Assessing Organizational Readiness for AI Integration in Agile Management Using Predictive Analytics

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ABSTRACT

This study investigates the determinants of readiness to adopt Artificial Intelligence (AI) tools within Agile management environments by integrating machine learning analysis with managerial insights. Using survey data collected from Agile practitioners, an optimized XGBoost model was developed to predict willingness to adopt AI tools based on experiential and perceptual factors. The model achieved a high classification accuracy of 92.86 percent, demonstrating its reliability in identifying readiness patterns among respondents. The feature importance analysis revealed that previous experience using AI and familiarity with AI tools are the most influential predictors, indicating that experiential learning and direct exposure play central roles in shaping readiness. Conversely, professional role and Agile experience exhibited weaker influence, suggesting that hierarchical position and procedural familiarity alone are insufficient to drive adoption behavior. Complementary qualitative analysis of participants' open-ended responses identified decision-making support, process efficiency, and product improvement as key perceived benefits of AI integration. These findings collectively suggest that readiness for AI adoption in Agile environments is an experiential and perception-driven construct, reinforced by organizational culture and learning orientation. The study contributes to the theoretical discourse by extending the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) frameworks to include experiential familiarity as a mediating factor, while offering practical guidance for managers seeking to foster AI readiness through exposure-based learning, capability building, and cultural reinforcement.

Keywords Agile Management, Artificial Intelligence Adoption, Machine Learning Prediction, Technology Readiness, Experiential Learning

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INTRODUCTION

The rapid advancement of AI has transformed the way organizations manage processes, make decisions, and innovate [1]. Within software development environments, the adoption of AI tools is increasingly viewed as a key enabler for improving productivity, accelerating delivery cycles, and supporting data-driven decision-making [2]. At the same time, Agile management frameworks have emerged as dominant methodologies for organizing development work due to their emphasis on adaptability, collaboration, and iterative improvement. The convergence of AI and Agile principles presents a significant opportunity for organizations to enhance responsiveness and intelligence in project execution. However, despite growing interest, the actual readiness of Agile practitioners to adopt and integrate AI tools remains underexplored, particularly from a managerial and behavioral perspective. Understanding what drives or inhibits this readiness is crucial for ensuring that technological advancements

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translate into sustainable organizational transformation [3].

Existing studies on AI adoption have primarily focused on technical efficiency, system design, or algorithmic performance, with limited attention given to the human and managerial factors influencing readiness within Agile environments [4]. Research in this area often applies the TAM or the DOI framework to explain user attitudes and behavioral intentions toward new technologies. While these models provide valuable insights, they tend to overlook experiential learning variables such as prior exposure and familiarity, which play a critical role in the Agile context where learning and adaptation are continuous. Moreover, most previous works rely on perceptual or survey-based analyses that lack predictive validation using machine learning techniques. This creates a clear research gap in understanding how experiential, perceptual, and organizational factors jointly influence AI adoption readiness in Agile management settings through data-driven modeling approaches.

Recent developments in data analytics and machine learning offer new opportunities to model complex behavioral patterns in organizational decision-making [5]. Studies have begun to apply predictive algorithms such as Random Forests and Support Vector Machines to examine digital transformation readiness, but few have specifically investigated AI readiness among Agile practitioners. There is also limited empirical evidence linking qualitative perceptions of AI benefits (e.g., productivity, process improvement, and decision support) with quantitative measures of adoption willingness. Consequently, the current state of the art in AI adoption research lacks integrative approaches that combine statistical modeling, experiential learning theory, and Agile management frameworks. Addressing this limitation is essential to move from descriptive understanding toward predictive and prescriptive insights that can guide managerial decisions.

