and rho for RS
    a0 = [2.02; 12; .69];

    % Predict the RS values using the Pavement performance model
    try
        [ahat,r,J,cov,mse] = nlinfit(x,y,mdl,a0);
        [ypred dlt] = nlpredci(mdl,pyear,ahat,r,'Covar',cov,'alpha',0.003);
    catch ME1
        ypred=-2;
    end
end
end
```

End Appendix E5

Appendix E6

Function to check if the predicted value is between 0 and 100.

It also checks if the predicted value is less than the previous year value

```
function c = check( a,b )
if a < 0 || a > 100
    c = -1;
else

    if a >=b
        c = b;
    else
        c = a;
    end
end

end
```

End Appendix E6

Appendix E7

Function to check if the predicted value is between 0 and 100.

```
function c = check2( a )
if a < 0 || a  > 100
    c = -1;
else
    c = a;

end

end
```
End Appendix E7

Appendix E8

Function to check if the predicted value of RS is between 0.10 and 5.0

```
function y = check3(x)
if x>= .1 || x<= 5
     y = x;
 else
     y = -1;
 end
end
```
End Appendix E8

Appendix E9

Function to check if the predicted value of RS is between .10 and 5.0

It also checks if the predicted value is less than the previous year value

```
function c = check4( a,b )

if a < .1 || a > 5
    c = -1;
else

    if a >=b
        c = b;
    else
        c = a;
    end
end
```

```
end
```

End Appendix E9

Appendix E10

Functions to run for Distress Score with one year missing data point for all districts

Functions to run for Condition Score with one year missing data point for all districts

Functions to run for Ride Score with one year missing data point for all districts

```
% CS
mazin_main_1yearsK CS All_Districts_MeetConditions_10dtpt_10thr
mazin_main_1yearsK CS All_Districts_MeetConditions_10dtpt_15thr
mazin_main_1yearsK CS All_Districts_MeetConditions_10dtpt_20thr
mazin_main_1yearsK CS All_Districts_MeetConditions_12dtpt_10thr
mazin_main_1yearsK CS All_Districts_MeetConditions_12dtpt_15thr
mazin_main_1yearsK CS All_Districts_MeetConditions_12dtpt_20thr

% DS
mazin_main_1yearsK DS All_Districts_MeetConditions_10dtpt_10thr
mazin_main_1yearsK DS All_Districts_MeetConditions_10dtpt_15thr
mazin_main_1yearsK DS All_Districts_MeetConditions_10dtpt_20thr
mazin_main_1yearsK DS All_Districts_MeetConditions_12dtpt_10thr
mazin_main_1yearsK DS All_Districts_MeetConditions_12dtpt_15thr
mazin_main_1yearsK DS All_Districts_MeetConditions_12dtpt_20thr

% RS
mazin_main_1yearsK RS All_Districts_MeetConditions_10dtpt_10thr
mazin_main_1yearsK RS All_Districts_MeetConditions_10dtpt_15thr
mazin_main_1yearsK RS All_Districts_MeetConditions_10dtpt_20thr
mazin_main_1yearsK RS All_Districts_MeetConditions_12dtpt_10thr
mazin_main_1yearsK RS All_Districts_MeetConditions_12dtpt_15thr
mazin_main_1yearsK RS All_Districts_MeetConditions_12dtpt_20thr
```

End Appendix E10

Appendix E11

Functions to run for Distress Score with two years missing data point for all districts

Functions to run for Condition Score with two years missing data point for all districts

Functions to run for Ride Score with two years missing data point for all districts

```
% CS
mazin_main_2yearsK CS All_Districts_MeetConditions_10dtpt_10thr
mazin_main_2yearsK CS All_Districts_MeetConditions_10dtpt_15thr
mazin_main_2yearsK CS All_Districts_MeetConditions_10dtpt_20thr
mazin_main_2yearsK CS All_Districts_MeetConditions_12dtpt_10thr
mazin_main_2yearsK CS All_Districts_MeetConditions_12dtpt_15thr
mazin_main_2yearsK CS All_Districts_MeetConditions_12dtpt_20thr

% DS
mazin_main_2yearsK DS All_Districts_MeetConditions_10dtpt_10thr
mazin_main_2yearsK DS All_Districts_MeetConditions_10dtpt_15thr
mazin_main_2yearsK DS All_Districts_MeetConditions_10dtpt_20thr
mazin_main_2yearsK DS All_Districts_MeetConditions_12dtpt_10thr
mazin_main_2yearsK DS All_Districts_MeetConditions_12dtpt_15thr
mazin_main_2yearsK DS All_Districts_MeetConditions_12dtpt_20thr

% RS
mazin_main_2yearsK RS All_Districts_MeetConditions_10dtpt_10thr
mazin_main_2yearsK RS All_Districts_MeetConditions_10dtpt_15thr
mazin_main_2yearsK RS All_Districts_MeetConditions_10dtpt_20thr
mazin_main_2yearsK RS All_Districts_MeetConditions_12dtpt_10thr
mazin_main_2yearsK RS All_Districts_MeetConditions_12dtpt_15thr
mazin_main_2yearsK RS All_Districts_MeetConditions_12dtpt_20thr
```

End Appendix E11

Appendix E12

Functions to run for Distress Score with two years missing data point for all districts

Functions to run for Condition Score with two years missing data point for all districts

Functions to run for Ride Score with two years missing data point for all districts

