Data-Driven Identification of Managerial Archetypes to Enhance Leadership Effectiveness in Agile Project Management

Joy April C. Andes[1,*], Ellen Joy Latina[2]

[1,2]Rizal Technological University, Philippines

ABSTRACT

This study explores the use of data-driven analysis to identify distinct managerial profiles that influence the success of Agile project management. Using a dataset of Agile project performance indicators, the research applied machine learning clustering techniques, dimensionality reduction, and explainable artificial intelligence to uncover patterns in managerial behavior and project outcomes. The analysis revealed three unique managerial archetypes: Efficient & Strategic, Risk-Controlled, and Agile-Driven. Each archetype represents a different balance between leadership involvement, operational efficiency, and strategic control. The results show that Agile project success can emerge from multiple managerial configurations rather than a single standardized model. Projects emphasizing governance and cost efficiency perform well under structured oversight, while those focusing on risk management achieve stability in complex environments. The most mature Agile projects demonstrate strong leadership engagement and team collaboration, resulting in high adaptability and consistent performance. These findings highlight that organizational agility depends on aligning management practices with contextual and strategic needs. The study contributes to Agile management research by demonstrating how machine learning can serve as a decision-support tool for identifying managerial maturity, guiding process improvement, and optimizing leadership strategies in dynamic project environments.

Keywords Agile Management, Machine Learning, Data-Driven Decision Making, Managerial Archetypes, Leadership

Submitted: 12 December 2024
Accepted: 5 February 2025
Published: 3 May 2025

Corresponding author
Joy April C. Andes,
jaandes@rtu.edu.ph

Additional Information and Declarations can be found on page 153

INTRODUCTION

Agile project management has emerged as a dominant framework for managing complex and uncertain projects in both software development and broader organizational contexts [1]. Its core principles of flexibility, collaboration, and iterative delivery have enabled teams to adapt more effectively to changing customer requirements and technological developments [2]. Organizations adopting Agile methodologies aim to increase responsiveness, improve stakeholder satisfaction, and reduce the risks associated with long planning cycles. Despite its widespread adoption, the success of Agile implementation varies significantly between organizations. Some achieve sustained performance improvements, while others struggle with inconsistent outcomes. This inconsistency suggests that project performance depends not only on following Agile techniques but also on how leadership, decision-making, and strategic control are exercised within Agile teams [3].

The growing emphasis on agility as a managerial capability has led researchers to explore the role of leadership and management practices in shaping Agile outcomes. While the principles of Agile management promote team autonomy

How to cite this article: J. A. C. Andes and E. J. Latina, "**Data-Driven Identification of Managerial Archetypes to Enhance Leadership Effectiveness in Agile Project Management**," *Agile Manag.*, vol. 1, no. 2, pp. 139-154, 2025.

and adaptive planning, they also require an appropriate balance of governance and control to ensure accountability and alignment with organizational objectives [4]. Achieving this balance is not uniform across organizations, as contextual factors such as culture, resource availability, and risk tolerance influence how Agile methods are applied. As a result, different managerial styles may produce different types of Agile performance, making it necessary to identify and understand these variations systematically. However, existing research has primarily approached this topic using qualitative case studies and conceptual frameworks, which provide valuable insights but lack the capacity to generalize patterns across large datasets.

Recent advances in artificial intelligence and data analytics have created new possibilities for studying management practices through a quantitative and evidence-based approach. Machine learning methods, particularly clustering algorithms, have been increasingly used to identify hidden structures and behavioral patterns within organizational data [5]. In project management research, these techniques have been applied to forecast timelines, assess risks, and optimize resource allocation. Nevertheless, current studies often focus on the technical aspects of project prediction and control rather than examining the managerial dimensions that influence project performance. This gap limits the understanding of how managerial configurations contribute to Agile success. The lack of empirical studies that connect data-driven modeling with management theory represents a critical opportunity for expanding the analytical scope of Agile research.

The state of the art in Agile management now calls for hybrid methodologies that integrate data science with managerial insight. While traditional management studies have examined leadership effectiveness, team performance, and decision-making through survey-based or descriptive methods, contemporary research suggests the potential for artificial intelligence to complement these approaches. The application of clustering and explainable artificial intelligence offers a systematic means to identify managerial archetypes and uncover the factors that differentiate successful Agile projects from less effective ones. Such methods make it possible to move beyond anecdotal evidence and develop empirically grounded models of managerial behavior. However, despite the growing interest in data-driven management, few studies have empirically analyzed how leadership engagement, efficiency, and strategic control interact to influence Agile project outcomes.

This study aims to address these limitations by employing a data-driven approach to explore the managerial structures that define Agile project success. Using a dataset of Agile project performance indicators, the research applies clustering analysis, principal component analysis, and SHAP (SHapley Additive Explanations) to identify distinct managerial profiles that capture variations in leadership and operational practices. The results reveal three archetypes that represent different balances between efficiency, control, and adaptability, providing a new perspective on how management influences Agile performance. By integrating machine learning with managerial theory, this research contributes to a more systematic understanding of Agile management and offers practical guidance for organizations seeking to improve their project strategies through evidence-based decision-making.

Literature Review and Related Works

Agile project management has gained widespread recognition as an adaptive framework that enables organizations to manage complexity, uncertainty, and frequent change in project environments. Studies have consistently highlighted its capacity to improve responsiveness, communication, and customer satisfaction compared to traditional project management methods [6]. Agile principles promote iterative development, collaborative decision-making, and continuous improvement, yet their success depends on how effectively organizations integrate these principles with managerial practices [7]. Several studies have emphasized that leadership involvement, organizational culture, and team autonomy are crucial for the successful adoption of Agile practices [8]. However, performance outcomes often vary significantly between organizations, suggesting that different managerial configurations can influence the degree of Agile maturity and success [9].

