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The International Journal of Engineering Research and Innovation Editors

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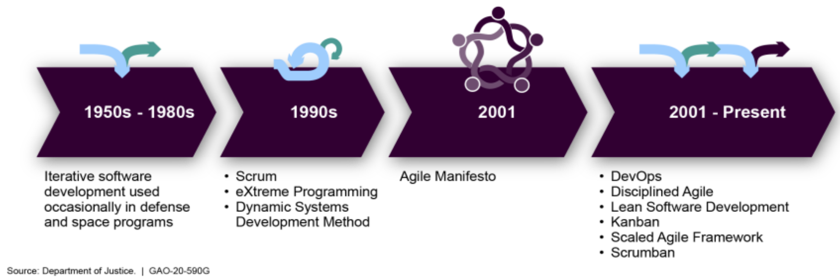
Navigating Agile Practices

Philip Weinsier, IJERI Manuscript Editor

The agile process is an iterative approach philosophy centered around the value of flexibility, collaboration, and customer satisfaction. Agile project management—a byproduct of software development teams that needed to break free from the rigid confines of traditional project management—is a compromise between structure and spontaneity that aims to go beyond just reaching a predetermined destination, while adapting and growing at every step along the way. That is, agile values allow us to consider our work as the status quo, but then to boldly move towards excellence as we evaluate and respond to each step along the road. Change is no longer a word to be feared, but rather a tool for improvement.

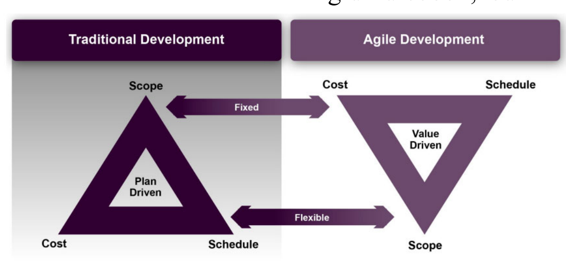


Agile is not a one-size-fits-all solution; it's a flexible framework that can be tailored to different industries and project types. The foundation of agile rests on the following four pillars. And while there continues to be value in the items on the right, with agile, the items on the left are valued even more.

Individuals and interactions over processes and tools
Working software over comprehensive documentation
Customer collaboration over contract negotiation
Responding to change over following a plan

The key principles of agile methodology are:

- Simplicity. Maximize the amount of work not done to minimize unnecessary complexity and increase efficiency.
- Continuous improvement. Regularly reflect on processes, identify areas for improvement, and make necessary changes to enhance productivity and quality.
- Collaboration and communication. Teams involve customers throughout the project development process to ensure that the product meets their needs and expectations.
- Flexibility and adaptability. Traditional project management methods follow a strict plan or timeline. Agile allows for changes throughout the development process so that teams can respond quickly to changing market conditions or customer feedback.



- Cross-functional teams. Teams with diverse skill sets can work together towards a common goal to ensure a more well-rounded and efficient approach to handling projects.

At the core of agile is a paradigm-shifting manifesto—a set of values and principles that prioritize the human spirit over mechanical processes and tools. From the manifesto, teams are directed to emphasize the importance of working software over comprehensive documentation, value customer collaboration more than strict contract negotiation, and respond to change rather than rigidly sticking to a plan. The art form that is agile is seen in the vast array of practices that agile teams can choose from to suit their unique needs and specifications; scrum, kanban, XP, FDD, APF, XPM, ASD, and DSDM, among others.

Among all of the agile practices, extreme programming (XP) stands out, as it focuses on precision, improvement, and close collaboration. Unlike rigid, pre-defined plans, XP embraces short development cycles and ongoing feedback to ensure that the final product aligns perfectly with evolving needs. This can be a game-changer for software development teams working in fast-paced environments, where requirements can shift quickly. XP takes the core agile principles to a new level and revolves around five core values: communication, feedback, simplicity, courage, and respect.

Benefits of XP in project management include increased responsiveness to change, improved software quality, enhanced team collaboration, and streamlining the flow. XP offers a compelling approach to software development, empowering teams to create high-quality, user-centric software. Agile users can leverage XP's strengths to streamline the development process. But remember that XP is not a rigid rulebook, but rather a framework that embraces its core principles of collaboration, continuous improvement, and responsiveness, and then adapts them to each unique project landscape. In our featured article (p.17), the authors showed that adherence to the agile manifesto, agile values, and XP practices was associated with higher levels of trust and lower levels of stress.

Editorial Review Board Members

The Impact of Imputed Weather Data Derived from Advanced Machine Learning Models on Building Energy Simulation

Seongchan Kim, Western Illinois University

Abstract

Accurate weather data are fundamental in building energy simulations, as they directly affect predictions of energy needs and efficiency. Localized weather data from site-specific weather monitoring stations are especially critical as they ensure that simulations accurately reflect the true environmental conditions each building will face. Localized weather data are also essential for the calibration of building energy simulation models, which are important for analyzing the specific characteristics of the building, thereby enabling more precise and reliable predictions of energy performance. This accuracy can be affected by equipment malfunctions, environmental factors, and occasional human errors. While broader meteorological models offer valuable data, they typically do not provide the detail required for site-specific simulations.

In this current study, the author focused on the impact of imputing missing weather data for building energy simulations. A comprehensive meta model combining different machine learning algorithms was developed to improve data imputation accuracy. In the study, the author assessed the impact of various levels of imputed weather data, ranging from 5% to 30% in 5% increments, on the accuracy of heating and cooling load simulations using EnergyPlus software. In addition, the author used a detailed sensitivity analysis, using 30% imputed weather data, to examine its influence on building energy simulations and identify key weather parameters affecting total heating and cooling load computations. This approach emphasizes machine learning's potential in enhancing building energy simulations by effectively imputing weather data with partial gaps. The findings suggest that the imputed data levels critically affect building energy modeling, making the choice of machine learning models and their training important.

Introduction

Weather data play a crucial role in building energy simulations, significantly impacting the accuracy and reliability of energy consumption analyses. The intricate interplay between a building's energy consumption and its specific meteorological conditions emphasizes the need for detailed and comprehensive weather data (Zeng, Kim, Tan, Hu, Rastogi, Wang & Muehleisen, 2023). For professionals in architecture, engineering, and energy analysis, weather data are more than numerical values; they accurately represent the environmental conditions faced by a building. Precise weather data for each location ensure that energy models are based on reality, aiding in the design and operation of buildings.

However, obtaining accurate and comprehensive weather data from site-specific weather monitoring stations can be challenging, due to gaps in weather station recordings. These gaps, which may arise from equipment issues, environmental challenges, or human errors, can introduce significant inaccuracies into energy simulations. Such inaccuracies can substantially impact the results of building energy models, especially for the calibration of building energy simulation models. Calibration is crucial for performing specific building energy simulations, as it ensures that the models accurately reflect the unique characteristics of the building. Accurate weather data are essential for predicting energy consumption and devising effective energy-saving strategies (Li, Wang & Hong, 2021).

Traditional protective algorithms such as error-checking routines, data-smoothing techniques, and outlier detection methods are critical for weather data collection to minimize errors. Although these algorithms are somewhat effective, they often fall short when applied to data from personal or site-specific weather stations, which may suffer from non-standardized setups and less rigorous maintenance. Consequently, energy simulations can become unreliable due to missing weather data (Patterson, Ferrari, Tan & Lee, 2023). Machine learning can offer a solution to fill these gaps with its pattern-recognition capabilities and feature-estimation models. In this current study, the author explored machine learning algorithms for data imputation, including support vector regression, Random Forest, XGBoost, and neural networks (Batra, Khurana, Khan, Boulila, Koubaa & Srivastava, 2022; Lyngdoh, Zaki, Krishnan & Das, 2022). A meta model combining these algorithms was developed to enhance prediction accuracy and capture a broader range of data patterns (Satish, Anmala, Rajitha & Varma, 2024).

The author also examined how different levels of data imputation affect simulation accuracy for total heating and cooling load computations, which are critical in building design and energy efficiency. Finally, a sensitivity analysis was conducted to assess the impact of various weather parameters required in building energy simulations, including dry bulb temperature, dew point temperature, relative humidity, atmospheric station pressure, horizontal infrared radiation intensity, direct normal radiation, diffuse horizontal radiation, wind direction, wind speed, total sky cover, and opaque sky cover.

The Role of Weather Data in Building Energy Simulations

Weather data are important in building energy simulations for ensuring that predictions align closely with real-world conditions. A study conducted by Patterson et al. (2023) explored the critical role of selecting appropriate weather-data reference periods for building energy simulation. Their study demonstrated the significant implications of climate variability on building energy models. By analyzing various climate data periods, the authors provided evidence that using updated and accurately representative weather data not only enhances the reliability of simulations but also helps in making more informed decisions regarding improvements in energy efficiency. The authors supported integrating recent climatic data into simulation practices to ensure that building designs are optimized for current and future environmental conditions. Furthermore, the synthesis of building operation datasets, which include HVAC, lighting, and miscellaneous electric loads, is influenced by weather conditions. Li et al. (2021) presented a synthetic building operation dataset incorporating environmental parameters and end-use energy consumption. Their dataset, derived from numerous simulations, highlighted the interplay between building operations and external weather conditions, emphasizing the need for accurate weather data for realistic building energy simulations.

Solar insolation predictions are another critical aspect of building energy simulations, especially for buildings with photovoltaic systems. Solar radiation, a key external factor, is crucial in determining a building's energy consumption and the efficiency of building-integrated photovoltaic systems. Accurate solar radiation data are crucial, as even minor inaccuracies can lead to significant deviations in simulated outcomes (An, Yan, Guo, Gao, Peng & Hong, 2020). These studies emphasize the importance of weather data in performing energy simulations for buildings. Accurate weather data ensure that simulations accurately reflect real-world conditions, enhancing the reliability of decisions in building design, operation, and energy consumption.

Machine Learning in Data Imputation: Applications and Potential in Weather Data

Machine learning has emerged as a powerful tool for data imputation across various disciplines. Many researchers and professionals prefer its ability to process large datasets, identify patterns, and predict missing values. Bochenek and Ustrnul (2022) reviewed machine learning methods in meteorology and climatology, analyzing 500 articles to highlight applications in weather forecasting and climate research. They used text mining to identify common themes and found that machine learning techniques like decision trees, neural networks, deep learning, and support vector machines were effective in weather predictions. Gorshenin and Lukina (2020) compared machine learning algorithms for imputing missing values in spatiotemporal precipitation data. Their methodology identified extreme gradient boosting as the most accurate, establishing it as a reliable method for meteorological data processing. Additionally, a survey of over 20 machine learning techniques for weather and climate predictions identified eight promising methods that improve forecast accuracy across different time scales. This review consolidates current knowledge and highlights recent advancements, guiding future interdisciplinary research (Chen, Han, Wang, Zhao, Yang & Yang, 2023).

While machine learning has been successfully employed across various domains, its potential application in addressing gaps in weather data for building energy simulations remains relatively unexplored. In this current study, the author examined the feasibility of using machine learning to impute missing weather data specifically for building energy simulations.

Evolution of Data Imputation: From Traditional Methods to Machine Learning Approaches

Missing data has long posed significant challenges in data analysis, especially when data are missing at random, reducing the statistical power of analyses and potentially leading to misleading results (Kwak & Kim, 2017). Addressing these gaps is crucial for maintaining the accuracy of simulations, particularly in fields such as building energy simulations, where weather data plays a pivotal role. Imputing missing values is an effective strategy for completing datasets, preventing analysis errors, performing analyses on data sets with missing values. However, imputing missing values also introduces certain limitations and risks, such as potential biases or errors, which can lead to inaccurate or unreliable data analysis results. Therefore, it is essential to select the appropriate imputation method based on the type and distribution of data, missing mechanisms, or other data-related factors. Simple imputation methods include mean imputation, which replaces missing values with the average of non-missing values in the attribute; mode imputation, which uses the most frequent value; and, median imputation, which uses the middle value in the sorted data. Despite their simplicity, these methods can reduce the overall variance of the imputed dataset and cause significant data uniformity (Li, Ren & Zhao, 2023).

Recent advances in machine learning offer more flexible and sophisticated approaches to handling missing data. Machine learning algorithms excel at identifying intricate patterns and relationships within datasets, which is crucial for effectively managing missing data scenarios. This ability to learn from data makes machine learning particularly adept in scenarios where the likelihood of a data point being missing is related to other variables in the dataset. Studies have underscored the superiority of machine learning approaches over traditional methods, showcasing significant improvements in accuracy, performance, and processing time for handling missing values (Alabadla et al., 2022). Support vector regression (SVR), Random Forest, XGBoost, and neural network models have shown promise in data imputation among various machine learning algorithms (Awad & Khanna, 2015; Ramosaj & Pauly, 2019; Madhu, Bharadwaj, Nagachandrika & Vardhan, 2019; Hameed & Ali, 2022). SVR, for instance, excels in capturing non-linear relationships in the data, while ensemble methods like Random Forest combine the predictions of multiple decision trees to offer a more robust imputation. XGBoost, with its gradient-boosting framework, has been celebrated for its efficiency and accuracy. Neural networks excel at processing time-series data by recognizing and analyzing data sequences. Integrating machine learning into data imputation expands researchers' resources, resulting in more accurate imputed values aligned with underlying data distribution and relationships (Alabadla et al., 2022).

Meta Model

Meta models are rooted in the principle that the collective wisdom of a group often surpasses that of individual members, particularly when the group's members bring varied perspectives and expertise to a problem (Dietterich, 2000). The meta model employed in this study was a specialized machine learning solution designed to optimize building energy simulation accuracy. The meta model represented an ensemble approach, where multiple base models were trained and their predictions then combined—typically through methods such as averaging, weighted averaging, or more complex stacking methods—to produce a refined final prediction. In a recent study by Satish et al. (2024), the authors demonstrated the efficacy of stacking the artificial neural network ensemble models in environmental data prediction, underscoring the enhanced performance and sophisticated integration capabilities of meta models. This technique effectively leverages the diversity of base models, aiming to capture a broader spectrum of patterns and correlations within the data that individual models might overlook.

Studies have consistently demonstrated that meta models tend to outperform single predictors. For instance, recent research conducted on wind speed prediction utilized a stacking ensemble learning model comprising several machine learning algorithms (Guo, Ren, Liu, Wang & Lin, 2024). This study found that the ensemble model significantly reduced forecast errors compared to individual model predictions, and effectively combined the strengths of the base models to improve accuracy and reliability in localized weather forecasting. The meta model was employed in this current study, as its ability to combine the strengths of various machine learning algorithms was expected to enhance the overall accuracy of estimations. This approach is particularly beneficial for complex tasks such as imputing missing weather data, where diverse data patterns and correlations exist.

Research Flow

Figure 1 depicts the entire research flow, providing a visual overview of the steps undertaken in this current study. The elaborate data preprocessing steps ensured the accuracy and reliability of subsequent analyses. The primary dataset employed was the Chicago TMY3 weather file, an integral component of the EnergyPlus building energy simulation program (U.S. Department of Energy, 2023).