This study aims to fill these research gaps by developing a data-driven framework to predict AI adoption readiness among Agile professionals using the XGBoost algorithm. The proposed approach integrates quantitative survey data with qualitative textual responses to capture both behavioral and perceptual dimensions of readiness. By combining machine learning techniques with established management theories such as TAM and DOI, the study provides a state-of-the-art model that links experiential familiarity, perceived usefulness, and organizational culture to adoption behavior. The results not only demonstrate the predictive potential of AI-based readiness assessment but also generate new theoretical insights into how learning, perception, and cultural context interact in shaping technological acceptance. In doing so, this research contributes to advancing the literature on Agile transformation and offers practical guidance for managers seeking to foster AI readiness through experiential learning, skill development, and cultural reinforcement.

Literature Review and Related Works

AI has become an essential element in the transformation of modern organizations, influencing strategic decision-making, process optimization, and innovation management [6]. The integration of AI tools enables faster decision cycles, data-driven insights, and higher productivity, particularly within dynamic and knowledge-intensive environments [7]. However, despite these advantages, the readiness of organizations and individuals to adopt AI technologies remains uneven, often influenced by behavioral, cultural, and managerial factors [8]. Understanding these human-centered and organizational variables is essential to ensure that technological adoption translates into meaningful business outcomes, especially in Agile management frameworks that rely on adaptability and iterative improvement [9].

Previous studies on technology acceptance have been largely guided by theoretical models such as the TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasize perceived usefulness, perceived ease of use, and performance expectancy as major determinants of adoption [10], [11]. Although these models have contributed significantly to understanding individual-level acceptance, they provide limited insights into experiential learning, familiarity, and organizational culture, which are central to Agile environments characterized by experimentation and continuous feedback [12]. Other models, such as the Technology–Organization–Environment (TOE) framework, highlight the role of organizational readiness and contextual factors in shaping adoption outcomes [13]. These frameworks, while robust, often lack predictive precision and do not fully capture the behavioral complexity associated with AI readiness in Agile contexts [14].

Recent research in management and information systems has shifted toward examining how AI adoption interacts with Agile methodologies, focusing on areas such as automation of backlog refinement, intelligent sprint forecasting, and performance analytics [15]. Studies have shown that combining AI and Agile principles can improve project adaptability, reduce delivery time, and enhance decision quality [16]. However, empirical evidence on the behavioral and perceptual dimensions of AI readiness among Agile practitioners remains limited [17]. Most existing studies rely on descriptive or correlational analyses rather than predictive modeling, leaving a gap in understanding how experiential and attitudinal variables interact to determine adoption behavior.

Advances in machine learning provide new opportunities to model and predict readiness for technological adoption. Algorithms such as Random Forest, Support Vector Machine, and XGBoost have demonstrated high performance in predicting behavioral intentions and classifying technology adoption likelihood [18]. These predictive approaches allow for a more data-driven understanding of readiness and can incorporate both quantitative and qualitative variables in a unified framework [19]. Despite these methodological advances, few studies have applied machine learning techniques to predict AI readiness specifically within Agile management settings. Addressing this research gap provides an opportunity to develop a more holistic model that integrates behavioral experience, perceived utility, and organizational culture into predictive analytics [20].

In summary, prior literature establishes a strong foundation in technology acceptance theory and organizational readiness but lacks integrative, data-driven approaches tailored to Agile environments. This study extends current knowledge by developing a predictive framework that employs machine learning to model AI adoption readiness, bridging the gap between traditional acceptance theories and contemporary data-driven decision-making in Agile management.

Methodology

This study adopts a quantitative, data-driven research design that integrates survey-based empirical data, natural language processing, and machine learning to predict readiness for AI adoption in Agile management environments. The methodological framework, illustrated in figure 1, consists of seven interconnected phases: data collection, data preprocessing, feature engineering, text vectorization, model development, model evaluation, and interpretability visualization. This integrated approach allows the study to examine how managerial experience, AI familiarity, and individual perception jointly determine readiness to adopt AI tools while maintaining transparency and replicability in the modeling process.