Existing research has explored the factors that contribute to Agile success, identifying leadership style, risk management, and governance mechanisms as key drivers [10]. Although this literature provides valuable insights, it is often based on qualitative case studies and survey-based analyses that focus on descriptive observations rather than empirical classification. These approaches have limited ability to detect deeper structural patterns that explain why certain managerial configurations perform better in specific contexts [11]. There is therefore a growing need for data-driven approaches that can systematically identify managerial patterns and link them to project outcomes. Such methods would allow researchers and practitioners to move beyond subjective interpretation and establish more objective, evidence-based foundations for understanding Agile management performance.

The integration of artificial intelligence and machine learning into project management research has created new opportunities for performance assessment and predictive analytics. Machine learning algorithms have been successfully applied to estimate project effort, predict risks, and monitor performance metrics in Agile environments [12]. These applications have enhanced forecasting accuracy and supported decision-making, but most studies focus primarily on technical or process-oriented aspects rather than managerial behavior [13]. Furthermore, the interpretability of machine learning models remains a challenge, limiting their practical use in managerial decision-making contexts where transparency and explainability are required [14].

Explainable Artificial Intelligence (XAI) has emerged as a key innovation to address this limitation by providing insight into how machine learning models make predictions. XAI helps translate complex algorithmic results into understandable information that managers can use to inform decisions [15]. Within project management, explainable models have been explored to clarify which variables most influence project success and how they interact to shape outcomes [16]. This shift toward interpretability aligns with the need for managerial accountability and better understanding of the relationships between performance indicators and leadership practices. However, few studies have combined XAI with unsupervised learning methods such as clustering to uncover hidden managerial archetypes that shape Agile project success [17].

Clustering techniques, as a core component of unsupervised machine learning, have proven effective in segmenting projects, teams, or organizations based on behavioral or performance characteristics. Applications of clustering in software and project management have revealed useful groupings that inform process optimization, resource allocation, and risk mitigation [18]. By identifying underlying patterns in performance data, clustering allows researchers to detect similarities and differences that may not be apparent in traditional analyses. However, the use of clustering to identify managerial profiles within Agile project management remains limited, representing a significant gap in current research [19]. Addressing this gap requires integrating clustering with explainable models to connect data patterns with managerial interpretation, thereby enhancing the practical relevance of machine learning for project leadership and decision support [20].

In summary, prior studies have advanced the understanding of Agile project management and artificial intelligence applications, but few have combined these perspectives to produce interpretable, data-driven models of managerial behavior. The current research builds on this gap by applying clustering and explainable AI techniques to identify and interpret distinct managerial archetypes in Agile environments. This approach contributes to both the theoretical understanding of management diversity in Agile contexts and the practical development of decision-support tools for organizations seeking to improve their Agile maturity.

Methodology

This study adopted a quantitative, data-driven methodology to identify and interpret distinct managerial archetypes within Agile project environments. The methodological framework combines classical statistical analysis, unsupervised machine learning, and explainable AI to derive both predictive and interpretable insights. The workflow of the research is illustrated in figure 1, which outlines the sequential analytical process beginning with data preprocessing and feature engineering, followed by clustering and validation, dimensionality reduction, and finally, interpretability analysis using explainable AI. Each stage in this pipeline was designed to ensure transparency, reproducibility, and analytical rigor while enabling meaningful managerial interpretation of data-driven results. The analysis was conducted in Python using the Pandas, NumPy, Scikit-learn, Seaborn, Matplotlib, and SHAP libraries.

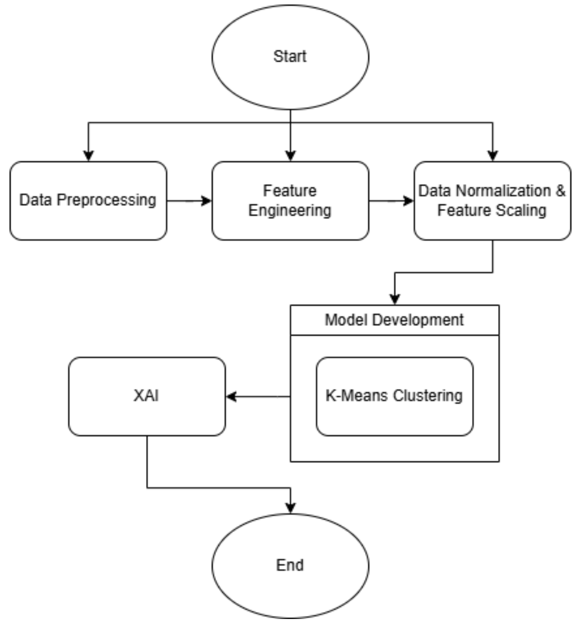

Figure 1 **Research Steps**

The dataset employed in this research consisted of Agile project performance indicators representing both operational and managerial dimensions. Each observation corresponded to a distinct project, characterized by quantitative metrics such as Agile Effectiveness, Risk Mitigation, Management Satisfaction, Supply Chain Improvement, Time Efficiency, and Cost Savings (%). These variables were selected because they reflect fundamental elements of Agile management, including adaptability, leadership engagement, process performance, and strategic control. Upon importing the dataset, exploratory data analysis was performed to examine completeness, consistency, and potential outliers. Missing values were handled using mean or median imputation, and all features were converted into numerical formats compatible with machine learning models. Outlier detection was performed using standardized z-scores, ensuring that extreme values did not distort the clustering process.