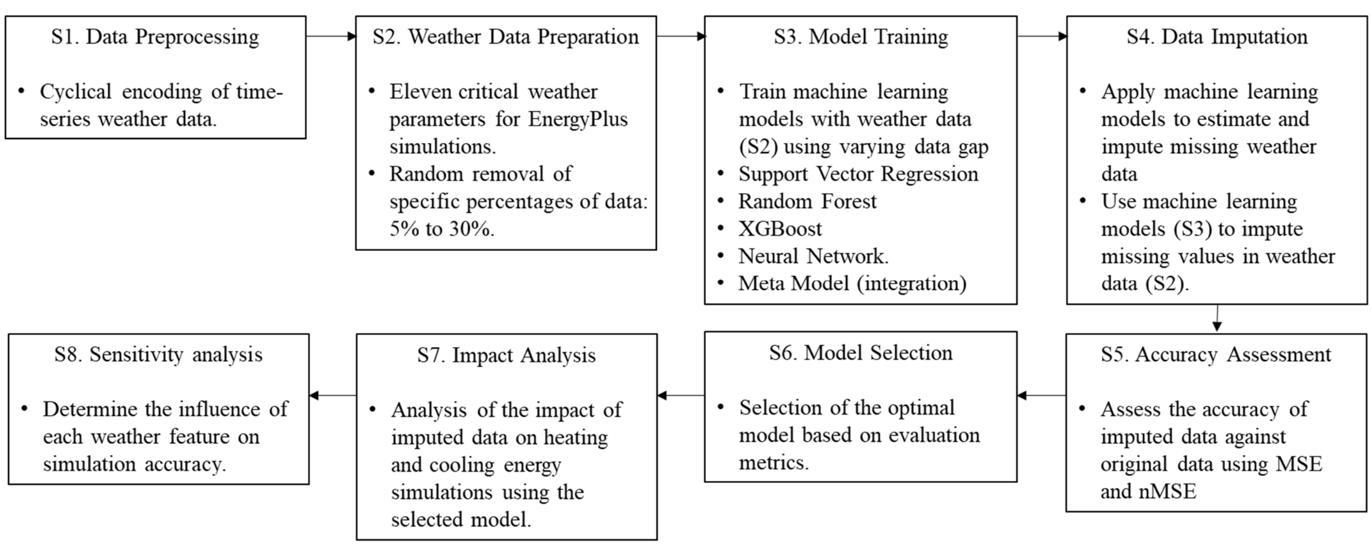


Figure 1. Research diagram.

This file was specifically chosen not for its geographical relevance but for its comprehensive coverage of one-year (8760 hours) data, making it an ideal candidate for simulating site-specific weather data conditions. This included the intentional introduction of data gaps to replicate real-world scenarios, where weather data may be missing due to equipment errors, malfunctions, or poor maintenance. By systematically removing portions of this comprehensive dataset, the author created controlled conditions to test the effectiveness of various machine learning techniques in imputing missing data and to assess their impact on building energy simulation accuracy.

In the early stages of data preparation for this study, the author recognized the necessity of accurately representing the cyclicality inherent in time-related data for machine learning training, such as hours, days, and months. To achieve this, a unique cyclical encoding process was applied. This approach was important, because it addressed the natural cycles where hours repeat every 24 hours, days cycle monthly, and months annually. Traditional linear or categorical representations often fail to effectively capture these dynamics, particularly at cycle boundaries, which can disrupt the pattern recognition capabilities of machine learning models (Mulenga, Phiri, Simukonda & Alaba, 2023). To overcome this, the sine and cosine transformations for encoding were employed (Equations 1 and 2). These mathematical transformations map each time unit onto a unit circle. For example, midnight (0th or 24th hour) and 1:00 AM (1st hour) are numerically 23 hours apart but are actually close in terms of daily cyclical progression.

$$\text{Sine of hour} = \sin\left(\frac{2\pi \times hour}{24}\right) \tag{1}$$

$$\text{Cosine of hour} = \cos\left(\frac{2\pi \times hour}{24}\right) \tag{2}$$

This transformation placed these hours next to each other on the circle, thus maintaining their cyclical relationship. Figure 2 visually demonstrates this technique, where the scatter plot of sine and cosine values for each hour clearly shows the cyclical continuity. This encoding not only preserves the natural order of time but also enhances the machine learning model's ability to interpret and learn from these patterns without the artificial discontinuities created by traditional encoding methods. Implemented using Python (Python Software Foundation, 2023) and its libraries, NumPy (Harris et al., 2020) and Pandas (McKinney, 2010), this cyclical encoding ensured that the models perceived the end of one cycle (e.g., the end of a day, month, or year) and the beginning of another as contiguous events. This methodological choice was crucial for improving the accuracy and reliability of predictive models in scenarios where time is a significant variable. Weather data are fundamental for accurate building energy simulations. However, obtaining consistent and complete weather data from site-specific weather stations is often challenging, due to reasons such as equipment malfunctions, environmental factors, or human errors.

To realistically simulate these challenges, certain data points were deliberately omitted from the initial weather file. This approach was adopted to mimic real-world situations where weather data might be missing, thereby creating a simulated environment for evaluating and testing how effectively various data imputation methods handle gaps in weather data. The data removal process was conducted through a randomized approach using the NumPy library in Python, designed to simulate the unpredictability with which data might be missing due to actual operational issues. This method ensures that the omission of data points does not follow any predictable pattern and mimics the random occurrence of data loss in real-world scenarios, thus maintaining the integrity of the simulation.

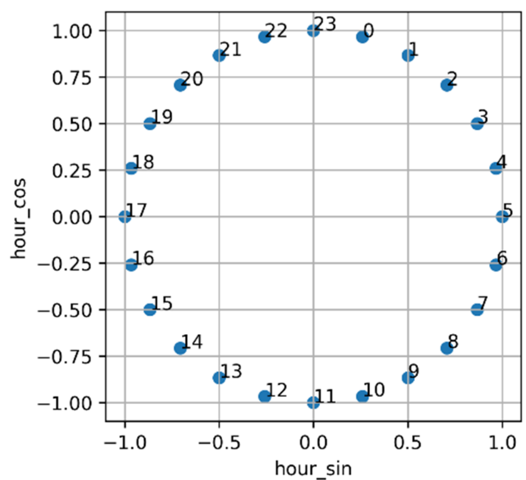


Figure 2. Scatter plot of sine and cosine of hour.

For this current study, the focus was placed on eleven key features used for EnergyPlus building energy simulations (U.S. Department of Energy, 2023). These features included dry bulb temperature, dew point temperature, relative humidity, atmospheric station pressure, horizontal infrared radiation intensity, direct normal radiation, diffuse horizontal radiation, wind direction, wind speed, total sky cover, and opaque sky cover. In order to understand the impact of missing data on deviation from the original dataset, a random data removal process was executed using NumPy. Specific percentages, 5%, 10%, 15%, 20%, 25%, and 30%, were chosen to simulate a spectrum of potential real-world scenarios, ranging from minor data loss to substantial data gaps. Each percentage corresponds to a certain number of days of data to be removed. For instance, a 20% data loss equals 73 days of missing data (365 x 0.20 = 73). These days are not consecutive but are randomly spread throughout the year, preventing concentration in a specific season or month.

In the subsequent phase of the research, several machine learning models were trained using the prepared weather data to impute missing values in weather data. The chosen models, including SVR, Random Forest, XGBoost, and a neural network sequential model, were implemented using the Scikit-learn (Pedregosa, Varoquaux, Gramfort, Michel, Thirion, Grisel & Vanderplas, 2011) and TensorFlow (Abadi et al., 2016) libraries. Each model offered unique strengths in data estimations, making them suitable for this study. Alongside these, a meta model, combining these individual models, was also developed and applied to enhance the estimation process and provide a comprehensive analysis. The missing values in the dataset were estimated using the computational power of the trained models. For instance, in a scenario with 20% data loss (equivalent to 73 days), the models were trained using 292 days of weather data.

After training, the models' estimation capabilities were used to fill in the missing data for the 73-day period. Each algorithm was tasked with filling in the missing data, ensuring the dataset was complete. The filled dataset was then compared to the original dataset using evaluation metrics such as mean squared error (MSE) and normalized mean squared error (nose), details of which are explained in the next section. After assessing various models, the best model was selected and applied to further the study, the specific purpose of; which was to investigate the impact of imputed weather data on total heating and cooling energy calculations within EnergyPlus simulations. The study concluded with a sensitivity analysis to understand how the accuracy of imputed data for different weather features affected energy-simulation outcomes. This step was critical in identifying key weather parameters significantly influencing energy consumption predictions in the EnergyPlus simulation.

Evaluation Metrics: Mean Squared Error and Normalized Mean Squared Error

As described in the previous section, the imputed data were evaluated against the original dataset. This assessment primarily used MSE, a standard metric measuring the average squared differences between estimated and actual values, as given by Equation 3:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{3}$$

where, y_i are the actual values, $\hat{y}_i$ are the predicted values, and n is the number of data points.

Next, to ensure a fair comparison of the imputation accuracy across different features, the MSE values were normalized with respect to the variance of the original data for each feature. Given the diverse range and scale of weather parameters, this step was important to make the MSE values comparable across all features. Normalization was carried out using Equation 4:

$$nMSE = \frac{MSE}{\delta^2} \tag{4}$$

where, nMSE is the normalized MSE and δ^2 is the variance of the original data for that feature.

Using the normalization procedure, the author adjusted the MSE values to better represent the actual error relative to the natural variations found in each weather parameter. This adjustment provided a clearer picture of how well each machine learning model performed across different weather features.

Statistical Analysis of Chicago O'Hare TMY3 Weather Parameters

Table 1 displays the statistical findings of Chicago O'Hare TMY3 weather parameters. The Dry Bulb Temperature in Chicago O'Hare averages around 9.9°C throughout the year. This average temperature was derived from a spectrum of readings spanning extreme lows of -22.8°C during the colder months to highs reaching 35.0°C during warmer periods. Dew point temperature, an essential metric providing insight into moisture content, averaged 4.3°C. The variability in this parameter is evident, with values ranging from a dry value of -28.3°C to a more humid value of 25.6°C. Chicago's relative humidity tends to lean towards higher values, averaging 70.3%. This average is situated within a range from a low of 17.0% to a saturated high of 100.0%. The atmospheric station pressure remained relatively consistent, with an average recorded value of 99188.7 Pa. Most values clustered between 98800.0 Pa and 99600.0 Pa, reflecting the region's stable atmospheric conditions. Horizontal infrared radiation intensity averaged 318.1 W/m².

This parameter, crucial for understanding radiant energy, tended to vary within a relatively narrow range, typically between 273.0 W/m² and 368.0 W/m². The average values for direct normal radiation and diffuse horizontal radiation were 147.8 W/m² and 75.4 W/m², respectively. Wind direction was characterized by an average bearing of 194.3°. This average was derived from a full circle of potential directions, from 0° right through to 360.0°, with 190.0° being the most common direction. Chicago's wind speed was moderately paced, averaging 4.6 m/s, and ranged from calm (0 m/s) to gusty (15.4 m/s). The average total sky cover and opaque sky cover metrics for Chicago were 5.9 and 5.3, respectively, indicating the extent of cloud cover.

Evaluating the Efficacy of Machine Learning Models in Weather Data Imputation

In this study, the author assessed the performance of machine learning models in estimating missing weather data

Table 1. Descriptive statistics of weather parameters from Chicago O'Hare TMY3 data.

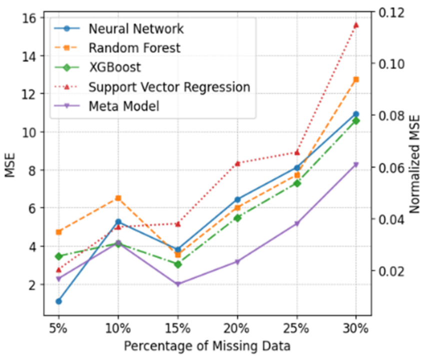
Parameter	Mean	Std. Dev.	Variance	Min	Max
Dry Bulb Temperature (°C)	9.9	11.7	135.9	-22.8	35.0
Dew Point Temperature (°C)	4.3	11.0	121.9	-28.3	25.6
Relative Humidity (%)	70.3	16.8	282.9	17.0	100
Atmospheric Station Pressure (Pa)	99188.7	714.7	510545.8	96200	101800
Horizontal Infrared Radiation Intensity (W/m²)	318.1	63.0	3963.1	157.0	476.0
Direct Normal Radiation (W/m²)	147.8	254.9	64980.4	0	942.0
Diffuse Horizontal Radiation (W/m²)	75.4	102.0	10407.4	0	465.0
Wind Direction (°)	194.3	99.8	9968.0	0	360.0
Wind Speed (m/s)	4.6	2.3	5.2	0	15.4
Total Sky Cover	5.87	4.21	17.74	0	10
Opaque Sky Cover	5.27	4.25	18.06	0	10

values across various features. The study analyzed eleven weather-related features: dry bulb temperature, dew point temperature, relative humidity, atmospheric station pressure, horizontal infrared radiation intensity, direct normal radiation, diffuse horizontal radiation, wind direction, wind speed, total sky cover, and opaque sky cover. To ensure a thorough evaluation, the author employed five distinguished machine learning models: Random Forest, XGBoost, neural network, support vector regression, and meta model. These algorithms were assessed using the mean squared error (MSE) and the normalized mean squared error (nMSE) to gauge accuracy. This dual-metric approach provided absolute and relative performance assessments across features. Figure 3(a-k) presents the MSE and nMSE values across machine leaning algorithms for various weather data features.

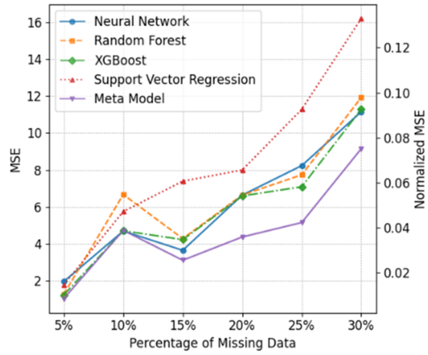
The results of this study demonstrated measurable differences in how various weather features respond to machine learning-based imputation. A clear example of this can be seen in the estimations for dry bulb temperature and dew point temperature. Both features have intrinsic physical relationships with other weather parameters, making their patterns more predictable. Dry bulb temperature, a direct measure of air temperature, and dew point temperature, indicating the temperature at which air becomes saturated with moisture, strongly correlate with many other atmospheric parameters. Consequently, when machine learning models, especially neural networks, utilize these interconnected relationships, they are better poised to make accurate predictions. The consistently low MSE and nMSE values for these features across different missing data levels demonstrate this fact.

On the contrary, wind direction and atmospheric station pressure presented distinct challenges. Wind direction, for instance, is inherently cyclical and can change rapidly, due to numerous factors including topography, time of day, and larger atmospheric systems. Its cyclical nature can sometimes be misinterpreted by models that expect relationships, leading to higher error rates. The MSE and nMSE metrics mirrored this complexity, particularly at higher missing data levels, revealing greater prediction errors. Similarly, atmospheric station pressure, a measure of the force exerted by the atmosphere at a given point, can exhibit subtle variations influenced by altitude, weather systems, and temperature gradients. This feature was challenging to predict accurately. This study revealed distinct performance patterns across different data imputation methods. The meta model generally demonstrated superior performance, exhibiting lower MSE and nMSE values for most features. These features showed a stable increase in MSE, as the percentage of missing data rose. However, some variables exhibited different trends, such as wind direction and wind speed, where MSE did not consistently increase with the missing data percentage.

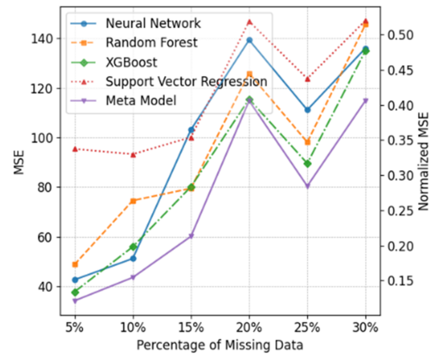
In some instances, there was a plateau or even a reduction in error rates at certain levels of missing data. This variability could be attributed to the randomness of the data-removal process used in this study, which sometimes resulted in non-linear patterns of error increase. Additionally, this can occur due to the complexity of their data patterns and their weak correlation with many other features. For instance, features such as atmospheric station pressure displayed varied responses; the neural network method showed significantly higher MSE values compared to others, indicating poor performance in this context, while XGBoost and the meta model maintained relatively low MSE values, with XGBoost showing the least variance in performance across different missing data scenarios. These observations suggest that, while some machine learning models like XGBoost are particularly adept at handling features with more regular patterns, the meta model's integration of multiple algorithms provided it with the flexibility and robustness needed to manage a broader range of data irregularities.