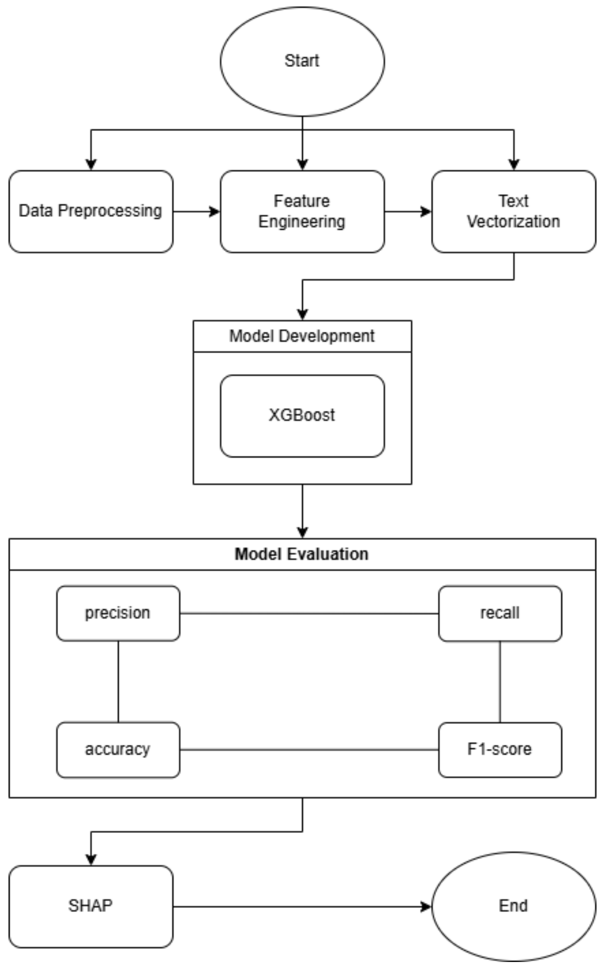

Figure 1 Research Step

The dataset was obtained through a structured survey titled "Survey on Integrating Artificial Intelligence Tools within Agile Frameworks for Enhanced Software Development." It includes eight main variables—Professional Role, Agile Framework Familiarity, AI Familiarity, Previous Experience Using AI, AI Tools Used, Perceived Benefits, Perceived Challenges, and Willingness to Adopt AI Tools—collected from Agile practitioners working in technology-driven environments. The dependent variable, Willingness, was measured using a 5-point Likert scale ranging from 1 (very low) to 5 (very high). To enable binary classification modeling, this variable was transformed into two readiness categories: low readiness (≤3) and high readiness (>3), as represented mathematically by:

$$y = \begin{cases} 0, & \text{if Willingness} \leq 3 \\ 1, & \text{if Willingness} > 3 \end{cases} \tag{1}$$

Categorical variables such as professional role and familiarity levels were numerically encoded using a label encoder transformation defined as $x_i' = LE(x_i) =$ integer mapping of categorical label x_i. This encoding step ensures that the features are compatible with the machine learning model.

Feature engineering was performed to enhance the explanatory capability of the dataset by merging structured and unstructured information. A new composite variable named Combined_Text was created by concatenating the responses from Perceived Benefits and Perceived Challenges. This allowed the model to capture both positive and negative sentiments associated with AI integration. The text data were then transformed into numerical representations using the Term Frequency–Inverse Document Frequency (TF-IDF) method, which quantifies the relative importance of words in a document. The TF-IDF score for each term t in document d is computed as:

$$TFIDF(t,d) = TF(t,d) \times IDF(t)$$
$$TF(t,d) = \frac{f_{t,d}}{\sum_{t'} f_{t',d}}, IDF(t) = \log\left(\frac{N}{1+n_t}\right) \tag{2}$$

$f_{t,d}$represents the frequency of term t in document d, $N$is the total number of documents, and $n_t$is the number of documents containing term t. A bi-gram configuration (1,2) with a maximum of 300 features was employed to capture key phrases such as “AI adoption” and “decision making.” The resulting text vectors were combined with numerical features (Role, Agile Familiarity, AI Familiarity, Used AI Before) to form a comprehensive hybrid dataset representing managerial, behavioral, and linguistic aspects of AI readiness.