Feature engineering was conducted to enhance the representativeness of managerial relationships by creating composite indicators that captured both direct and interaction effects among features. The Efficiency Index (EI) was defined as the average of Time Efficiency (TE) and Agile Effectiveness (AE), representing operational agility:

$$EI = \frac{TE + AE}{2} \tag{1}$$

The Leadership Impact (LI) was calculated as the mean of Management Satisfaction (MS) and Risk Mitigation (RM), capturing the influence of leadership and managerial engagement:

$$LI = \frac{MS + RM}{2} \tag{2}$$

Cross-dimensional interaction variables were also introduced to represent synergistic managerial effects. The Operational Synergy (OS) measured the interaction between Supply Chain Improvement (SCI) and AE:

$$OS = SCI \times AE \tag{3}$$

The Strategic Control (SC) indicator captured the combined influence of financial oversight and risk awareness, defined as:

$$SC = RM \times CS \tag{4}$$

CSrepresents Cost Savings (%). Lastly, the Performance Synergy (PS) variable was derived from the interaction of Efficiency Index and Leadership Impact, representing the alignment between operational performance and managerial influence:

$$S = EI \times LI \tag{5}$$

These engineered variables enabled a richer and more holistic representation of managerial performance dynamics, allowing the model to capture nonlinear and higher-order interactions that are characteristic of Agile environments.

Before clustering, all quantitative variables were standardized to ensure uniform contribution to distance-based algorithms. Since the features were measured on different scales, normalization was applied using z-score standardization, expressed as:

$$z_i = \frac{x_i - \mu}{\sigma} \tag{6}$$

$x_i$is an observation, $\mu$is the mean, and $\sigma$is the standard deviation of the corresponding variable. This transformation produced normalized features with zero mean and unit variance, ensuring comparability across all dimensions.

The K-Means clustering algorithm was employed to segment projects into groups with similar managerial and performance characteristics. K-Means is an iterative optimization algorithm that minimizes the within-cluster Sum of Squared Errors (SSE), formulated as:

$$\arg\ \min\ \mathrm{C} \sum_{i=1}^{k} \sum_{x_j \in C_i} \| x_j - \mu_i \|^2 \tag{7}$$

$C_i$denotes the set of observations in cluster i, $\mu_i$represents the cluster centroid, and $x_j$is an observation. To determine the optimal number of clusters (k), two diagnostic methods were used: the Elbow Method and the Silhouette Coefficient. The Elbow Method identified the value of $k$where the SSE reduction began to plateau, indicating diminishing returns in model fit improvement. The Silhouette Coefficient, defined as:

$$s = \frac{b - a}{\max{(a, b)}} \tag{8}$$

Was used to validate the cohesion and separation of clusters, where

$a$represents the mean intra-cluster distance and $b$represents the mean distance to the nearest neighboring cluster. Higher silhouette scores indicate well-separated and cohesive clusters. Both methods consistently indicated that three clusters ($k = 3$) provided the most meaningful segmentation of the data.

Following model fitting, projects were assigned to one of the three identified clusters. The mean values of all managerial and operational metrics were computed for each cluster to produce a Cluster Summary Table, which served as the basis for interpreting managerial archetypes. The resulting clusters were visualized using a heatmap, which displayed comparative strengths across indicators, followed by a Principal Component Analysis (PCA) for dimensional reduction and visualization. PCA transformed the high-dimensional data into two principal components that captured the majority of the dataset's variance. The transformation is mathematically expressed as:

$$Z = XW \tag{9}$$

$X$is the standardized data matrix, $W$is the matrix of eigenvectors derived from the covariance matrix of X, and Zrepresents the transformed two-dimensional component space. The resulting PCA plot displayed three distinct clusters, providing visual confirmation of the segmentation and validating the heterogeneity of managerial behavior across Agile projects.

While K-Means clustering effectively segments data, it does not inherently indicate which variables most influence cluster formation. To address this limitation, an XAI approach using SHAP was implemented. A Random Forest Classifier was trained on the scaled features to predict cluster membership, and SHAP values were computed to quantify the marginal contribution of each variable to the model's output. SHAP values are derived from cooperative game theory and measure the average contribution of a feature across all possible combinations, mathematically expressed as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \tag{10}$$

$\phi_i$represents the SHAP value for feature i, $N$is the set of all features, $S$is a subset excluding i, and $f(S)$denotes the model's prediction based on subset S. The resulting SHAP summary plot ranked features by their relative influence, revealing that Performance Synergy, Efficiency Index, and Management Satisfaction Level were the most significant contributors to cluster differentiation. This interpretability step transformed the clustering output into actionable managerial insights.

Finally, the complete dataset, including all derived variables and cluster assignments, was exported to an Excel file titled Agile_Clustered_Profiles_Final.xlsx to support further managerial analysis and replication. Random seeds were fixed throughout the process to ensure reproducibility of results. Overall, the integrated methodological design enabled a structured identification of managerial archetypes, balancing computational precision with managerial interpretability. By combining K-Means clustering, PCA visualization, and SHAP explanation, the study provides a robust analytical framework that connects artificial intelligence techniques with practical Agile management insights.

Algorithm 1: Data-Driven Agile Project Segmentation

Input: Dataset $D = \{x_1, x_2, \ldots, x_n\}$containing Agile project indicators Feature set $F = \{AE, RM, MS, SCI, TE, CS\}$

Output: Cluster assignments $C = \{C_1, C_2, C_3\}$ Feature importance values ϕ_i

Process:
Start

Data Preprocessing

For each feature $f_j \in F$: If missing, replace with mean value Standardize using

$$z_{ij} = \frac{f_{ij} - \mu_j}{\sigma_j}$$

Feature Engineering

Construct new managerial indicators:

$$EI = \frac{TE + AE}{2}$$
$$LI = \frac{MS + RM}{2}$$
$$OS = SCI \times AE$$
$$SC = RM \times CS$$
$$PS = EI \times LI$$