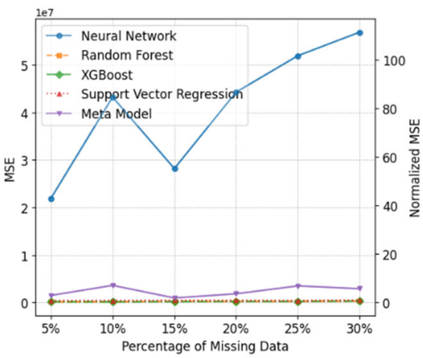
(a) Dry bulb temperature.



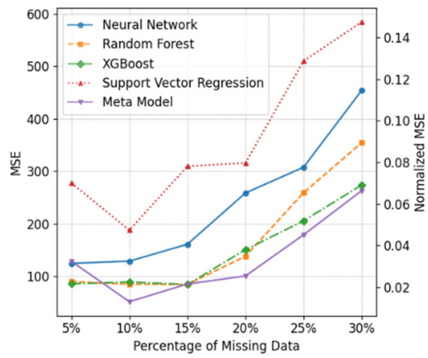
(b) Dew point temperature.



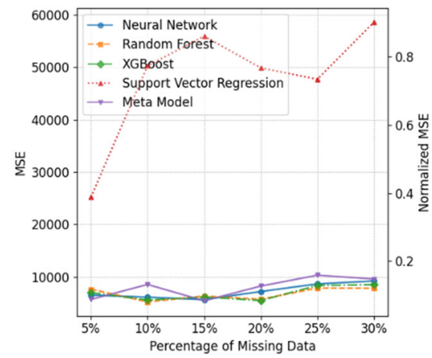
(c) Relative humidity.



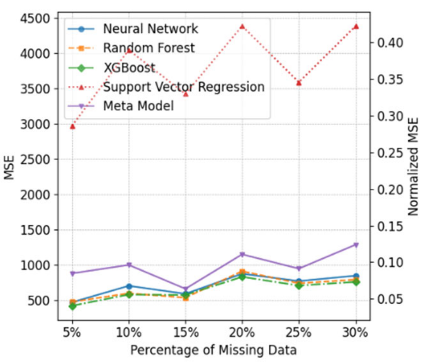
(d) Atmospheric station pressure.



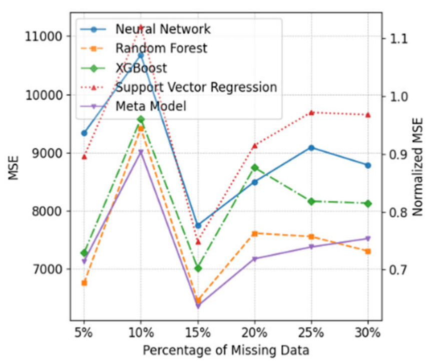
(e) Horizontal infrared radiation intensity.



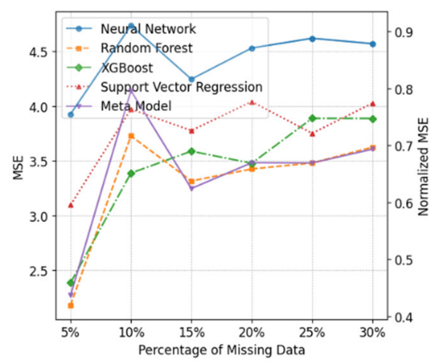
(f) Direct normal radiation.



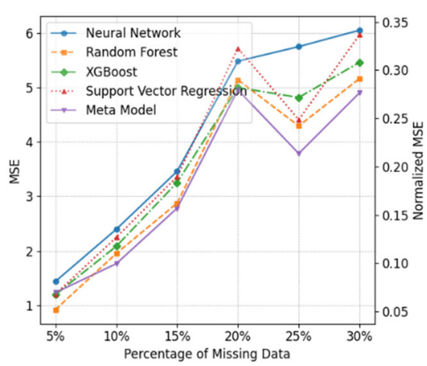
(g) Diffuse horizontal radiation.



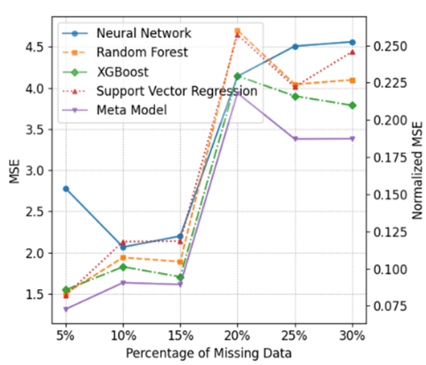
(h) Wind direction.



(i) Wind speed.



(j) Total sky cover.



(k) Opaque sky cover.

Figure 3. Comparison of MSE and nMSE values across algorithms.

The analysis of the horizontal infrared radiation intensity, direct normal radiation, and diffuse horizontal radiation parameters further confirmed the efficacy of the meta model. The support vector regression's significant spikes in MSE suggested model inconsistencies, while the meta model's performance remained steady, pointing to its effectiveness in handling missing data variability. The neural network method showed an irregular trend in wind speed, with high MSE values at minimal missing data. Notably, the MSE improved with increased missing data, indicating a random sensitivity to the dataset's completeness. When examining total sky cover and opaque sky cover, a convergence of MSE values among all methods was observed at higher missing data percentages, indicating a similar performance decline. Nonetheless, the meta model maintained the lowest nMSE value, further advocating its use as a reliable imputation method.

In summary, the meta model's superior performance across various parameters underscores its viability for imputation tasks in weather datasets. While neural network and support vector regression presented higher errors and inconsistencies, the meta model's integrated approach offered a beneficial solution to data imputation challenges in weather data for building energy simulations.

Simulation with Imputed Weather Data

The simulations with imputed weather data from the meta model were performed using the EnergyPlus software (version 23), developed by the U.S. Department of Energy. The input file used for the analysis was part of the standard distribution of EnergyPlus. Figure 4 shows the building was modeled as a single zone without any interior partitions, emphasizing a lightweight construction approach.

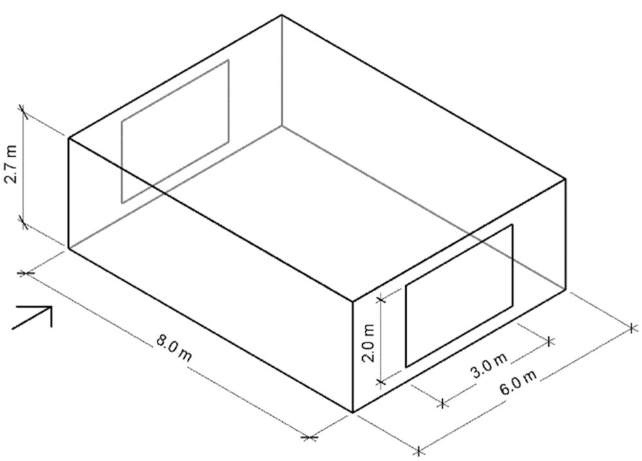


Figure 4. Schematic representation of the simplified building model used for energy simulation.

The walls, roof, and floor had U-values of 0.56 W/m-K, 0.54 W/m-K, and 17.04 W/m-K, respectively. The windows were double-paned with a U-value of 0.9. The space conditioning settings were straightforward, with a heating setpoint of 20°C and a cooling setpoint of 24°C, without any setback. This fixed setpoint approach eliminated variables related to temperature fluctuation, ensuring that the analysis focused on the impact of the building's physical characteristics rather than operational strategies. Choosing a simple building shape and configuration for sensitivity analysis offered another benefit; it reduced the complexity of variables, facilitating easier isolation and understanding of imputed weather data effects on total heating and cooling load computations and enhanced the overall efficiency of the sensitivity analysis.

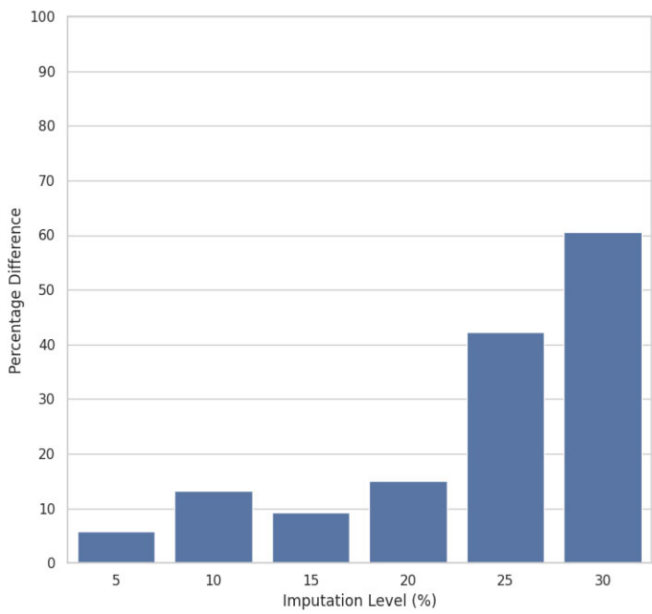
Impact of Data Imputation Levels on Simulation Accuracy for Total Heating and Cooling Load Computations

The bar charts in Figure 5(a-b) illustrate the differences in simulation results for total heating load (a) and total cooling load (b), when using imputed versus original weather data across imputation levels from 5% to 30%. These charts show the absolute differences to better demonstrate the impact of data imputation on simulation accuracy. It is noteworthy that the percentage difference in heating load was generally larger than that in cooling load. This could be attributed to the selected weather data being from a heating-dominated area, where the demand for heating is higher than that for cooling. Consequently, inaccuracies in weather data imputation had a more pronounced effect on heating load simulations.

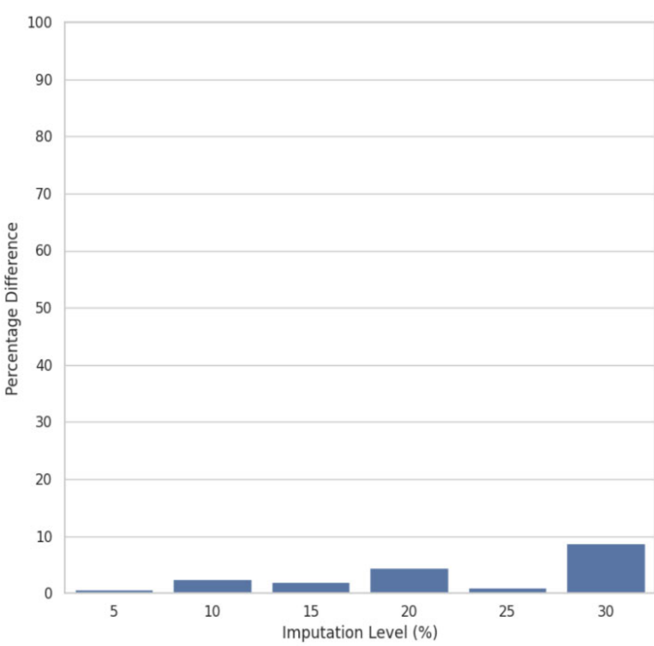
Figure 5(a) shows that, for total heating load simulations, the increase in imputation levels generally correlated with greater deviations from the original data. A significant increase in the differences from 25% imputation levels was also observed. This phenomenon can be explained by a threshold effect, where the amount of missing data reaches a critical point, thereby significantly impacting the model's accuracy in predicting the missing values. At lower levels of imputation, the model was able to compensate for the missing data more effectively, maintaining a relatively stable performance. However, as the imputation level increased and exceeded the threshold of 25%, the quantity of missing data began to overwhelm the model's predictive capabilities. This resulted in a noticeable deterioration in performance. The model struggled to accurately predict the missing values, leading to larger deviations from the original data. This threshold effect highlights the importance of maintaining a lower percentage of missing data to ensure the reliability and accuracy of the imputed weather data used in building energy simulations.

Figure 5(b) shows that, for total cooling load simulations, the results were not as pronounced as those for heating loads. However, an unusual pattern was noted where the deviation at 25% imputation was less than at 20%.

This anomaly could be attributed to the characteristics of the specific data points missing at these levels. If more critical data points, which significantly influence the model's calculations, are absent at the 20% level compared to the 25% level, the simulation could show better performance even at the higher imputation level.



(a) Absolute percentage difference in total heating load.



(b) Absolute percentage difference in total cooling load.

Figure 5. Comparisons of absolute percentage differences for total heating and cooling loads at varied imputation levels.

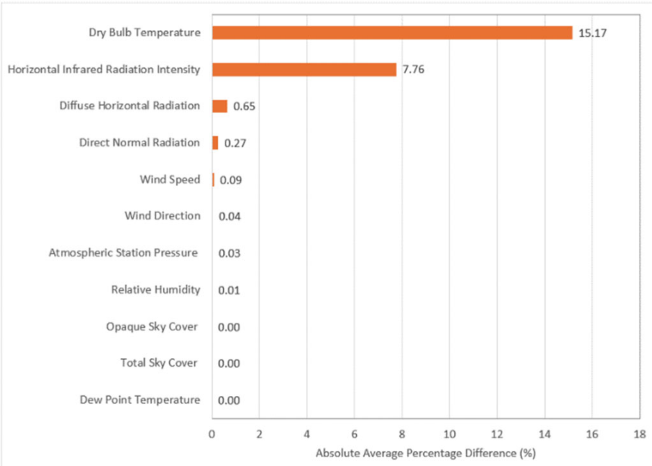
These observations emphasize the need for precision in the imputation process, especially at higher levels of data absence. While the imputation techniques demonstrated reasonable accuracy at lower levels of imputation with minor deviations from the original data, the effectiveness diminished significantly at higher imputation percentages, especially in total heating load. This pattern highlights the challenges in maintaining the integrity of weather data simulations, particularly under substantial data loss, and underscores the importance of developing robust imputation methods to ensure accurate energy performance assessments.

Sensitivity Analysis of Building Energy Simulations to Imputed Weather Data

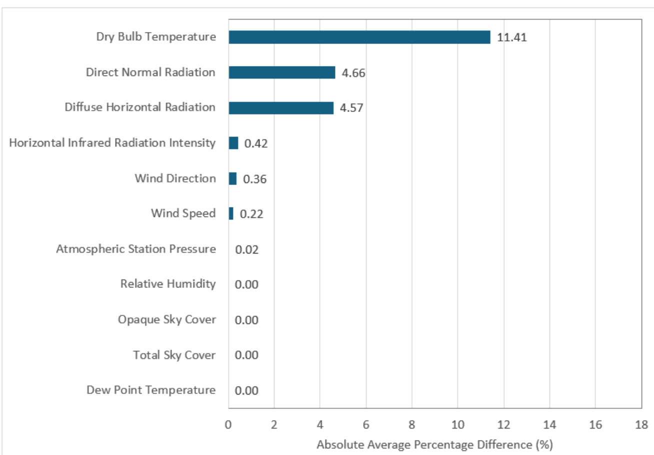
The sensitivity analysis conducted as part of this study aimed to assess the impact of imputed weather data on building energy simulations. Eleven distinct sets of weather data were created to analyze the impact of each specific weather parameter on building energy simulations. In each set, one weather feature from the original dataset was substituted with 30% imputed data. Twelve simulations were performed for each weather data set, including the original and eleven imputed datasets. These simulations spanned one calendar year, January to December, allowing for the assessment of total heating and cooling loads across different seasons and conditions.