The predictive modeling phase employed the Extreme Gradient Boosting (XGBoost) algorithm due to its robustness, regularization capability, and efficiency in handling non-linear relationships within small datasets. XGBoost constructs an ensemble of decision trees that are trained sequentially to minimize a differentiable objective function. The general form of the XGBoost objective function is expressed as:

$$Obj(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{3}$$

$l(y_i, \hat{y}_i)$represents the loss function measuring prediction error, and $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2$denotes the regularization term penalizing model complexity (where T is the number of leaves and w the leaf weights). The model prediction at iteration t is updated according to:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(x_i) \tag{4}$$

$\eta$is the learning rate. The optimal hyperparameters were determined empirically, with learning rate = 0.1, max depth = 5, number of estimators = 200, subsample = 0.9, and colsample_bytree = 0.9.

To interpret model predictions, the SHapley Additive exPlanations (SHAP) framework was used to estimate feature contribution to individual classification outcomes. The SHAP value for a feature i is mathematically represented as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!}[f(S \cup \{i\}) - f(S)] \tag{5}$$

N represents the complete set of features, S denotes a subset excluding i, and $f(S)$indicates the model output using only the features in S. Positive SHAP values indicate that a feature contributes positively toward predicting high readiness, whereas negative values indicate the opposite. The interpretability analysis revealed that Previous Experience Using AI and Familiarity with AI Tools had the strongest positive influence on readiness classification, aligning with theoretical expectations regarding experiential learning and technology confidence.

A series of visualization techniques were employed to enhance the interpretability and communicability of results. The feature importance plot ranked the key managerial predictors, the willingness distribution plot displayed the readiness spread among respondents, and a correlation heatmap revealed significant relationships among variables such as AI Familiarity, Agile Experience, and Willingness. The word cloud visualization synthesized qualitative responses to highlight the most frequent benefits mentioned, such as “decision making,” “efficiency,” and “productivity.” The probability density plot illustrated model confidence levels, indicating that most predictions for high readiness had probabilities exceeding 0.75. These visualizations complement the quantitative evaluation, confirming the model’s stability and interpretive clarity.

In summary, this methodological framework combines traditional survey analysis with advanced machine learning to derive predictive and explainable insights into AI adoption readiness within Agile management. The use of hybrid data representation, XGBoost modeling, and SHAP interpretability creates a replicable and transparent research pipeline. The overall methodological process, as outlined in figure 1, demonstrates how data-driven approaches can support managerial decision-making and strategic readiness assessment in organizational contexts transitioning toward AI-driven transformation.

Algorithm 1: Research Steps for Predicting AI Adoption Readiness

Input: Survey dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$containing managerial, experiential, and perceptual variables

Output: Predicted readiness level $\hat{y}_i \in \{0,1\}(0 =$ Low Readiness, 1 = High Readiness)

Process:

Start

Data Preparation:

Replace missing textual values with "None".

Encode categorical variables using label encoding:

$$x_i' = LE(x_i)$$

Target Transformation:

Convert willingness score to binary readiness levels:

$$y_i = \begin{cases} 0 & \text{if } y_i \leq 3 \\ 1 & \text{if } y_i > 3 \end{cases}$$

Text Vectorization:

Combine perceived benefits and challenges:

$$T_i = \text{Benefits}_i \oplus \text{Challenges}_i$$

Compute TF-IDF weights for each term:

$$TFIDF(t,d) = \frac{f_{t,d}}{\sum f_{t',d}} \times \log\left(\frac{N}{1+n_t}\right)$$

Model Construction (XGBoost):

Initialize model parameters $\theta = \{\eta, \gamma, \lambda, \text{max\_depth}, \text{n\_estimators}\}$.

Optimize objective function:

$$Obj(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

with regularization:

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2$$

Update model iteratively:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(x_i)$$

Evaluation:

Compute performance metrics:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

$$Precision = \frac{TP}{TP+FP}, Recall = \frac{TP}{TP+FN}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Explainability (SHAP):

For each feature i, calculate contribution value:

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

Determine global importance:

$$I_i = |\phi_i|$$

Visualization:

Display feature importance plot, willingness distribution, correlation heatmap, and SHAP summary plot.