Update feature set $F' = F \cup \{EI, LI, OS, SC, PS\}$

Determine Optimal Number of Clusters

For $k = 2 \text{to } 10$:

Apply K-Means clustering

Compute within-cluster sum of squares:

$$SSE(k) = \sum_{i=1}^{k} \sum_{x_j \in C_i} \| x_j - \mu_i \|^2$$

Compute Silhouette Coefficient:

$$s(k) = \frac{b - a}{\max(a, b)}$$

Select $k^* = 3$based on Elbow and Silhouette results

Cluster Assignment

Apply K-Means with $k = k^*$

Assign each $x_i$to nearest centroid:

$$\text{assign}(x_i) = \arg\min_c \| x_i - \mu_c \|^2$$

Compute cluster means:

$$\bar{x}_c = \frac{1}{|C_c|} \sum_{x_i \in C_c} x_i$$

Dimensionality Reduction (PCA)

Compute covariance matrix

$$\Sigma = \frac{1}{n-1} Z^T Z$$

Find eigenvectors W

Transform data: $Z' = ZW$

Retain first two principal components for visualization

Explainable AI (SHAP)

Train Random Forest model $f(\cdot)$using features $Z$and labels C

Compute SHAP values for each feature f_i:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)]$$

Rank features by average absolute SHAP value | ϕ_i |
Identify top drivers: $\{PS, EI, MS\}$
End

Result

The clustering analysis was conducted to uncover meaningful managerial patterns within Agile projects using multidimensional performance and leadership indicators. Since the effectiveness of clustering depends heavily on the number of groups defined, determining the optimal number of clusters was a critical step in the analytical process. To achieve this, two complementary evaluation techniques were employed: the Elbow Method and the Silhouette Coefficient. Both techniques are widely recognized in machine learning and organizational analytics for balancing model interpretability with statistical accuracy. The Elbow Method was used to assess the rate of decline in the within-cluster SSE as the number of clusters increased, while the Silhouette Coefficient measured how similar each data point was to its assigned cluster compared to other clusters.

As presented in figure 2, the Elbow curve showed a pronounced bend at k = 3, suggesting that adding more clusters beyond this point yields only marginal improvement in model performance. In practical terms, this inflection indicates that the data's internal structure is best captured by three clusters, beyond which segmentation becomes less meaningful and potentially redundant. The steep decline in SSE between two and three clusters represents a significant improvement in compactness, whereas the gradual flattening of the curve after k = 3 demonstrates diminishing returns. This balance between parsimony and explanatory power supports the selection of three clusters as the most appropriate configuration for this dataset.

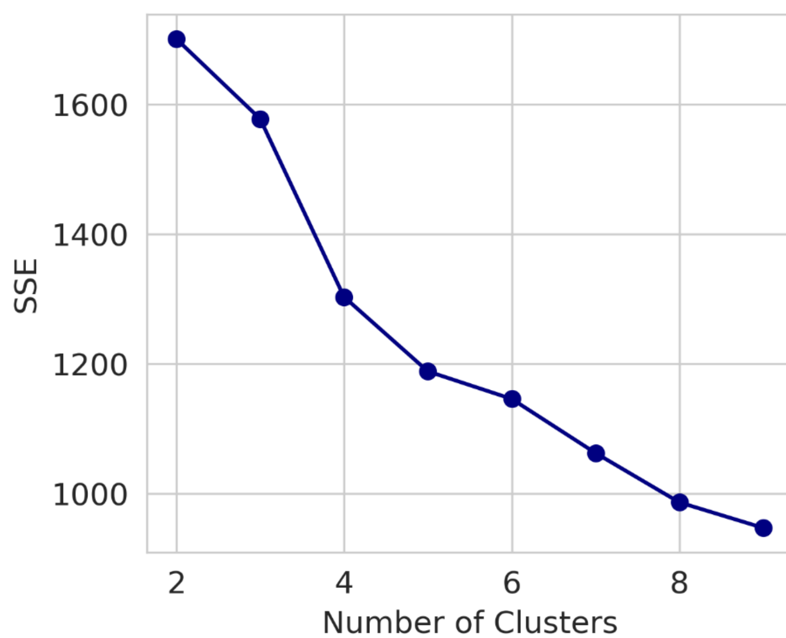

Figure 2 Elbow Method for determining optimal clusters

Figure 3 further strengthens the justification for selecting three clusters by illustrating the pattern of the Silhouette Coefficient across multiple cluster configurations. The Silhouette Coefficient quantifies the quality of clustering by measuring both the cohesion within each cluster and the separation between clusters. A higher coefficient indicates that projects within a cluster are closely related to each other while being distinctly different from those in other clusters. In this study, the coefficient reached one of its highest average values at k = 3, signifying that this configuration achieves a desirable balance between compactness and separation. This result suggests that projects grouped under the same cluster share strong managerial similarities in terms of performance indicators, leadership effectiveness, and operational focus, while projects assigned to different clusters demonstrate meaningful divergence in these managerial dimensions.

Minor variations in the Silhouette values were observed for higher numbers of clusters, but these differences were relatively small and lacked theoretical justification for further subdivision. Increasing the number of clusters beyond three would introduce additional complexity without providing new insights into the underlying managerial patterns. Such over-segmentation risks fragmenting conceptually similar projects into smaller, less interpretable groups. Therefore, the combination of the Elbow Method and Silhouette Coefficient results provides empirical support for adopting a three-cluster solution. This configuration preserves statistical robustness while maintaining conceptual clarity, ensuring that each identified cluster represents a coherent and meaningful managerial archetype within the Agile project dataset.