Figure 6(a-b) presents the percentage differences in heating and cooling loads resulting from simulations using original weather data compared to those using imputed weather data. The differences were calculated for each weather parameter to illustrate the impact of data imputation on the predictive accuracy of building energy simulations. This visual representation helps in the understanding of how each specific weather parameter affected the overall simulation outcomes, when subjected to imputed data. The sensitivity analysis focused on evaluating how each weather feature's imputation influenced the simulations' total heating and cooling loads. The methodology employed the use of absolute values of percentage changes. This approach was chosen to measure the impact of each feature, regardless of whether it resulted in an increase or decrease in total heating and cooling load, and provided a more accurate representation of the sensitivity of the building simulations to variations in weather data.

Figure 6(a) illustrates the absolute sensitivity of weather features in total heating load. It shows that the dry bulb temperature significantly impacted the heating load, with an absolute percentage difference exceeding 14%. This suggests that even minor inaccuracies in the imputation of this feature could lead to substantial errors in total heating load simulations. Horizontal infrared radiation intensity followed, with a difference of under 8%. Its substantial effect underscores the importance of accurately imputing this parameter to avoid significant deviations in total heating load estimates. Other features, such as diffuse horizontal radiation, direct normal radiation, wind speed, and wind direction, had much less influence individually, with differences ranging from around 0.2% to 0.7%.



(a) Absolute sensitivity in total heating load.



(b) Absolute sensitivity in total cooling load.

Figure 6. Bar chart of weather parameter sensitivity on total heating and cooling load simulations.

Figure 6(b) shows total cooling load sensitivity, indicating that the dry bulb temperature again showed the most significant impact, with an absolute percentage difference of 11.4%. The consistency of this feature's influence across total heating and cooling suggests that it should be a primary focus in machine learning model training for weather data imputation. Direct normal radiation and diffuse horizontal radiation displayed substantial sensitivity, with absolute differences of 4.7% and 4.6%, respectively. In simulations of total cooling load, attention should be given to these weather features. Horizontal infrared radiation intensity was less sensitive than the heating load, impacting the cooling load with a difference of about 0.4%. The sensitivity analysis demonstrated that certain weather features were highly sensitive in total heating and cooling load simulations, and emphasized the necessity of prioritizing these sensitive features during the training of machine learning models. The models can be refined by focusing on these features to ensure greater accuracy in predicting weather data, leading to more reliable simulation outcomes.

Conclusions and Future Work

From this study, the author demonstrated the importance of accurate and comprehensive weather data for creating energy simulations. The introduction of the meta model, which integrated various machine learning algorithms, showed a reasonable advancement in the field. This model enhanced the accuracy of imputing missing weather data, strengthening the reliability of building energy simulations. The study extended to simulations of total heating and cooling loads with varying imputed weather data levels, providing insights into the data imputation's effect on energy model accuracy. These observations highlight the importance of precision in imputation, especially at higher levels where machine learning algorithms might not capture the complexities of the original data and potentially skewing energy performance assessments. However, at lower imputation levels, the discrepancies were notably smaller, indicating a high reliability in the simulation results derived from data with minimal imputation. Furthermore, the conducted sensitivity analysis revealed the impact of imputed weather data on specific features, highlighting the need to prioritize sensitive features while training machine learning models.

When training machine learning models, it is crucial to prioritize features based on their sensitivity to predicted outputs. The results showed that dry bulb temperature had the most significant impact on total heating and cooling loads, indicating that it should be prioritized during model training. Horizontal infrared radiation intensity also showed a notable effect, especially on heating load, and should be considered next. Features such as wind direction and opaque sky cover, which exhibited lesser sensitivity, could be prioritized lower. By focusing on the most influential parameters, models can be trained more effectively to predict energy loads. While this study primarily utilized the comprehensive weather file from Chicago O'Hare TMY3, encompassing 8760 hours of diverse weather data across a complete annual cycle, it highlights the importance of extending the analysis to encompass broader geographic variations. Future studies should expand this work to examine weather data from diverse climate regions, including hot, humid, dry, cold, and mixed zones. This will enable an assessment of whether there are discernible differences in predicting missing weather data across these varied regions. Such an expansive approach will refine the understanding and enhance the robustness of machine learning models in imputing weather data for specific climatic conditions in building energy simulations.

Future work should also focus on refining the meta model and exploring additional base machine learning algorithms to enhance the accuracy of imputed weather data. Additionally, expanding the scope of simulations to include more diverse building types and environmental conditions could provide a broader understanding of the models' applicability.

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Agile and Extreme Programming (XP) and Their Relationship with Stress and Trust in Distributed Programming Environments

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Abstract

As this fast-paced world evolves technologically, agile methods with the potential to increase productivity are being widely adopted. Several methodologies utilize the core principles of agile (e.g., Scrum/Kanban, feature-driven development), but some are better than others for a specific task. Extreme programming (XP) is an agile methodology that promotes improved team performance, based on its adherence to the agile manifesto, values, and specific practices. This study was designed to add to the body of knowledge on agile methodology by determining to what degree agile ideals and XP are related to perceived worker stress and management trustworthiness. Data collection for this study was completed over a seven-week period via a survey instrument designed for software engineers and agile practitioners (N =134) primarily working in distributed work environments. From the analysis of the data, the authors confirmed that a relationship between adherence to the agile manifesto, values, and XP practices. They further found that trust was higher and stress was lower, with increased adherence to agile values and increased utilization of XP practices. The results signify a beneficial relationship with trust satisfaction and reduced stress. These results could have strong implications if this relationship were to be established as causal. Additional research is required to fully understand how these factors impact stress and trustworthiness.

Introduction

In today's environment of rapid change, organizations evolve in ways that are hard to predict. In the aftermath of the pandemic, organizational leaders and change management practitioners have been challenged to swiftly manage complex projects and work arrangements. Likewise, software engineers are challenged to develop and produce ever more complex solutions faster to support rapidly evolving work (Thomke & Reinertsen, 2012). Gartner (2023) reported that the average organization has undergone five large-scale change initiatives in the past three years and that 75% of enterprises will assume even more change projects in the next three years. Cultivating the ability to meet changes, adapt, and even thrive under pressure are preferred outcomes of managing change, whether through an improvement to an organizational process, software application, or developing a new product (Society for Human Resources Management, 2017).

Managing organizational change is an ongoing and evolving challenge. The goal of this current study was to better understand agile as a means of enabling change within the software development industry and to evaluate the impact of agile adherence on perceived management trustworthiness and employee stress. As organizations continue to adopt agile methods, workers are encouraged to collaborate with team members and rely on relationship trust, particularly as organizations embrace distributed work models. Working collaboratively often requires work-sharing, which can be stressful for some employees because of issues around free-riding and sharing of rewards and recognition. Due to the collaborative environment advocated by proponents of agile, its methods may be related to stress and trust in distributed work environments. Researching various agile methods and their relationship with stress and trust could benefit organizations, because reducing stress in the workplace and increasing trust could positively impact business outcomes, job satisfaction, and employee tenure (Venkatesh, Thong, Chan, Hoekle & Spohrer, 2020).

Development of Agile

To adapt to a changing environment and maintain high quality output, software developers have adopted agile principles, methods, and practices. The Waterfall method was introduced in 1970 and revolutionized the software industry because it brought standardization to software development. As explained by Sacolick (2022), "The Waterfall manufacturing method was derived from Henry Ford's 1913 assembly line innovations, which provided certainty about each step in the production process to ensure the final product matched what was originally specified." The Waterfall development process required a business analyst to:

1. Write business requirements
2. Provide documents that captured what the business needed from an overall strategy
3. Develop comprehensive functional specifications
4. Create visual user interface designs

Traditional Waterfall development advocates for planning from beginning to end before customers see the final product (Martin, 2017) and, in an era of fast-paced change, this has led to criticisms of the Waterfall method. The level of documentation required before any coding and production outcomes were possible led to excessive delays for customers to evaluate the product and accept or change requirements. Over time, managers determined that the traditional Waterfall system needed streamlining (Sacolick, 2022).

The experience gained from the Waterfall method led to the introduction of the *Agile Manifesto* in 2001 (Sacolick, 2022). As explained by Hohl et al. (2018), "In 2001, agile methodology was introduced after 17 technologists gathered to write four major tenets for agile project management." The four tenets documented their shared beliefs about how a modern software development process should operate and became known as the agile manifesto. The agile manifesto can be summarized as follows (Hohl et al., 2018; Stellman & Greene, 2014):

- Individuals and interactions are more important than processes and tools.
- Working software is more important than comprehensive documentation.
- Customer collaboration is more important than contract negotiation.
- Responding to change is more important than following a plan.

Unlike the Waterfall method, the agile manifesto stressed relationship over documentation, self-organization rather than strict management practices, customer value, and the capability to oversee continual adjustments rather than adhere to an inflexible Waterfall operations process (Sacolick, 2022; Saddington, 2020). Additional thought leadership refined the agile manifesto's mindset into specific values and practices. Stellman and Greene (2014) explained the agile values emphasizing team communication, simplicity, feedback (iterative development), courage, and respect. As an elaboration of the agile manifesto, agile values explicitly note that developers should communicate with teams, find the most straightforward solution, incorporate iterations and tests during development rather than just prior to delivery to the client, allow debate to make the best choices for the project, and acknowledge that all team members are valuable to the project. This differs from the Waterfall method in which developers work from start to finish in an insular fashion, create a solution and then hand it over to testing to ensure that it meets customer requirements (Martin, 2017). Agile values make it clear that all team members are to collaborate with each other and the customer in order to stay focused on the most elegant, effective solution.

Furthermore, Stellman and Greene (2014) explained the practice of extreme programming, known as XP, to further delineate agile practices. XP includes 13 specific practices that developers are expected to use when creating software. XP is popular because it enables dual-learning opportunities through paired programming and creating redundancy (less potential for loss of project knowledge), while facilitating teamwork (Stellman & Greene, 2014). Table 1 provides key agile terms and the 13 tenets of the XP methodology.

Agile Viewed as a Change Method

Various studies explored the role of agile and its application within organizational change initiatives. Martin (2017) recognized that change is endemic to the modern workplace rather than an event that can be planned for and executed, as previously presented (Lewin, 1958; Schein, 1988). Therefore, agile is entirely in line with management goals to find means of enabling the organization to renew itself and succeed in a turbulent environment, while focusing on customer value (Denning, 2019). Agile is also considered to be a method that can be broadly applied, even in concert with other programs such as lean and Six Sigma (Flumerfelt, Bella Siriban-Manalang & Kahlen, 2012) and the capability maturity model integration (Henriques & Tanner, 2017).

However, practitioners face a significant challenge in setting the stage for adopting agile methodology and realizing its benefit (Martin, 2017). Denning (2019) provided ten steps to use agile as a change methodology; from focusing on value, to implementing agile practices, to achieving agile fluency. Denning's work provided valuable context for how companies should approach this organizational shift; however, the type of agile method being used is another point of consideration when determining if it works. Jules and Worley (2020) addressed this question from the perspective of agile organizational change. They challenged agile organizations and practitioners to become "change fluent," as they acknowledged the discontinuity of change events, confronted previously undiscussable issues, and evolved organizational culture in service of change.

Agile Effectiveness in Software Development

Scholars have examined the effectiveness and penetration of agile methods and practices in software development. Stavru (2014) and Könnölä, Suomi, Mäkilä, Jokela, Rantala, and Lehtonen (2016) demonstrated that agile practices constitute a significant part of the techniques used in software development. Maruping, Venkatesh, and Agarwal (2009) provided an excellent foundation for examining agile software development research over the early 2000s. The researchers examined conditions in which agile practices are most effective in improving software project quality. Results from this work suggest that agile methodology positively influences software development quality, and that bug severity is impacted by a three-way interaction between control, agile methodology, and requirement change (Maruping et al., 2009). This type of research aids practitioners and leaders in understanding which agile methods work best.

Qumer and Henderson-Sellers (2008) described the Agile Software Solution Framework to aid in aligning agile processes with the business values. Similarly, Calo, Estevez, and Fillottrani (2010) focused on understanding which agile methods best adhered to the agile manifesto and values. The researchers developed a framework to evaluate how well each of the methods adhered to the agile manifesto.

Table 1. Definition of agile terms.

Key Term	Definition
Agile	A set of methodologies that allow teams to work efficiently. Agile is also a mindset, as how it is utilized affects how effective the practice is (Stellman & Greene, 2014, p. 2).
Agile Manifesto	Common values and ideas that lead to effective teams (Stellman & Greene, 2014, p. 38). "Individuals and interactions over processes and tools." "Working software over comprehensive documentation." "Customer collaboration over contract negotiation." "Responding to change over following a plan."
Agile Values	Five values that enable teams to adopt XP effectively (Stellman & Greene, 2014, pp. 195-196). Communication: Each team member is aware of the work everyone else is doing. Simplicity: Developers focus on writing the most simple and direct solutions possible. Feedback: Constant tests and feedback loops keep the quality of the product in check. Courage: Each team member is focused on making the best choices for the project, even if it means having to discard failing solutions or approach things differently Respect: Every team member is important and valuable to the project.
Agile Methodology	A collection of practices combined with ideas, advice, and a community of practitioners (Stellman & Greene, 2014, p. 46).
Kanban	An agile method for improving the way that a team builds software (Stellman & Greene, 2014, p. 44)
Scrum	An agile method where software is built using timeboxed iterations (Stellman & Greene, 2014, p. 86).
Extreme Programming (XP)	13 primary practices, divided into five categories (programming, integration, planning, team and holistic) help to guide teams through software development (Stellman & Greene, 2014, pp. 178, 249). The 13 primary practices are: Test-Driven Development: Building an automated test before writing code Paired Programming: A set of two programmers that develop code together, virtually or physically Developing User Stories: A way to express one very specific need that a user has 10-Minute Build: An automated build for the entire codebase that runs in under 10 minutes Continuous Integration: A practice that teams use to let many people work on a single set of source code files simultaneously Incremental Design: A technique that allows programmers to design a system that is complete and easy for the team to modify as the project changes Weekly Cycle: A one-week iteration, and this practice works closely with the stories practice Quarterly Cycles: A quarterly meeting where the team meets to take a look strategically at the project Slack Planning: Adding minor, lower-priority stories to each weekly cycle Sitting Together: Team members sit near each other and have easy access to everyone else on the team Create Informative Workspace: The team's working environment is set up to automatically communicate important project information to anyone nearby Whole Team Practices: Helping the individuals on the team come together as a whole. When they encounter obstacles, they work together to overcome them Energized Work: Establishing an environment where every team member is given enough time and freedom to do the job.

The researchers concluded that XP is more consistent with the properties of the agile manifesto than other agile methods. The findings of this literature are highly valuable to understanding agile XP efficacy and support focusing on the 13 XP practices, as opposed to scrum (Calo et al., 2010) or Kanban (Stellman & Greene, 2014). Therefore, the authors focused on XP methodology. Similarly, Ghani, Bello, and Bagiwa (2015) found that "the highest percentage of respondents say that agile approaches increased managers, developers, and customers' satisfaction significantly, which indicates that IT organizations should embrace agile methods more." Importantly, four key challenges to success that Ghani et al. (2015) noted are addressed by the agile manifesto, namely, communication, coordination, cooperation, and collaboration, all of which facilitate software development under conditions of fast-paced change. Some scholars criticize the agile literature for being slow to inform practitioners about how agile implementation and management of projects leads to value generation. Estler, Nordio, Furia, Meyer, and Schneider (2014) compared agile to structured (Waterfall) methods across 66 projects to investigate how software development methods impacted overall project success. They conclude that, "The collected data shows that the correlations between process type and other measures are negligible and without statistical significance: choosing an agile rather than a structured process does not appear to be a crucial decision for globally distributed projects" (Estler et al., 2014). While some scholars criticize the redundancy inherent in XP teams (Beecham, Sharp, Baddoo, Hall & Robinson, 2007; Melo, Cruzes, Kon & Conradi, 2011), others note that the redundancy may make agile unsuitable for the most volatile projects (Syed-Abdullah, Holcombe & Gheorge, 2006). Thus, there is need for additional research, given the conflicting views of agile effectiveness.