```
% CS
```

```
mazin_main_3yearsK CS All_Districts_MeetConditions_10dtpt_10thr
mazin_main_3yearsK CS All_Districts_MeetConditions_10dtpt_15thr
mazin_main_3yearsK CS All_Districts_MeetConditions_10dtpt_20thr
mazin_main_3yearsK CS All_Districts_MeetConditions_12dtpt_10thr
mazin_main_3yearsK CS All_Districts_MeetConditions_12dtpt_15thr
mazin_main_3yearsK CS All_Districts_MeetConditions_12dtpt_20thr

% DS
mazin_main_3yearsK DS All_Districts_MeetConditions_10dtpt_10thr
mazin_main_3yearsK DS All_Districts_MeetConditions_10dtpt_15thr
mazin_main_3yearsK DS All_Districts_MeetConditions_10dtpt_20thr
mazin_main_3yearsK DS All_Districts_MeetConditions_12dtpt_10thr
mazin_main_3yearsK DS All_Districts_MeetConditions_12dtpt_15thr
mazin_main_3yearsK DS All_Districts_MeetConditions_12dtpt_20thr

% RS
mazin_main_3yearsK RS All_Districts_MeetConditions_10dtpt_10thr
mazin_main_3yearsK RS All_Districts_MeetConditions_10dtpt_15thr
mazin_main_3yearsK RS All_Districts_MeetConditions_10dtpt_20thr
mazin_main_3yearsK RS All_Districts_MeetConditions_12dtpt_10thr
mazin_main_3yearsK RS All_Districts_MeetConditions_12dtpt_15thr
mazin_main_3yearsK RS All_Districts_MeetConditions_12dtpt_20thr
```

End Appendix E12

Curriculum Vitae

Mazin Mohammad Faleh Al-Zou'bi was born on the seventeenth of May, 1964, in Al Ramtha city, Jordan. He holds a BSc in Civil Engineering from Jordan University of Science and Technology (JUST), since 1988, and MSc in Civil Engineering from (JUST), Jordan, since 1993. His Master's thesis was about evaluation of the engineering properties of limestone rocks in Jordan. He worked during his Master studies as a teaching assistant, and after graduation, he worked in several public agencies and private companies in different profession positions as well. He worked as project manager, consultant, quality control, construction materials, and dams engineer as a supervisor of Roller Compacted Concrete (R C C). He worked in iadditions to teaching and research assistant supervisor for construction material, soil mechanics, rock mechanics and highway laboratories in civil engineering department at different universities in Jordan. Then he returned to Jordan University of Science and Technology as a supervisor engineer in the Civil Engineering Department for about four years.

Mazin came to the United States in August, 2008 to join the Civil Engineering PhD program at the University of Texas at El Paso. During his study at UTEP he participated in several national and international conferences, workshops and seminars. While at UTEP, he worked as graduate research assistant at the Center for Transportation Infrastructure Systems (CTIS) for the Texas Department of Transportation project of evaluation and development of pavement scores, performance models and need estimates for the TxDOT Pavement Management Information System (PMIS). He assisted professors in Civil Engineering Department, UTEP in the courses, laboratories teaching and provided support for course improvement and enhances student educational development. Some of these courses are:

geotechnical engineering, geotechnical engineering laboratory, mechanics of materials, mechanics, and materials for civil & construction engineers including its laboratories as well. Mazin recent publications, presentations and conference participations are enlisted below.

Publications

Al-Zou'bi M.M., C. M. Chang, S. Nazarian, and V. Kreinovich (2013), A Systematic Statistical Approach to Populate Missing Performance Data in Pavement Management Systems, ASCE Journal of Infrastructure Systems, manuscript number ISENG-532.

(It has been forwarded to the Editor to begin the review process for publication)

Conference Presentations

Al-Zoubi, M. and M., C. M. A. Chang (2012), A Systematic Approach to Predict Missing Performance Data in Pavement Management Systems, The Annual Doctoral Research Exposition, El Paso, TX.

Al-Zoubi, M. and M., C. M. A. Chang (2011), A Systematic Approach to Manage Missing Data in Pavement Management Systems, The Annual Doctoral Research Exposition, El Paso, TX.

Al-Zoubi, M. and M., C. M. A. Chang (2011), A Systematic Approach to manage Missing Data in Pavement Management Systems, The 7th Annual Inter-university Symposium on Infrastructure Management, Northwestern University in Evanston, IL.

Conferences

5th Annual Systems Engineering Symposium, Innovative Green Systems of Systems, UTEP, El Paso, TX, April 25-26, 2013.

International Sun Conference on Teaching and Learning, UTEP, TX, February 28-March 1, 2013.

Reenergize the Americas 2012, Las Cruces Convention Center, New Mexico State University, New Mexico, October 17&18 2012.

Academic Technologies Summit, UTEP, El Paso, TX, October 13, 2012.

4th Annual Conference System of Systems, Design and Sustainability in the 21ST Century, UTEP, El Paso, TX, April 26, 2012

International Sun Conference on Teaching and Learning, UTEP, TX, March 1-2, 2012.

A University Wide Student Experience Conference on Leadership, Innovation, Vision, Engagement (LIVE), UTEP, El Paso, TX, February 24, 2012.

8th Annual Border Security Conference, University of Texas El Paso, Aug 15-16, 2011.

7th Annual Inter-university Symposium on Infrastructure Management, Northwestern University in Evanston, IL. June 3-4, 2011.

The Sustainability on the Border Conference: Water, Climate, and Social Change in a Fragile Landscape, UTEP, El Paso, TX. May 16-18, 2011.

International Sun Conference on Teaching and Learning, UTEP, TX, March 10-11, 2011.

International Sun Conference on Teaching and Learning, UTEP, TX, March 4-5, 2010.

The Building Partnerships and Pathways to Address Engineering Grand Challenges Conference, UTEP, El Paso, TX, February 8-10, 2010.