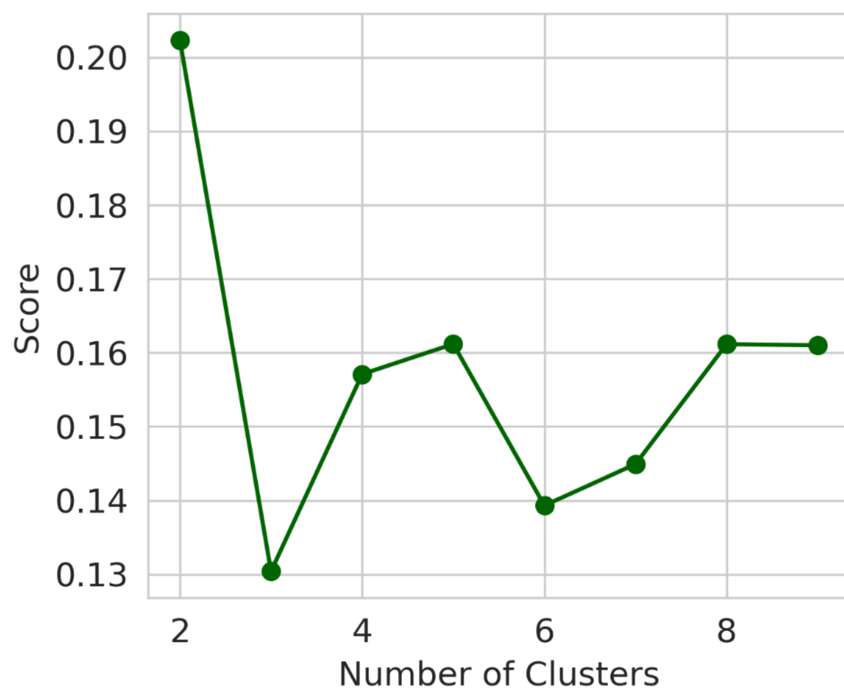

Figure 3 Silhouette Score for cluster validation

Based on the clustering metrics, the model identified three distinct managerial profiles among the Agile projects, consisting of Cluster 0 with 75 projects, Cluster 1 with 63 projects, and Cluster 2 with 62 projects. Figure 4 illustrates the average values of key managerial performance indicators for each cluster, providing a clear visual representation of the underlying patterns that differentiate them. Cluster 0, labeled Efficient & Strategic, is characterized by moderate levels of Agile Effectiveness (2.80) and Management Satisfaction (3.08) but relatively high scores in Strategic Control (80.85). This cluster represents projects that emphasize financial governance, structured coordination, and managerial oversight as the primary mechanisms for ensuring consistent outcomes. The management approach reflected in this cluster suggests that these projects operate within organizations that prioritize accountability, cost control, and process efficiency over flexibility or iterative experimentation.

Cluster 1, identified as Risk-Controlled, exhibits higher Risk Mitigation (3.71) and Strategic Control (117.41) while maintaining moderate scores in efficiency-related variables. This cluster typifies projects functioning in environments characterized by volatility or uncertainty, where systematic risk management and budgetary stability are key success factors. These projects appear to integrate Agile principles selectively, balancing adaptability with formal control to maintain project predictability. In contrast, Cluster 2, referred to as Agile-Driven, demonstrates the highest overall performance across nearly all dimensions, including Agile Effectiveness (4.15), Leadership Impact (4.03), and Strategic Control (122.06). Projects in this cluster exhibit high levels of collaboration, rapid response to change, and strong alignment between leadership and operational teams. This pattern indicates a mature Agile culture where management practices are oriented toward empowerment, innovation, and sustained delivery performance.

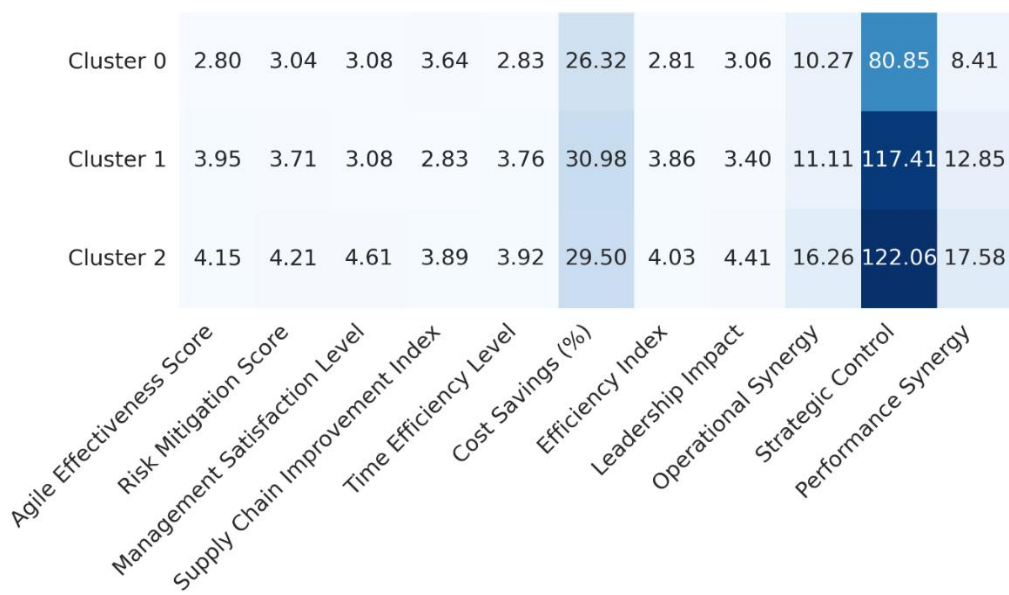

Figure 4 **Average managerial metrics by Agile project cluster**

To better understand the structural relationships among the identified clusters, a two-dimensional PCA was conducted to reduce the multidimensional managerial dataset into a simplified visual representation. PCA was chosen because it allows for an interpretable visualization of complex data while preserving the maximum possible variance from the original features. The first two principal components captured a substantial proportion of the total variance, ensuring that the reduced space adequately reflects the underlying data structure. As shown in figure 5, the resulting projection reveals that the three clusters occupy distinct regions within the two-dimensional plane, indicating that the clustering algorithm successfully captured inherent managerial differences across Agile projects. The spatial separation between these groups reflects meaningful divergence in performance and leadership characteristics, while the partial overlap of certain points demonstrates the continuous nature of management practices within Agile environments.