A likely cause of these conflicting findings is the lack of a consistent definition of agile. Table 1 shows how a conceptualization can form the basis for a coherent definition of the agile manifesto, values, and practices (Stellman & Greene (2014). As more practitioners adhere to a common definition and measurement of agile adoption, more rigorous evaluation of agile will be possible. To that end, the authors of this current study examined whether the Stellman and Greene conceptualization could be applied to quantify agile adoption.

Agile, Perceived Trustworthiness of Management, and Perceived Employee Stress

The potential of agile to facilitate change and deliver value invites examination of agile adherence as it relates to perceived trustworthiness of management and perceived work stress. Kokate, Gaikwad, and Nayakwadi (2016) noted that trustworthiness of management and stress are relatively unexplored in relation to agile. In their research model, the authors directly stated that, "Historically, well-being in [a] software system development group has been seen as necessary, however not as necessary as the product prepared." Yet, Buvik and Tkalich (2022) demonstrated the critical importance of trustworthiness among high-performing agile development teams in terms of project quality and speed. Therefore, trustworthiness and stress merit additional exploration as they relate to agile. The authors of this current study used the Mayer and Davis (1999) conceptualization of trustworthiness as the combination of perceived ability, benevolence, and integrity. The World Health Organization (WHO, 2021) offers a helpful definition for understanding work stress: "A response an individual may have when presented with work demands and pressures that are not matched to their knowledge and abilities and which challenge their ability to cope."

Several thought leaders (Dirks & Ferrin, 2001; Colquitt & Rodell, 2011) conceptualized trustworthiness as having affective and cognitive components. The affective component invokes a personal connective that provides the foundation for a trusting relationship. The cognitive component relies on an expectation that the trust target is reliable, has integrity, is predictable, and will tell the truth. Mayer and colleagues (Mayer, Davis, & Schoorman, 1995; Mayer & Davis, 1999) developed the three-dimensional "ABI" model of trustworthiness that includes Ability (competence), Benevolence (considering the well-being of others), and Integrity (adhering to ethical principles). The ABI model has been widely influential and is supported by numerous studies, showing that the perception of a trust target's possession of these three traits constitutes perceived trustworthiness of management (Colquitt & Rodell, 2011; Davis, Schoorman, Mayer & Tan, 2000; Dirks & Skarlicki, 2009; Ferrin, Bligh & Kohles, 2008; Kim & Benbasat, 2006; Kim & Benbasat, 2003; Mayer & Davis, 1999; Mayer & Gavin, 2005).

Hence, the ABI model provides a useful framework for understanding trustworthiness in the workplace and other settings. Utilizing ABI to evaluate perceived trustworthiness of management enables further exploration of the role of trustworthiness among agile developers and provides a proven metric for assessing trustworthiness.

The fast pace of change has itself become a stressor, and software development is no exception. The concept of change fatigue has emerged in response to the frequency of organizational interventions (Bernerth, Walker & Harris, 2011) and refers to the phenomenon that occurs when an organization engages in too many changes over time, leading employees to feel overwhelmed and stressed. It is important to note that employees can distinguish between stress caused by the pace of change and stressful changes resulting from managerial incompetence (i.e., a lack of ability) (Bernerth et al., 2011). When changes are frequent, but well-planned and executed, employees may feel challenged and energized by the prospect of growth and development.

However, when changes are poorly communicated or implemented, employees may experience stress and frustration, leading to decreased trustworthiness and a reluctance to embrace future changes. Given that agile methods are designed to enable rapid change but also provide a structure for effective execution, exploring stress among developers whose work methods adhere to agile methods may prove illuminating. Indeed, stress mitigation recommendations, such as communicating effectively with employees and involving them in the change process, are part of agile methods. Hence, adherence to agile methods should likely reduce perceived stress.

Research Questions

To address the expectations and criticisms of agile development, the authors of this current study utilized a set of variables to tease apart the impact of adherence to the agile manifesto, agile values, and agile practices, as they relate to trustworthiness and work stress.

1. Can use of agile methods be captured by quantifying adherence to the agile manifesto, agile values, and agile XP practices?
2. Is there a relationship between agile and trustworthiness of management?
3. Is there a relationship between agile and stress?

As previously presented, the foundation for practicing agile methods begins with the agile manifesto. Agile values build upon ideas of the agile manifesto, and XP practices are a set of ceremonial steps or processes that practitioners engage in to complete the work and are an example of an implementation of agile values. Figure 1 summarizes these three concepts and their relationship to stress and trustworthiness, which was the focus of this current research project.

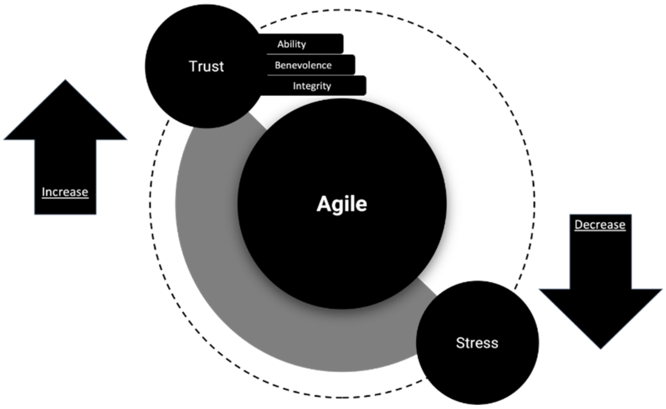

Figure 1. Agile XP, stress, and trust logic model.

Research Methods

In this study, the authors developed a survey to gather data. Data collection occurred over a seven-week timeframe. Participants were extended an invitation to participate in the study via email or Slack channel. The data for the study were collected through distribution of a Qualtrics survey that began with a pre-screening question to acquire the participants' informed consent. Data were protected in line with requirements defined by the University Institutional Review Board. Participants were recruited from five software engineering companies, a project management association, and an agile association. These groups were selected because of their varying degrees of experience applying agile practices, methodologies, and distributed work environments. It was expected that companies with varying levels of experience with agile would prevent range restriction on constructs of interest. Table 2 shows that the five software engineering companies that participated in the study ranged from small to large. The size of the respective companies that participated in the study were classified using the Small Business Administration's table of size standards (SBA, 2022).

The first of these companies had less than ten associates and utilized agile methodologies to a moderate degree. The second and third companies employed roughly 50 associates each and also used agile methodologies to varying degrees. The fourth company also had approximately 50 associates, but practiced a high degree of agile methodologies, specifically agile XP practices. The fifth company was a startup that had 1450 associates and utilized agile methodologies to a lower degree. Table 2 shows that the survey was also distributed to a project management company and an agile association, both of which had over 10,000 associates/members who worked in organizations of all sizes.

In this study, the authors intentionally sampled participants from companies that used contrasting approaches to agile to evaluate how it affected stress and trust. As a deliberate measure, two different companies (n = ~30 and n = ~41, based on the pattern of responses and characteristics reported by participants) with different levels of agile methodology penetration were selected to better understand how organizational factors affect results in the exploratory analyses that follows. This ensured that there was some variation in agile adherence within the sample.

Table 2. Company size.

Company Size as Number of Employees	Frequency	Percent
< 10	2	2
11-24	2	2
25-99	41	43
100-499	3	3
500-999	2	2
1,000-4,999	30	32
5,000+	15	16
Total	95	100

Participants reflected the characteristics of employees in most software development firms (SBA, 2022) and included software engineers, project/product owners, project/product managers, and other agile practitioners who employed agile methods. Most participants were under 40 years of age, with 52% of the respondents reporting an age of 30-39, and 22% of respondents reporting an age of 18-29. Most participants held bachelor's degrees (69%), and an additional 25% of the respondents had master's degrees. Males represented 71% of the sample, with 76 participants describing their race as white. Regarding participants' occupation, 35 respondents listed themselves as managers, 51 as individual contributors, and 21 as internal/external consultants. Table 3 details participant demographics. Figure 2 and Table 3 illustrate that sample respondents indicated that they were predominantly engaged in remote work.

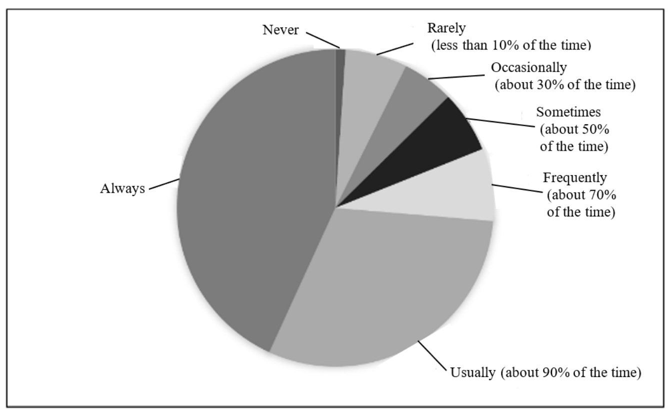

Figure 2. Extent of remote work from the collected sample.

It was necessary to develop an instrument that included original questions to quantify adherence to the agile manifesto, agile values, and agile XP practices. Figure 3 illustrates the selected constructs of each of the concepts used in this study. A measure of adherence to the agile manifesto was developed using the four principles, as defined by Stellman & Greene (2014; see Table 1). The measure was scored using a sliding scale ranging from 0 to 100 to indicate the extent to which participants adhered to the agile manifesto in their work processes. A lower score in this area indicated low adherence to the agile manifesto, while a higher score indicated high adherence to the agile manifesto. This scale demonstrated acceptable psychometric properties (Cronbach's alpha = .79).

Table 3. Participant demographics.

Demographic Category	Frequency	Percent
Gender		
Male Female	67	71%
Prefer not to answer	25	26%
Total	3	3%
	95	100%
Age		
18-29	21	22%
30-39	28	30%
40-49	23	24%
50-59	13	14%
60-69	6	6%
Prefer not to answer	4	4%
Total	95	100%
Education		
High school graduate	8	9%
Associate's degree	3	3%
Bachelor's degree	54	57%
Master's degree	23	25%
Doctorate	6	6%
Total	94	100%
Occupation		
Manager	35	30%
Individual Contributor	51	44%
Consultant	21	18%
Educator	5	4%
Researcher	2	2%
Student	2	2%
Total	116	100%
Remote Work		
Never	1	2%
Rarely (<10%)	6	6%
Occasionally (~30%)	5	5%
Sometimes (~50%)	6	6%
Frequently (~70%)	7	7%
Usually (~90%)	29	31%
Always (100%)	41	43%
Total	95	100%

A measure of adherence to agile values was developed using the five values, as defined by Stellman and Greene (2014; see Table 1). The measure was scored using a sliding scale ranging from 0 to 100 to indicate the extent to which participants adhered to the agile values in their work processes. A lower score in this area indicated low adherence to the agile values, while a higher score indicated high adherence to the agile values. This scale demonstrated acceptable psychometric properties (Cronbach's alpha = .87). A measure of adherence to agile XP practices was developed using the 13 practices defined by Stellman & Greene (2014; see Table 1). The measure was scored using a sliding scale ranging from 0 to 100 to indicate the extent that participants utilized each of the agile XP practices in their work processes. A lower score in this area indicated low adherence to agile XP practices, while a higher score indicated high adherence to the agile XP practices. This scale demonstrated acceptable psychometric properties (Cronbach's alpha = .89).

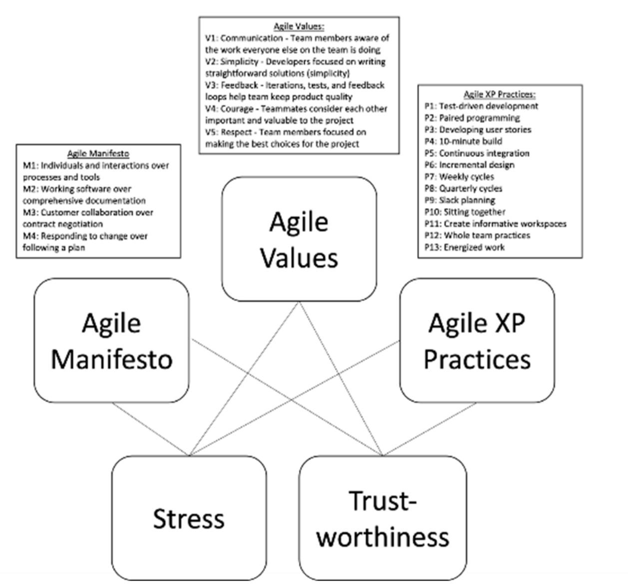

Figure 3. Agile manifesto, values, and XP practices and their relationship with trust and stress.

The SIG scale (Yankelevich, Broadfoot, Gillespie & Gillespie, 2011) was selected to measure stress due to the availability in the U.S. of normative data from 2009, which enabled a comparison of participant stress levels to the U.S. population. Participants completing the SIG responded to eight questions that measured general job stress. The SIG scale utilized the options "yes," "no," or "?" for participants to describe their jobs using the short words or phrases in the SIG. Specific questions are available in the appendix. The responses collected for these survey items were coded in accordance with Brodke et al. (2009) such that scores ranged from 0 to 3 with a higher score indicating a higher degree of stress. This scale demonstrated acceptable psychometric properties (Cronbach's alpha = .79).

The ABI measure of trustworthiness (ability, benevolence, and integrity) was used due to its wide adoption (Mayer & Davis, 1999). Participants were instructed to think about their organization's top management, when responding to each of the 17 items. Participants utilized a Likert scale ranging from 1 (disagree strongly) to 5 (agree strongly), where a higher score indicated higher levels of trustworthiness in top management— such as "Top management tries hard to be fair in its dealings with others." This scale demonstrated acceptable psychometric properties (Cronbach's alpha = .97).

Descriptive Statistics and Data Cleaning

Data were cleaned prior to analysis (i.e., incomplete answers were removed and responses were converted to numerical codes according to SIG instrument procedures). Additionally, data were checked for outlier values, though none existed. There were no straight-line responses and no out-of-range values were detected. Negatively worded items were reverse scored. These steps were followed to ensure high-quality information for further analysis. Finally, scores were calculated for each measure from their respective items. Table 4 presents their descriptive statistics.

Table 4. Descriptive statistics.

Measure	N	Mean	SD
Trustworthiness	93	3.70	.85
Stress	97	.99	.80
Agile Manifesto	103	76.3	16.4
Agile Values	100	78.5	16.9
XP Practices	56	58.7	21.0

Table 5 shows that the items on the agile manifesto scale were moderately correlated, ranging from .43 - .45. Table 6 shows that items on the agile values scale were moderately correlated, ranging from .50 - .67. Positive correlations were immediately observed, but negative correlations could not be disregarded; therefore, two-tailed significance levels were used. Table 7 shows that the correlations among items measuring agile XP practices were more varied, ranging from .03 - .67. Tables 6-8 present correlations among the items within the agile manifesto, agile values, and XP practices, respectively, supporting the possible development of new measures of agile adherence.

Table 5. Agile manifesto correlations.

	M1	M2	M3	M4
Manifesto # 1: Individuals and interactions over processes and tools				
Manifesto # 2: Working software over comprehensive documentation	.55**			
Manifesto # 3: Customer collaboration over contract negotiation	.46**	.55**		
Manifesto # 4: Responding to change over following a plan	.45**	.53**	.43**	

** Correlation is significant at the 0.01 level (2-tailed).

Table 6. Agile values correlations.

	V1	V2	V3	V4
Value # 1: Team members aware of the work everyone else on the team is doing				
Value # 2: Developers focused on writing straightforward solutions (simplicity)	.58**			
Value # 3: Iterations, tests, and feedback loops help team keep product quality	.54**	.65**		
Value # 4: Teammates consider each other important and valuable to the project	.51**	.63**	.50**	
Value # 5: Team members focused on making the best choices for the project	.61**	.64**	.55**	.67**

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed

Descriptive Statistics and Data Cleaning

Table 8 illustrates the intercorrelations of the agile manifesto, agile values, and agile XP scales (relationships between agile and the other constructs are described below). The agile manifesto and agile values were strongly related, with a correlation of .50. Additionally, agile values and agile XP practices were strongly correlated with a correlation of .64. Interestingly, there was not a statistically significant relationship between the agile manifesto and agile XP practices. Tables 6-9 provide a summary of the results and suggest that adherence to the agile manifesto, agile values, and agile practices can be quantified using the items put forward in this research.

Table 8 tells us that, for the relationship between agile and other constructs, the agile manifesto was significantly positively correlated with trustworthiness (.54) and negatively correlated with stress (-.30). The agile values were positively correlated with trustworthiness (.57) and negatively correlated with stress (-.53). Finally, XP practices followed a similar trend, being positively correlated with trustworthiness (.54) and negatively correlated with stress (-.49). Interestingly, correlations between the agile manifesto, agile values, and XP practices were similar in magnitude to their relationship with trust and stress, suggesting that agile elements are strongly related to each other and to employees' perception of job stress and trustworthiness of management. These parallels lend direct support to research question #2 and research question #3 that there is a relationship between agile values and XP practices, and stress and trustworthiness (see Table 8). It could be that agile practices are decreasing stress and increasing trust, but it may also be the case that these environments were more open to agile because of higher trust and decreased stress level.

Table 7. Agile XP practices correlations.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
Practice # 1: Engage in Test-Driven Development	--												
Practice # 2: Engage in Paired Programming	.67**	--											
Practice # 3: Engage in developing user stories	.51**	.46**	--										
Practice # 4: Engage in the 10-minute build	.47**	.42**	.27*	--									
Practice # 5: Engage in continuous integration	.38**	.32**	.35**	.49**	--								
Practice # 6: Engage in incremental design	.53**	.38**	.49**	.47**	.62**	--							
Practice # 7: Engage in weekly cycles	.43**	.50**	.32**	.59**	.30**	.43**	--						
Practice # 8: Engage in quarterly cycles	.03	-.19	.10	.18	.11	.17	.03	--					
Practice # 9: Engage in slack planning	.28**	.22*	.35**	.26*	.26*	.24*	.32**	.22*	--				
Practice # 10: Engage in the practice of sitting together	.54**	.59**	.41**	.55**	.29**	.45**	.50**	.14	.46**	--			
Practice # 11: Engage in creating an informative workspace	.35**	.40**	.51**	.39**	.26*	.40**	.40**	.29**	.44**	.59**	--		
Practice # 12: Engage in whole team practices	.39**	.42**	.52**	.40**	.41**	.50**	.37**	.15	.32**	.49**	.54**	--	
Practice # 13: Engage in energized work	.28**	.31**	.40**	.31*	.40**	.47**	.36**	.25*	.23*	.30**	.46**	.53**	--

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

The causality of this relationship could be explored in future research studies. The implication of the findings suggests that adherence to agile, particularly agile values, and XP practices is associated with lower perceived job stress and higher perceived trustworthiness. This could be an important finding, particularly in increasingly distributed work environments that are becoming increasingly common and challenging to properly administer.

Table 8. Agile values, XP practices, and correlations with stress and trustworthiness.

	Agile Manifesto	Agile Values	XP Practices	SIG	ABI
Agile Manifesto	1				
Agile Values	.50**	1			
XP Practices	.16	.64**	1		
Stress	-.30**	-.53**	-.52**	1	
Trust-worthiness	.54**	.57**	.54**	-.49**	1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed)

To better understand how the agile manifesto, values, and XP practice measures relate to stress and trustworthiness, Table 9 presents the correlations for each scale as related to stress and trustworthiness. Differences among companies that were unrelated to agile adherence, stress, and trustworthiness were suspected to have the potential to influence these results (i.e., potential for confounding). Recall that one company of small size was a heavy user of paired programming, while the larger company was not as strict of an adherent to agile. Fortunately, each company could be identified using company size and use of paired programming, and each company provided a reasonable number of participants. Therefore, partial correlations were computed controlling for company size and then both company size and use of paired programming. Considering the agile manifesto, correlations were generally significant in the expected direction, albeit with some exceptions. The correlation between adherence to the agile manifesto and stress was no longer significant, when controlling for company size and the use of paired programming. In contrast, the trustworthiness measure retained significance with the agile manifesto.

In contrast, the correlations between agile values, stress, and trustworthiness were strong and in the expected direction. The correlations were only slightly attenuated by controlling for company size and the use of paired programming. Therefore, adherence to agile values has a robust

Table 9. Correlations of agile manifesto, values, and XP practices with stress and trustworthiness.

	Pearson Correlations		Controlling for Company Size		Controlling for Company Size and Paired Programming	
Agile Scale	SIG	Trustworthiness (ABI)	SIG	Trustworthiness (ABI)	SIG	Trustworthiness (ABI)
Manifesto Adherence	-.30**	.54**	-.15	.27	-.15	.27
Value Adherence	-.53**	.57**	-.36**	.42**	-.36**	.42**
XP Practice Adherence	-.52**	.54**	-.32*	.33*	-.42**	.37**

**: p<.01
±: Computed without item 2 "Engage in Paired Programming"

negative relation with stress and a positive relation with trustworthiness, as expected. Considering XP practices, correlations were generally significant in the expected direction with some exceptions, but they were again slightly attenuated when controlling for company size and the use of paired programming. Therefore, adherence to XP practices had a robust negative relation with stress and a positive relation with trustworthiness, as expected. In sum, this pattern of results suggests that trustworthiness and stress are meaningfully related to adherence, to agile values, and to XP practices.

Finally, the SIG scores from the respondents in this study were compared with the norms from the original 2009 SIG scale norms. Figure 4 reveals that, for the comparison of the 2009 SIG scale norms to the 2022 respondents, respondents generally experienced somewhat lower stress. These results are consistent with the research assumptions that adherence to the agile manifesto, agile values, and XP practices impact stress. Even though programing and development are considered to be stressful (Kropp, Meier, Anslow & Biddle, 2020), these programmers and other respondents in this sample (most of whom were utilizing some XP practices and had some adherence to agile principles) actually reported less stress than the general population. This could have important practical implications, as these practices may be of high value for decreasing stress and increasing trustworthiness.

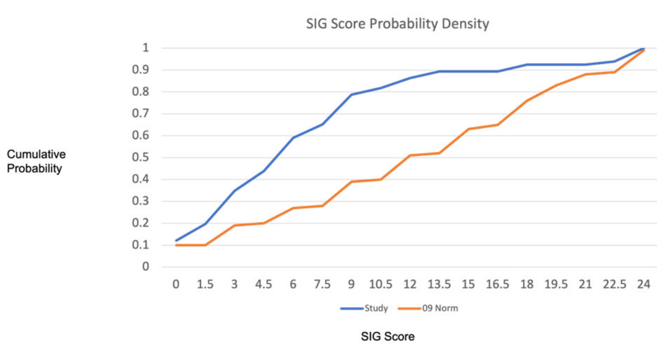

Figure 4. SIG score probability density comparing trust in this study versus the norms.

Discussion

In this study, the authors sought to understand adherence to the agile manifesto, agile values, and XP practices and usage as it relates to stress and trustworthiness in software development engineering environments. By conducting an in-depth research study on these variables, the data support the idea that agile method adherence and usage is related to increased trust and reduced stress. These results might have useful extensions to distributed work environments. Distributed environments can benefit from high levels of trust and, if agile practices are increasing trust within the organizations, agile can be an important tool in these environments, if they are able to decrease stress and increase trust.

The impact of organizational culture on adherence to agile can also be significant. Ghani et al. (2015) reported that agile adoption is strongly influenced by organizational culture and leadership. This finding is valuable, as it reveals important staff perceptions and their relationship to agile adoption, specifically in real-world, real-time organizational studies. As suggested in Table 9, the results signify a beneficial relationship with trust satisfaction and reduced stress. A positive organizational culture that supports and values agile methodologies can lead to higher levels of adherence, as individuals and teams are more likely to embrace and follow the practices and principles of agile. On the other hand, a negative organizational culture that is resistant to change or views agile as unimportant can lead to lower levels of adherence, as individuals and teams are less likely to engage with the practices and principles of agile. Within the software development environment this likely has profound negative consequences for software development performance.

Future work could explore differences in adherence to agile methodologies and their relation to individual, leader, or team characteristics. Such an analysis could help to identify differences in adherence to agile among different departments, teams, or individuals, and shed light on why these differences exist. By understanding the differences in adherence to agile and the impact of organizational culture, organizations can make data-driven decisions to improve their processes and practices, promoting a positive organizational culture and improving overall adherence to agile methodologies. This can lead to better results and improved organizational performance.

Consistent with Figure 1 and Table 9, the agile manifesto, practices, and values denote a relationship with reduced perceptions of stress and greater perceptions of trustworthiness. Therefore, as organizations proceed in adopting agile XP and other practices under the agile umbrella, (e.g., scrum, kanban, crystal) this instrumentation can be used to monitor the relationship between reduced stress and increased trustworthiness, or if the inverse is occurring (i.e., lower stress and a more trusting environment enables the adoption of agile). The instrument used to assess agile adherence here could be used as a starting point for additional research on adherence to agile practices. The way in which adherence to agile was operationalized in this current study could aid further research studies. By providing a strong foundation, other researchers can further refine the measure. Another advantage to having a measure of agile participation is having the ability to evaluate the extent to which individuals and teams are involved and engaged in the practices and principles of agile methodologies. The benefits of measuring adherence to agile include:

1. Improved accountability: To ensure that all team members are following the agreed-upon processes and standards, promoting accountability among team members.
2. Better visibility: To provide visibility into the effectiveness of agile practices, helping to identify areas for improvement and enabling teams to make data-driven decisions.
3. Improved collaboration: To promote collaboration by encouraging individuals and teams to work together more effectively and openly communicate their progress.
4. Enhanced product quality: To ensure delivery of high-quality products that meet customer needs and requirements.

Ultimately, these outcomes result in increased efficiency by identifying new opportunities where processes can be streamlined, thereby reducing waste and improving the overall efficiency of the team. Knowing how agile and XP practices adherence relates to stress and trust may give managers tools for impacting the levels of stress and trust within an organization. The benefits of learning about this relationship may result in:

1. Improved employee well-being: Having the ability to promote a healthier work environment, reducing stress, and improving employee well-being.
2. Stronger team relationships: Creating stronger relationships among team members by promoting collaboration and improving communication.
3. Enhanced organizational performance: Improving overall performance by promoting a healthy work environment and enabling stronger team relationships, thereby more effectively achieving company goals.

Companies can use this information to:

1. Evaluate their current agile practices and identify areas where they can improve adherence and reduce stress levels.
2. Promote transparency and open communication, helping to build trust among team members.
3. Improve employee satisfaction, reducing stress, and promoting a positive work environment.
4. Enhance collaboration and improve the overall effectiveness of their teams, especially as remote work environments continue to proliferate.

Additionally, the norm for stress in the workplace can help in the understanding of the impact of agile on workers and the workplace by providing a baseline for comparison. Understanding the norms for stress in the workplace allows organizations to measure the impact that agile methodologies are having on these important factors. If the adoption of agile methodologies results in increased stress levels among workers, it may indicate that the processes and practices are not well-suited to the needs of the organization or that they are not being implemented effectively. Conversely, if they lead to reduced stress levels, then they may be well-suited to the needs of the organization. By understanding the norms for stress in the workplace, organizations may be able to use this information to evaluate the impact that agile methodologies are having and make data-driven decisions to improve their processes and practices.

The norms available for comparison for SIG seem to indicate that there was a lower level of stress and a higher level of trust in these programming environments than in the general populace in 2009. This is a notable result, given that programming and development have a reputation for being indicative of a high-stress environment. If follow-up studies confirm that agile adherence and XP practices are driving this, this has important implications in the software development world, particularly as it relates to retaining the workforce. This can help to promote healthier distributed work environments, improve employee well-being, and enhance overall organizational performance.

If the adoption of agile methodologies results in increased trustworthiness, it may indicate that the agile approach is promoting open communication, transparency, and collaboration. This, in turn, can lead to better relationships among team members and improved organizational performance. This has great relevance for organizations that embrace distributed work models, because developing relationship trust across teams is a common problem that practitioners face. As trust in the ability of management and trust in the ability of the employee is a symbiotic relationship, adherence to agile values and XP principles may have significant positive implications for individuals working in organizations with distributed work environments.

Future Scope

Although the data demonstrated that adherence to agile values and utilizing agile XP practices is associated with decreased stress and increased trust, causality was not determined. That is, adherence to agile values and XP practices could lead to lower stress and higher trustworthiness, or lower stress and higher trustworthiness of management create an environment where agile values and XP practices are more easily adhered to. It was not possible to establish the causal nature of the relationships between the constructs in this study. Future research could seek to bridge this deficiency as the implications are significant for managers. Although different companies were specifically chosen to ensure variability on the measures of agile usage, future work should seek to capture more developers from a greater variety of organizations. When looking across each of the items, particularly in the correlation of agile manifesto, agile values, and XP practices with stress and trustworthiness when controlling for company size and paired programming, some of the significance disappeared as a function of the data (see Table 9). A larger sample from a more diverse population of software developers with varying degrees of agile usage could enable further refinement of the measures of agile adherence as well as the relationship between agile adherence, stress, and trust.

Conclusions

From this study, the authors showed that adherence to the agile manifesto, agile values, and XP practices was associated with higher levels of trust and lower levels of stress. The instrument designed for this study may be adapted by future researchers to analyze agile XP practices and other agile methodologies (e.g., scrum, kanban, test-driven development). The study added understanding of how adherence to the agile manifesto, agile values, and XP practices impact stress and trust. Future studies could build upon this data set by gathering a larger overall sample to expand the understanding of agile methodologies in business management and the potential significance of these relationships to the general population.

As future work improves upon the measurement of agile in the workplace, many assertions about the value of agile could be explored. For example, Tessem (2014) asserted that there is value in further exploring psychological and structural empowerment, especially in how these concepts related to job satisfaction and employee attrition. With a well-constructed measure of agile adherence, such assertions could be tested and causality ascertained. While there has been considerable research dedicated to the concept of agile, there is also extensive work that could be done. Future research dedicated to understanding how agile, trustworthiness, and stress affect productivity, job satisfaction, and employee retention could be of great interest and value to organizations. Furthermore, an interesting study could consider if agile methods improve technical skills, such as software coding practices and how agile methods affect leadership practices. Ultimately, more work around agile adherence measurement could prove to be very beneficial to both researchers and to organizations that are seeking understand how different leadership and change philosophies impact both individuals within organizations as well as the over performance of the organization. It could lead to the implementation of agile practices that make organizations better places for employees to work and lead to better overall organizational outcomes.

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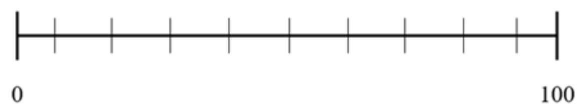
APPENDIX: THE INSTRUMENT

<u>Adherence to Agile Manifesto:</u>

Instructions:

In your day to work, please consider the extent to which you adhere to each question by using the sliding scale to answer each question.

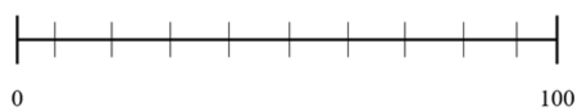


- To what extent does your organization prioritize individuals and interactions over processes and tools?
- To what extent does your organization prioritize working software over comprehensive documentation?
- To what extent does your organization prioritize customer collaboration over contract negotiation?
- To what extent does your organization prioritize responding to change over following a plan?

<u>Adherence to Agile Values:</u>

Instructions:

In your day to work, please consider the extent to which you adhere to each question by using the sliding scale to answer each question.