Closer examination of the PCA plot indicates that Clusters 0 and 1 exhibit moderate overlap, suggesting that projects emphasizing efficiency and those emphasizing risk control share several managerial similarities. Both clusters tend to focus on structured decision-making, consistent planning, and formalized control systems. However, Cluster 2 appears more distinct and concentrated in a separate region of the PCA space, highlighting its unique managerial orientation. Projects in this group display higher levels of adaptability, team autonomy, and leadership engagement, which collectively enhance their responsiveness to change. The positioning of Cluster 2 away from the other groups reinforces the interpretation that these projects represent a more mature and dynamic Agile environment. Overall, the PCA visualization validates the clustering process and provides empirical evidence that Agile project management can evolve along multiple strategic pathways, each characterized by different balances of control, risk management, and adaptability.

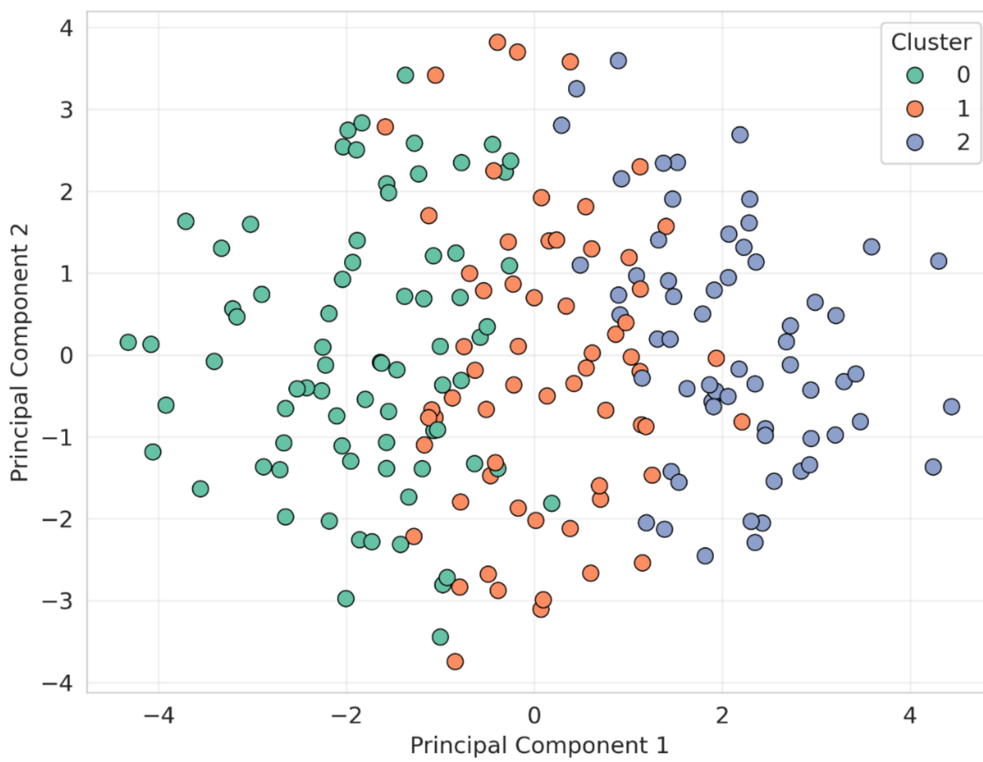

Figure 5 Two-dimensional PCA projection of Agile project clusters

To gain a deeper understanding of the variables that most strongly contributed to the differentiation among clusters, a SHAP analysis was conducted using a

Random Forest classifier trained on the cluster assignments. SHAP was selected because it provides a transparent and interpretable approach to explaining complex machine learning models by quantifying the contribution of each variable to the final classification. Figure 6 presents the relative importance of each managerial feature in determining cluster membership. The results reveal that Performance Synergy, Efficiency Index, and Management Satisfaction Level exert the greatest influence on the clustering outcome. This indicates that the interaction between operational efficiency and managerial leadership plays a decisive role in shaping project groupings. The presence of these variables as dominant predictors highlights the combined effect of performance coordination and leadership dynamics as a key driver of project differentiation in Agile contexts.

Further interpretation of the SHAP values provides insights into how specific managerial attributes are associated with the different clusters. Projects displaying higher Performance Synergy and Efficiency Index scores are more likely to belong to the Agile-Driven cluster, where strong collaboration and well-integrated processes contribute to enhanced agility and consistent delivery outcomes. In contrast, projects with moderate efficiency and stronger emphasis on financial control or risk mitigation are more frequently aligned with the Efficient & Strategic or Risk-Controlled clusters. These findings suggest that the interaction between leadership engagement and process efficiency distinguishes Agile maturity levels across project types. Collectively, the SHAP analysis validates the clustering model and provides empirical evidence that leadership quality and operational alignment are critical determinants of project success in Agile management environments.