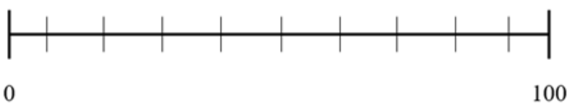
- To what extent is each team member aware of the work everyone else on the team is doing (i.e., communication)?
- To what extent are developers focused on writing the most direct and straightforward solutions possible (i.e., simplicity)?
- To what extent do Iterations, tests, and feedback loops help the team keep up the quality of the product (i.e., feedback)?
- To what extent does everyone believe that each of their teammates is important and valuable to the project (i.e., respect)?

- To what extent is each team member focused on making the best choices for the project, even if it means having to admit mistakes, discard failing solutions, approach things differently, or question management?

<u>Adherence to Agile XP Practices:</u>

Instructions:

In your day to work, please consider the extent to which you adhere to each question by using the sliding scale to answer each question.



- To what extent does your organization engage in Test-Driven Development?
- To what extent does your organization engage in Paired Programming?
- To what extent does your organization engage in developing user stories (i.e., starting cycles with a planning meeting and working with customers to select stories, then break down stories into tasks)?
- To what extent does your organization engage in the 10-minute build?
- To what extent does your organization engage in continuous integration?
- To what extent does your organization engage in incremental design (i.e., building up systems from small, reusable units)?
- To what extent does your organization engage in weekly cycles (i.e., one-week iterations)?
- To what extent does your organization engage in quarterly cycles (i.e., long-term planning sessions, once a quarter)?
- To what extent does your organization engage in slack planning (i.e., prioritization of major to minor "stories" or problems)?
- To what extent does your organization engage in the practice of sitting together?
- To what extent does your organization engage in creating an informative workspace (i.e., visual management through information radiators?)
- To what extent does your organization engage in whole team practices (i.e., working as a whole team)?
- To what extent does your organization engage in energized work (i.e., allowed time and freedom to do your job)?

<u>Stress in General:</u>

Instructions

Do you find your job stressful? For each of the following words or phrases below, select the option that best describes how much you agree or disagree with that statement.

Response:

Select: Y = Yes | N = No | ? = Cannot Decide

- Demanding
- Pressured
- Calm
- Many things stressful
- Hassled
- Nerve-Racking
- More stressful than I'd like
- Overwhelming

<u>Benevolence:</u>

Instructions

Think about your organization's top management [i.e., Director, VP etc.]. As you consider each statement, select the number that best describes how much you agree or disagree with that statement.

Response:

1 = Strongly Disagree | 2 = Disagree | 3 = Neither Agree nor Disagree | 4 = Agree | 5 = Agree Strongly

- Top management is very concerned about my welfare.
- My needs and desires are very important to top management.
- Top management would not knowingly do anything to hurt me.
- Top management really looks out for what is important to me.

<u>Ability:</u>

Instructions

Think about your organization's top management [i.e., Director, VP etc.]. As you consider each statement, select the number that best describes how much you agree or disagree with that statement.

Response:

1 = Strongly Disagree | 2 = Disagree | 3 = Neither Agree nor Disagree | 4 = Agree | 5 = Agree Strongly

- Top management is very capable of performing its job.
- Top management is known to be successful at the things it tries to do.
- The top management has much knowledge about the work that needs to be done.
- I feel very confident about top management's skills.
- Top management has specialized capabilities that can increase our performance.
- Top management is well qualified.

<u>Integrity:</u>

Instructions

Think about your organization's top management [i.e., Director, VP etc.]. As you consider each statement, select the number that best describes how much you agree or disagree with that statement.

Response:

1 = Strongly Disagree | 2 = Disagree | 3 = Neither Agree nor Disagree | 4 = Agree | 5 = Agree Strongly

- Top management has a strong sense of justice.
- I never have to wonder whether top management will stick to its word.
- Top management tries hard to be fair in dealings with others.

- Top management's actions and behaviors are not very consistent.
- I like top management's Values.
- Sound principles seem to guide top management's behavior.

Demographic Information:

What best describes your current position? (check all that apply)
- Manager
- Individual Contributor
- Consultant
- Educator
- Researcher
- Student

How many years of Agile experience do you have?
- I am not a manager
- 0-5 years
- 6-10 years
- 11-15 years
- 16-20 years
- 21-25 years
- 26-30 years
- 31+ years

At what level in the organization is your position?
- Executive Level (i.e., CTO, SVP, VP)
- Senior Level (i.e., Director, Sr. Manager)
- Mid-level Manager (Manager, Supervisor)
- Individual Contributor

What is your gender?
- Male
- Female
- Non-binary
- Other
- Prefer not to answer

What is your highest education level?
- High school graduate
- Trade School
- Associate's degree
- Bachelor's degree
- Master's degree
- Doctorate (e.g., Ph.D., ED.D., Psy.D. or other)
- Medical degree (e.g., MD, DO, or other)

Please choose one or more races that you consider yourself to be.
- American Indian or Alaska Native
- Asian
- Black or African American
- Hispanic/Latino
- Native Hawaiian or Other Pacific Islander
- Native American or Alaska Native
- White
- Two or More Races
- Other
- Prefer not to answer

Demographic Information:

Counting all locations where your employer operates, what is the total number of persons who work for your employer?
- Under 10
- 11-24
- 25-99
- 100-499
- 500-999
- 1,000-4,999
- 5,000+

What best describes the type of organization for which you work?
- For-Profit
- Non-Profit
- Government
- Higher Education
- Self-Employed
- Other

How would you best describe the industry group of your employer?
- Construction
- Education
- Engineering &, Technology
- Healthcare
- Manufacturing
- Professional and Business Services
- Public Administration
- Transportation, Warehousing, and Utilities
- Wholesale and Retail Trade

How often do you work from home (remote)?
- Never
- Rarely (less than 10% of the time)
- Occasionally (about 30% of the time)
- Sometimes (about 50% of the time)
- Frequently (about 70% of the time)
- Usually (about 90% of the time)
- Always

What is your current age range?
- 18-29
- 30-39
- 40-49
- 50-59
- 60-69
- 70+
- Prefer not to answer

What is your job title? (Insert response)

Benchmarking the Level of Project Managerial Inputs of Industrial Projects

Jiyong Choi, Central Connecticut State University; Namhun Lee, Central Connecticut State University

Abstract

Although benchmarking is widely recognized as a strategic tool that enables project stakeholders to enhance competitiveness through continuous improvement in project outcomes, there has been limited focus on measuring the level of fundamental managerial inputs from project teams as performance indicators. In particular, benchmarking the extent of management efforts could be highly beneficial for industrial projects, given the inherent complexities and unique challenges involved in their delivery. To address this gap, the authors of this current study developed a novel benchmarking approach tailored to evaluate core managerial functions within industrial projects focusing on planning, organizing, leading, and controlling (POLC). To fulfill the research goal, a panel of subject matter experts (SMEs) prioritized a variety of key practices associated with each function by project phase, which led to the development of a phase-based benchmarking framework designed to quantify the extent of POLC efforts on a project phase basis. With a sample of 104 phase-level data collected through the phase-based benchmarking questionnaires, the authors evaluated the implementation level of POLC functions and analyzed the levels with respect to project phase and type. In this paper, then, the authors delve into how the proposed framework can serve as a valuable tool for industrial projects, aiding in the enhancement of managerial efforts and ultimately contributing to successful project outcomes.

Introduction

The construction of industrial facility projects, including petrochemical plants, power generation facilities, and refineries, involves intricate processes. These projects typically exhibit significant physical scale and complexity, necessitating advanced technologies across disciplines such as civil, architectural, mechanical, electrical, instrumentation, and automation (Yun & Jung, 2017). Moreover, industrial facilities often integrate heavy equipment, requiring specialized installations to sustain production and distribution demands (Bubshait,2003). To address such unique challenges inherent in these projects, proficient managerial skills of project team members are imperative, which enables timely and effective decision-making, thereby achieving positive project outcomes (Choi, Yun, Mulva, Oliveira & Kang, 2015; Thamhain, 2004). Management can be defined as the science and art of planning, organizing, leading, and controlling organizational efforts and resources to attain organizational goals (Lloyd & Aho, 2020). To this end, in the construction industry, the principles of management—encompassing POLC—has been recognized as a fundamental framework guiding managerial responsibilities crucial for ensuring favorable project outcomes (Lamond, 2004; Yun, Choi, Oliveira, Mulva & Kang, 2016). However, there have been no previous studies aimed at measuring the level of POLC efforts in industrial projects.

Over the past few decades, performance benchmarking of capital projects has been extensively employed as a strategic tool for enhancing competitiveness through continuous improvement (Choi, Leite & de Oliveira, 2018; Choi, Leite & de Oliveira, 2020). Benchmarking is a systematic, data-driven process aimed at continuous improvement by evaluating performance to identify, achieve, and sustain best practices. The results allow organizations to establish improvement targets by pinpointing gaps in comparison to their peers, enabling changes that lead to improved project outcomes. In this regard, benchmarking is widely recognized as a key practice for managing capital projects and providing numerous benefits that contribute to the overall advancement of the construction industry (Choi et al., 2018). The majority of benchmarking approaches employed in construction projects involves tracking lagging indicators measuring cost, schedule, changes, safety, or productivity performance. As these indicators are typically evaluated after the completion of a project, they tend to limit project teams' ability to enact changes to project performance or outcomes while projects are still underway (Yun et al., 2016). Hence, benchmarking is still largely a tool for "looking in the rear-view mirror" after projects are already completed.

To address this limitation, some researchers have introduced leading indicators that can promote proactive management for improved project outcomes (Choi, Anderson & Kim, 2006). However, previous research has paid little attention to developing a comprehensive benchmarking framework for evaluating the performance of core managerial functions using leading indicators. In addition, previous benchmarking approaches tend to measure project performance after project completion rather than during the course of project execution. To fill this gap, the Construction Industry Institute (CII) developed a phase-based benchmarking framework for evaluating project team practices across phases by using key managerial inputs as leading indicators. Through this framework, industrial project leaders can conduct benchmarking at any phase using a set of phase-specific benchmarking questionnaires, enabling comparisons with preceding or subsequent phases and similar projects, thus ensuring anticipated progress. In this paper, the authors introduce a phase-based benchmarking framework for assessing POLC efforts in industrial projects and identifying industry norms associated with POLC functions across project phases and types.

Approach to Benchmarking Managerial Inputs

Each phase of the project management lifecycle defines specific project objectives, delineating results, deliverables, processes, and milestones. These phases can be determined by distinct beginning and end points and are characterized by typical participants and activities. In this current project, the authors adopted five major phases for industrial projects: Front End Planning (FEP), Engineering (ENG), Procurement (PRO), Construction (CON), and Startup (STA), following CII's phase definitions (Choi et al., 2015). Table 1 provides descriptions of these phases.

Table 1. CII's definitions of the start and end of industrial project phases.

Phase	Start	End
Front-End Planning (FEP)	Single project concept adopted & formal project team	Project authorization
Detailed Engineering (ENG)	Contract award to engineering firm	Release of all drawings & specifications
Procurement (PRO)	Development of procurement plan for major equipment	All major equipment delivered to site
Construction (CON)	Beginning of continuous substantial construction activity	Mechanical completion
Startup (STA)	Mechanical completion	Custody transfer

Figure 1 illustrates how the phase-based benchmarking framework was designed to measure the degree of managerial efforts during or at the conclusion of each phase in order to facilitate both phase-focused and phase-wide assessments. The phase-focused assessment evaluates the levels of POLC efforts at a specific phase and compares them with those of similar projects at the same phase. However, the phase-wide assessment assesses the levels over time and compares them with preceding or subsequent phases, which enables projects to gauge changes in the degree of managerial functions across phases. This two-dimensional benchmarking approach enables project teams to derive benchmarking benefits by assessing POLC efforts at specific phases and across different phases.

The evaluation of POLC inputs was conducted in two steps during each project phase. Initially, emphasis was placed on quantifying the level of POLC inputs by assessing the adequacy of activities or practices linked to POLC functions. This involved selecting and prioritizing key practices representing POLC functions, and subsequently transforming these practices into survey questions that respondents could readily answer. Interestingly, the survey instrument was designed to gather responses from multiple team members unanimously to evaluate the degree of POLC efforts derived from a single project. To this end, the distribution of individual responses from project team members can be detected, which provides insights into the alignment of team members within each phase.

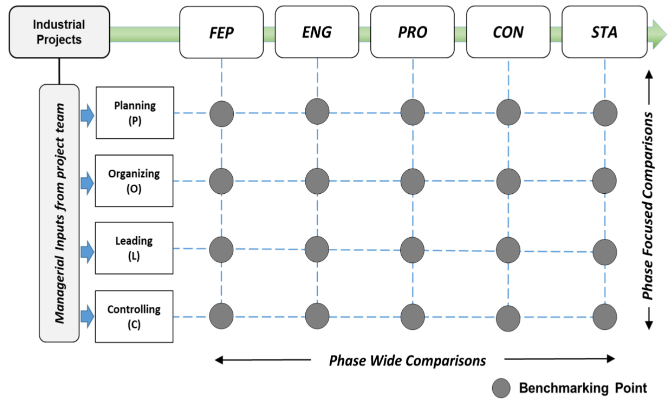


Figure 1. POLC benchmarking framework.

The next step involved aggregating individual responses into each of the POLC inputs by project phase. Through this process, each POLC function could be scored with a single numeric value, enabling quantitative evaluation of the level of POLC inputs within the organization. Moreover, the representative score of each function facilitated a comparison with similar projects within the industry and with other functions within the same project. Leveraging benchmarking results, the project team can devise proactive strategies to enhance POLC inputs in subsequent phases prior to project completion.

Selection of Key Practices and Development of Survey Questionnaires

Given the variation in main activities and personnel involved during each phase, the practices associated with POLC functions can differ. Through an extensive literature review, critical practices associated with each function were initially identified. Subsequently, the authors collaborated with a panel of industry experts to prioritize 100 key practices relevant to POLC in industrial projects. Examples of such practices included the implementation of craft or professional work-training programs, the effectiveness of project team meetings and problem-solving mechanisms, the appropriateness of project cash flow management and control systems, and the accessibility of project information.

These 100 leading indicators were then categorized into 12 types of management practices based on their managerial characteristics, namely project planning management, design management, procurement management, construction management, facility startup and operation management, human resource management, project organization management, business and project process management, project control management, safety/health/environment management, and information management. Finally, each practice categorized into one of these 12 types was mapped to one or more POLC functions. Figure 2 provides a schematic illustrating how the defined measures were linked to individual POLC indicators, focusing on practices in project planning management, business and project process management, and risk management categories as examples. The next section describes the development of phase-based benchmarking questionnaires using the identified key practices and the quantitative measurement of POLC inputs for benchmarking purposes. The prioritized practices were transformed into simple statement-based questions, answerable on five-point Likert scales (strongly disagree to strongly agree). The questions across the five questionnaires varied slightly to accommodate specific or unique practices conducted in each phase, and accordingly, a set of five questionnaires was developed to evaluate the degree of POLC efforts in the industrial projects.

Quantification of Leading Indicators

Before collecting data using the developed survey questionnaires, it was essential to establish a detailed procedure for quantifying the practices associated with each POLC effort and for scoring the overall level of POLC functions. The quantification of POLC scores involved three steps utilizing data collected from the questionnaires. First, point values were established for responses to questions, with "strongly disagree" assigned a value of 0 through "strongly agree" assigned a value of 5. Since the questionnaires were designed to collect responses from multiple team members from a single project, a practice score was captured by averaging the point values based on a variety of responses to a single question. Second, certain practices could have a more substantial impact on each POLC function than others. To address this issue, the weights were considered when calculating the scores of leading indicators. The weights were determined by industry experts through a series of workshops held at CII and CII events. On average, the experts

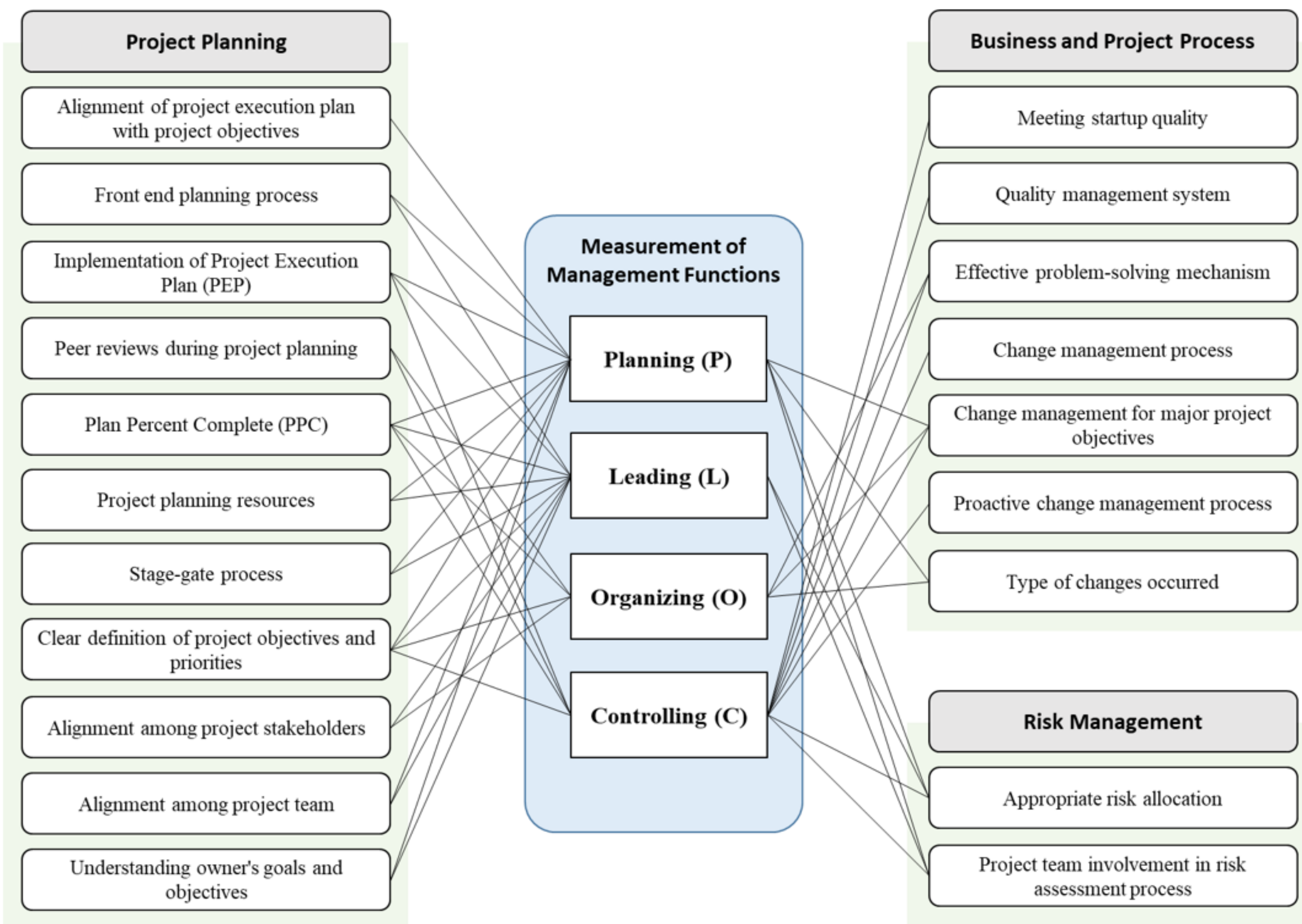


Figure 2. Linkages between leading indicators and POLC inputs (examples).

reported having over 20 years' of industry experience, with many having served as project managers or benchmarking analysts within their organizations or possessing specialized expertise in performance benchmarking. After the weights were determined, they were used to calculate an individual weighted score for each question (or practice). Thereafter, weighted scores of questions classified into a common leading indicator were aggregated in order to generate a single score for leading indicators.

Lastly, score normalization was performed to standardize the scores of leading indicators, ensuring they were on a common scale ranging from 0 to 100, regardless of their initial scale. To this end, high scores close to 100 represented a higher level of POCL efforts than did low scores.

Data Collection and Analysis

In 2013, CII initiated a phase-based performance assessment program, gathering project data from its member companies, which consisted of owners, contractors, and suppliers from top-tier business classes, via a web-based data-collection system. The dataset used in this study was extracted from CII's phase-based benchmarking database after a substantial amount of phase-level project data had been submitted from industrial projects. The dataset comprised a total of 434 phase-based project entries submitted by CII member companies. Table 2 illustrates the frequencies of the collected dataset categorized by main project types (i.e., processing and non-processing projects) and their subtypes.

Table 2. Frequencies of the collected project data by project types.

Project Type		Processing Projects	Non-processing projects	Total
Project Phase	FEP	82	31	113
	ENG	73	27	100
	PRO	59	34	93
	CON	53	34	87
	STA	19	22	41
Total	Count	286	148	434
	Percentage	66%	34%	100%

The primary objective of this study was to evaluate managerial inputs across various phases of industrial projects and their types. For analysis, the authors employed two distinct approaches: first, measuring and comparing leading indicators (managerial inputs) through phase-wide assessment; second, examining the indicators via phase-focused assessment while considering project types. Given the focus of this study, presenting findings from multiple comparative analyses across diverse groups, it was imperative to verify basic assumptions for statistical comparisons. Initially, an ANOVA was employed to ascertain whether there were differences in the means of POLC scores among project phases. ANOVA is a widely used technique, which focuses primarily on statistical correlation and estimation and is used to compare the variances between different groups based on sample data. Subsequently, as necessary, post hoc comparisons were performed using Tukey's HSD test to pinpoint which combination of project phases exhibited statistically significant differences.

Results of Phase-Wide Assessment

Table 3 presents the descriptive statistics of POLC scores across project phases, along with corresponding metrics. Mean values indicate the degree of implementation for each input, while standard deviation values represent the extent of variability in implementation levels. Test results indicated statistically significant differences in all managerial inputs across phases at a significance level of 0.05. Notably, organizing and leading practices consistently displayed higher mean values across phases compared to planning and controlling, indicating a greater dedication and alignment towards executing these practices among project team members. Organizing and leading primarily entail task arrangements and implementation plans to foster effective action among team members. Regarding phase implementation levels, the startup phase showed the highest mean value across all managerial inputs, whereas the procurement phase recorded the lowest mean values.

Table 3. Descriptive statistics and ANOVA results of managerial inputs by project phase.

Managerial Inputs	Project Phase	Mean	S.D.	F	Sig.
Planning	FEP	66.14	14.28	4.78	0.001
	ENG	64.72	10.37		
	PRO	62.85	15.26		
	CON	68.87	14.97		
	STA	74.78	17.20		
Organizing	FEP	76.53	12.62	4.07	0.003
	ENG	74.35	12.83		
	PRO	71.19	15.41		
	CON	75.26	11.36		
	STA	80.53	14.45		
Leading	FEP	72.59	12.32	5.18	0.001
	ENG	74.28	11.60		
	PRO	71.66	15.49		
	CON	73.08	13.62		
	STA	80.48	9.26		
Controlling	FEP	69.90	13.10	2.69	0.033
	ENG	69.00	12.41		
	PRO	66.27	17.13		
	CON	67.95	12.73		
	STA	75.00	13.86		

Note: S.D.= Standard Deviation

Table 4 provides a summary of the post hoc comparison results aimed at identifying significant differences between phases for specific managerial functions. For the planning function, the mean value of the startup phase was statistically higher than that of the front-end planning ($p = 0.043$), detailed engineering ($p = 0.008$), and procurement ($p = 0.003$) phases, at a significance level of 0.05. However, no statistical difference was observed between the construction phase and the startup phase at the same significance level. Regarding the organizing function, the mean values of the front-end planning ($p = 0.037$) and startup ($p = 0.002$) phases were significantly higher than that of the procurement phase. For the leading function, the startup phase exhibited a significantly higher mean value compared to other phases at the same significance level. Similarly, for the controlling function, the startup phase displayed a significantly higher mean value than the procurement phase ($p = 0.022$).

Table 4. Post hoc comparisons of managerial inputs by project phase.

Managerial Input	Phase (I)	Phase (J)	Mean Difference (I-J)	S.E.	Sig.
Planning	STA	FEP	8.64	3.01	0.043
		ENG	10.06	2.88	0.008
		PRO	11.93	3.12	0.003
Organizing	FEP	PRO	5.34	1.88	0.037
	STA	PRO	9.34	2.51	0.002
Leading	STA	FEP	7.89	1.96	0.001
		ENG	6.20	1.96	0.018
		PRO	8.82	2.26	0.002
		CON	7.40	2.17	0.008
Controlling	STA	PRO	8.72	2.82	0.022

Note: S.E.= Standard Error

Results of the Phase-Focused Assessment (by Project Type)

This section examines whether there are significant differences in the implementation levels of managerial functions across different project types. The various industrial project types were categorized into two groups: processing projects and non-processing projects. Processing projects encompassed chemical manufacturing, natural gas processing, and oil refining projects, while non-processing projects included electrical generating, oil, or gas exploration and production projects. Tables 5 and 6 display descriptive statistics of managerial functions' implementation levels and ANOVA results categorized by project phase and project type. Managerial functions that did not exhibit statistical differences between project types for a certain project phase were removed from those tables. Due to the small sample size (less than 20), comparisons for the startup phase were excluded.

Table 5. Descriptive statistics of managerial inputs by project type.

Phase	Managerial Function	Project Type			
		Processing		Non-processing	
		Mean	S.D.	Mean	S.D.
FEP	Organizing	77.97	12.35	72.68	12.75
	Leading	74.21	11.32	68.28	13.95
	Controlling	71.54	11.70	65.51	15.65
ENG	Planning	67.00	8.59	58.43	12.31
	Controlling	70.54	11.65	64.67	13.67
PRO	Planning	66.05	14.49	57.30	15.15
	Organizing	74.14	13.92	66.16	16.72
	Leading	74.09	14.65	67.25	16.22
	Controlling	69.98	16.31	59.84	16.82
CON	Organizing	77.23	10.36	72.21	12.28

Table 6. ANOVA results of managerial inputs by project type.

Phase	Managerial Function	F	Sig.
FEP	Organizing	3.94	0.050
	Leading	5.25	0.024
	Controlling	4.79	0.031
ENG	Planning	10.69	0.002
	Controlling	4.44	0.038
PRO	Planning	7.62	0.007
	Organizing	6.06	0.016
	Leading	4.17	0.044
	Controlling	8.15	0.005
CON	Organizing	4.06	0.047

Processing projects demonstrated higher implementation scores in mean values across the given categories in Table 5 compared to non-processing projects, indicating better alignment and implementation of managerial functions among team members in processing projects. In the front-end planning phase, organizing, leading, and controlling scores of processing projects exhibited statistically significant higher mean scores compared to those of non-processing projects at a significance level of 0.05. In the detailed engineering phase, processing projects showed statistically significant higher implementation scores than non-processing projects in planning and controlling at the same significance level. In the procurement phase, all managerial functions' implementation scores were statistically significant and higher in processing projects compared to non-processing projects. For the construction phase, organizing in processing projects exhibited significantly higher scores compared to non-processing projects at the same significance level.

Discussion

As mentioned previously, POLC functions are essential for enhanced project outcomes. Despite the identified significance of POLC efforts, they were rarely measured quantitatively throughout project delivery. To overcome the limitations, this authors presented a phase-based benchmarking framework that evaluated the level of POLC functions as leading indicators throughout project delivery from FEP to STA phases. Using the industry norms for POLC inputs assessed by project phase and project nature, the authors discuss here the potential applications for use of the benchmarking outcomes. The implementation level of POLC functions was assessed using various key practices developed in this study. The benchmarks measured at each phase can serve as early warning indicators, enabling managers to establish proactive strategies to enhance their projects' capabilities in addressing managerial challenges during each phase, in subsequent phases, or in future projects. In this paper, the authors explore the potential application of utilizing POLC scores from a benchmarking perspective.

Figure 3 illustrates the distribution of planning scores for processing projects across each phase, utilizing quartile rankings to assess the implementation level of planning function relative to those of all other processing projects. The distribution shows the mean planning score (♦) along with four quartiles. The first quartile represents the top 25% of projects with the best performance, while the fourth quartile includes the bottom 25% with the poorest performance. Industry practitioners can use this distribution of planning scores to benchmark their projects' implementation of planning practices against the industry norm.

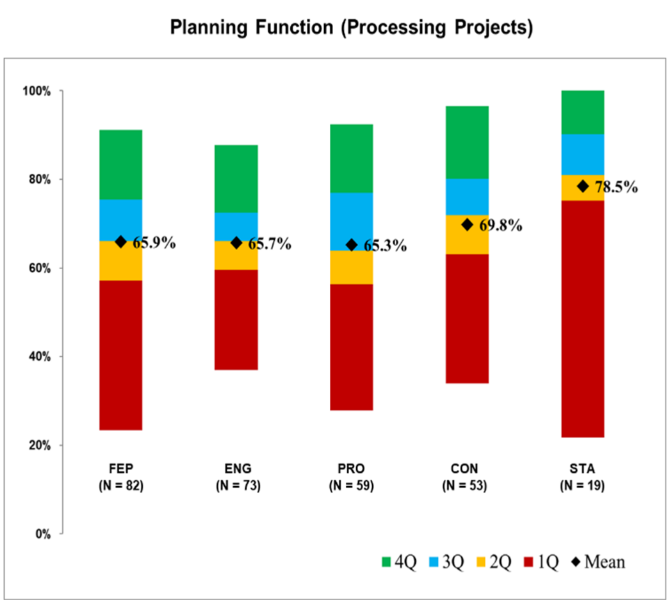


Figure 3. Distribution of planning scores in processing projects.

This distribution can also be used for a phase-wide evaluation of planning practices across a project's phases. The phase-wide assessment enables industry practitioners to identify which project phase requires more planning efforts, allowing them to develop proactive strategies to enhance organizational capabilities in subsequent or future project phases. Figure 3 shows how the distribution of planning scores can be compared across project phases. On average, it indicates that the level of planning effort in processing projects is comparatively lower during the FEP (65.9), ENG (65.7), and PRO (65.3) phases, and improves during the CON (69.8) and STA (78.5) phases. This research lays the groundwork for an advanced benchmarking approach designed to measure managerial inputs across different phases and promote proactive strategies for performance improvement. Practically, the findings can help managers identify opportunities to assess and enhance a project's POLC performance by comparing it with similar projects. Additionally, the results can guide the development of targeted strategies to improve managerial performance.

Conclusions

Project benchmarking serves as a strategic tool offering valuable insights to various stakeholders and avenues for sustainable growth. However, existing studies in the construction domain primarily rely on lagging indicators to assess project performance post-completion. The authors of this current study introduced a phase-based benchmarking framework focused squarely on evaluating managerial capabilities while projects are in progress. It assesses four leading indicators: planning, organizing, leading, and controlling, using data from 434 industrial phase-based projects. Phase-wide and phase-focused assessments were conducted, considering project type.

This study contributes to construction benchmarking by introducing a phase-based framework assessing managerial capabilities. It highlights four leading indicators, presenting the current status of industrial projects based on project phases. Moreover, the framework lays a foundation for a proactive tool guiding managerial direction and optimizing implementation levels for better project performance outcomes. Future research should explore the relationship between managerial functions and project performance outcomes. Despite its contributions, this study has limitations. Insufficient sample sizes for certain project characteristics necessitated their exclusion from statistical analyses, underscoring the need for additional data collection to assess managerial function implementation across a wider array of industrial projects.

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