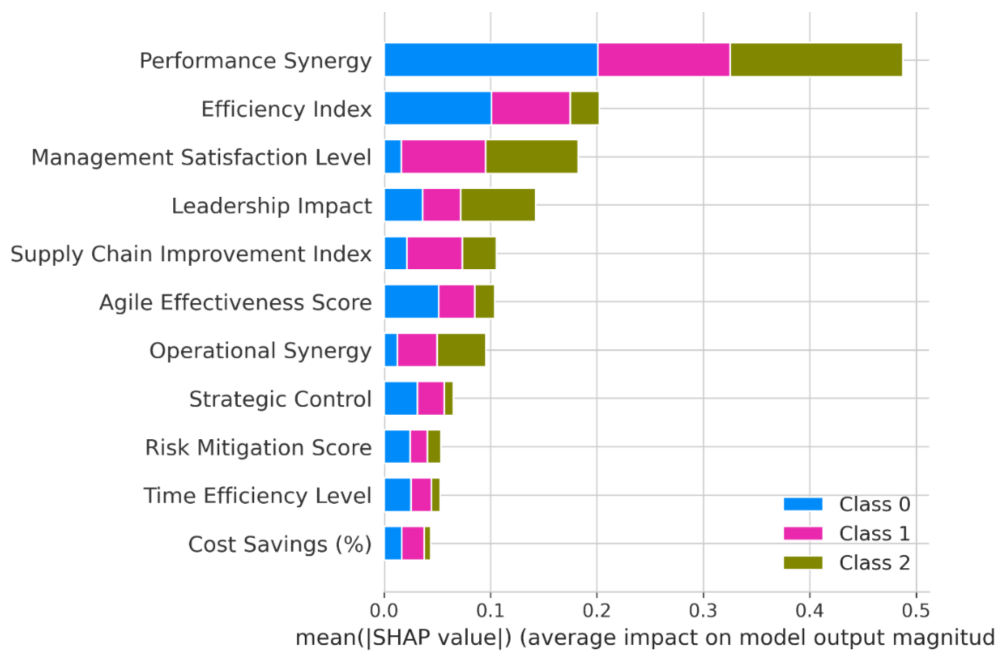

Figure 6 SHAP summary

In summary, the analysis identified three distinct managerial archetypes that represent different approaches to achieving success in Agile project environments. The first archetype, Efficient & Strategic, is characterized by a focus on financial governance, structured oversight, and a balanced yet moderate level of agility. These projects rely on efficiency, stability, and managerial control to deliver consistent outcomes. The second archetype, Risk-Controlled, emphasizes predictability, risk management, and disciplined decision-making to ensure reliable performance in complex or uncertain contexts. This approach reflects organizations that value planning accuracy and risk mitigation as central to their Agile implementation. The third archetype, Agile-Driven, represents the most mature form of Agile practice, where adaptability, strong leadership engagement, and continuous collaboration are deeply embedded in the project culture. Projects in this group demonstrate the capacity to respond quickly to change, leverage cross-functional teamwork, and align strategic intent with operational execution. Collectively, these three archetypes illustrate that Agile project success is not confined to a single management style but can emerge through multiple effective pathways, each suited to different organizational contexts. The findings reinforce the value of data-driven segmentation as a decision-support tool for managers seeking to align project strategies with leadership priorities, risk tolerance, and organizational maturity.

Discussion

The results of this study reveal that Agile project success can emerge through several distinct managerial configurations rather than through a single standardized model of practice. The three identified archetypes Efficient & Strategic, Risk-Controlled, and Agile-Driven represent different ways organizations balance leadership, operational efficiency, and strategic control to achieve desired outcomes. These archetypes demonstrate that Agile management is inherently adaptable, allowing organizations to tailor their practices to match internal structures and environmental conditions. The presence of multiple clusters indicates that successful Agile execution depends not only on methodological rigor but also on how management aligns decision-making processes, team autonomy, and risk-handling strategies with organizational priorities. The diversity across clusters also emphasizes that agility functions as a continuum of managerial maturity, where organizations evolve from efficiency-based coordination to more dynamic and leadership-driven forms of project delivery.

From a managerial standpoint, these findings highlight the importance of achieving balance between structure and flexibility in Agile project environments. Projects in the Efficient & Strategic cluster demonstrate that strong governance and cost discipline can coexist with iterative development, provided that leadership maintains transparency and adaptability. The Risk-Controlled cluster shows that Agile methods can be effectively implemented in uncertain or regulated environments when proactive risk management and process stability are prioritized. Meanwhile, the Agile-Driven cluster exemplifies the highest maturity level, where collaborative leadership and operational synergy enable rapid decision-making and continuous improvement. Together, these findings suggest that data-driven segmentation can serve as a practical tool for diagnosing project management maturity and guiding resource allocation. Managers can use this approach to identify which archetype best represents their current Agile practices and to plan targeted improvements in leadership engagement, team empowerment, and performance alignment to enhance overall project outcomes.

Conclusion

This study concludes that Agile project success is shaped by diverse managerial approaches that integrate leadership, efficiency, and strategic control in different proportions. Using data-driven clustering and explainable artificial intelligence, three distinct managerial archetypes were identified, each illustrating how organizational priorities influence Agile implementation. The Efficient & Strategic archetype reflects projects that rely on structured governance and cost discipline to achieve consistent results, while the Risk-Controlled archetype highlights the importance of proactive management and stability in uncertain environments. The Agile-Driven archetype represents the highest level of maturity, were leadership engagement and team collaboration drive adaptability and continuous improvement. These findings demonstrate that there is no single formula for Agile success; instead, effective project management depends on the ability to balance structure and flexibility in response to contextual demands. From a practical standpoint, the results offer managers a diagnostic perspective for assessing their organizational maturity and refining leadership practices to enhance project performance. By integrating machine learning as a decision-support tool, organizations can adopt more informed and adaptive strategies to align Agile principles with operational and strategic objectives.

Declarations

Author Contributions

Conceptualization: J.A.C.A. and E.J.L.; Methodology: E.J.L.; Software: J.A.C.A.; Validation: J.A.C.A. and E.J.L.; Formal Analysis: J.A.C.A. and E.J.L.; Investigation: J.A.C.A.; Resources: E.J.L.; Data Curation: E.J.L.; Writing Original Draft Preparation: J.A.C.A. and E.J.L.; Writing Review and Editing: E.J.L. and J.A.C.A.; Visualization: J.A.C.A.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] C. Koudriachov, C. Tam, and M. Aparicio, "Success with Agile Project Management: Looking back and into the future," *Journal of Systems and Software*, vol. 226, no. August, p. 112428, Aug. 2025. doi: 10.1016/j.jss.2025.112428

[2] A. A. ForouzeshNejad, F. Arabikhan, A. Gegov, R. Jafari, and A. Ichtev, "Data-Driven Predictive Modelling of Agile Projects Using Explainable Artificial Intelligence," *Electronics*, vol. 14, no. 13, Art. no. 2609, Jul. 2025. doi: 10.3390/electronics14132609

[3] H. Dong, N. Dacre, and D. Baxter, "What is Agile Project Management? Developing a New Definition Following a Systematic Literature Review," Project Management Journal, vol. 55, no. 1, pp. 32–48, 2024. doi: 10.1177/87569728241254095

[4] R. Steegh, K. Van De Voorde, and J. Paauwe, "Understanding how agile teams reach effectiveness: A systematic literature review to take stock and look forward," *Human Resource Management Review*, vol. 35, no. 1, p. 101056, Jan. 2025. doi: 10.1016/j.hrmr.2024.101056

[5] A. Khalfan Al Jabri and M. Khairul Islam, "The nexus between success factors and adoption of Agile project management methodology: A moderated perceived compatibility paradox from the Omani oil and gas sector," *Journal of Innovation in Project and Program Management*, vol. 8, no. 1, pp. 15–27, 2024. doi: 10.24294/jipd.v8i1.2621

[6] J. Sithambaram and M. H. N. B. M. Nasir, "A compilation of factors associated to the governance and management of agile projects: a systematic literature review," Malaysian Journal of Computer Science, vol. 34, no. 3, pp. 241–258, 2021. [Online]. Available: http://mojes.um.edu.my/index.php/MJCS/article/view/31486

[7] "Critical Success Factors and Challenges in Applying Agile," International Journal of Social and Organizational Dynamics in IT, vol. 5, no. 2, pp. 55–70, 2025.

[8] J. Highsmith, Agile Project Management: Creating Innovative Products, 2nd ed., Boston, MA: Addison-Wesley/Pearson Education, 2004.

[9] T. Dingsøyr, P. Schneider, G. R. Bergersen, and Y. Lindsjørn, "Challenges in Understanding the Relationship between Teamwork Quality and Project Success in Large-Scale Agile Projects," arXiv preprint, arXiv:2401.09092, Jan. 2024. [Online]. Available: https://arxiv.org/abs/2401.09092

[10] B. Leech and R. Hanslo, "The Evolution of Agile and Hybrid Project Management Methodologies: A Systematic Literature Review," arXiv preprint, arXiv:2311.04567, Nov. 2025. [Online]. Available: https://arxiv.org/abs/2311.04567

[11] V. Oza, P. Kettunen, P. Abrahamsson, and J. Münch, "Attaining high-performing software teams with agile and lean practices: An empirical case study," arXiv preprint, arXiv:1311.6933, Nov. 2013. [Online]. Available: https://arxiv.org/abs/1311.6933

[12] International Organization for Standardization, ISO 21500:2012—Guidance on project management. Geneva, Switzerland: ISO, 2012. [Online]. Available: https://www.iso.org/standard/50003.html

[13] "Scrum (project management)," Wikipedia, 2025. [Online]. Available: https://en.wikipedia.org/wiki/Scrum_(project_management)

[14] I. Lindstedt Hidiri, “Leveraging AI to Enhance Knowledge Sharing and Agile Project Management,” Ph.D. dissertation, Univ. of [Institution name not found], 2025.

[15] S. Yang, “A systematic literature review on the disruptions of artificial intelligence within the business world: in terms of the evolution of competences,” in Proc. 27ème Conférence de l'AIM, 2022. [Online]. Available: https://hal.science/hal-03694170

[16] M. Sameer and M. Salama, “A Systematic Literature Review of Explainable AI for Software Engineering,” Journal of Software Engineering and Applications, vol. 16, no. 3, pp. 78–95, 2023, doi: 10.4236/jsea.2023.163006.

[17] J. Zhang, J. Sun, Y. Wang, and K. Zhang, “ExplAIner: A Visual Analytics Framework for Interactive and Explainable Machine Learning,” in Proceedings of the 24th International Conference on Intelligent User Interfaces (IUI '19), 2019, pp. 77–87, doi: 10.1145/3301275.3302316.

[18] H. K. Dam, T. Tran, J. Grundy, and A. Ghose, “Towards effective AI-powered agile project management,” in *Proc. 2019 IEEE/ACM 41st International Conference on Software Engineering: New Ideas and Emerging Results (ICSE-NIER)*, Montreal, QC, Canada, 2019, pp. 41–44, doi: 10.1109/ICSE-NIER.2019.00021.

[19] T. Chow and D. B. Cao, “A survey study of critical success factors in agile software projects,” *Journal of Systems and Software*, vol. 81, no. 6, pp. 961–971, Jun. 2008, doi: 10.1016/j.jss.2007.08.020.

[20] D. Stankovic, V. Nikolic, M. Djordjevic, and D. B. Cao, “A survey study of critical success factors in agile software projects in former Yugoslavia IT companies,” Journal of Systems and Software, vol. 86, no. 6, pp. 1663–1678, Jun. 2013, doi: 10.1016/j.jss.2013.01.014.