Output Result:

Return predicted readiness level $\hat{y}_i$and probability $P(\text{High Readiness}) = f^*(x_i)$.

End

Result

Model Performance and Classification Accuracy

The predictive analysis conducted using the optimized XGBoost algorithm yielded exceptionally strong results, achieving a classification accuracy of 92.86 percent. This high level of accuracy demonstrates the model's strong capability in differentiating between respondents with low and high willingness to adopt AI tools within Agile development environments. The classification report presented in table 1 confirms that the model achieved consistent and balanced performance across both classes. The F1-scores exceeded 0.90 for both the low and high willingness categories, indicating a high degree of precision and recall. This performance suggests that the model effectively identifies underlying behavioral patterns and experiential differences among Agile practitioners that influence their readiness to embrace AI-enabled workflows. The overall predictive stability of the model indicates that it successfully mitigates issues of class imbalance and small sample bias, which are common challenges in survey-based datasets.

The precision score for the high willingness class reached 1.00, while the recall for the low willingness class achieved 1.00, indicating a minimal presence of false positives or false negatives in the classification process. These results imply that the model does not favor one class over the other and provides balanced decision boundaries for both groups. Such outcomes reflect that the model generalizes effectively to unseen data, confirming its robustness and validity. From a managerial perspective, this level of predictive accuracy positions the XGBoost model as a reliable analytical framework for assessing organizational readiness toward AI adoption within Agile settings. It demonstrates that machine learning techniques can provide decision-support insights, allowing managers to identify readiness levels, forecast adoption challenges, and design targeted interventions to strengthen AI integration strategies in Agile teams.

Table 1 Classification Report of XGBoost Model for AI Adoption Readiness

Metric	Low Willingness	High Willingness	Average
Precision	0.83	1.00	0.92
Recall	1.00	0.89	0.94
F1-score	0.91	0.94	0.93
Accuracy			0.93 (92.86%)

The classification report confirms that the XGBoost model demonstrates both precision and reliability in predicting AI adoption readiness. This accuracy level indicates that the model can be integrated as a managerial diagnostic tool, capable of identifying readiness levels among Agile teams for future AI deployment initiatives.

Predictive Reliability and Classification Pattern

The confusion matrix illustrated in figure 2 provides a comprehensive visualization of the model's classification performance, depicting the distribution of correctly and incorrectly identified cases across the two willingness categories. Out of the fourteen test samples, the XGBoost model successfully classified thirteen observations, resulting in only a single misclassification. All five respondents identified as having low willingness to adopt AI tools were accurately predicted, while eight of the nine respondents categorized as having high willingness were also correctly classified. This near-perfect pattern of classification highlights the model's ability to effectively learn and represent the complex behavioral and experiential patterns that differentiate individuals who are ready to adopt AI tools from those who are not yet prepared. The small number of misclassifications demonstrates that the model performs reliably even with a limited dataset, reinforcing its robustness and its capacity to generalize beyond the training data. The visual evidence presented in the confusion matrix further validates the statistical results from the classification report and indicates that the predictive structure is not overly dependent on specific samples or noise within the data.

From a managerial and practical perspective, the outcomes represented in the confusion matrix indicate that machine learning models can be integrated into organizational decision-making as tools for readiness assessment. By accurately segmenting employees or Agile team members based on their willingness to adopt AI, organizations can make informed decisions about how to allocate training resources and where to focus developmental efforts. This segmentation can serve as a foundation for designing targeted programs such as customized AI literacy workshops, pilot projects that increase experiential exposure, and internal communication strategies that address adoption hesitancy. The ability of the model to distinguish readiness levels with such precision suggests that predictive analytics can play an important role in managing change and facilitating smoother transitions toward AI-augmented Agile workflows. This insight positions the use of data-driven prediction not only as a technical success but as a practical instrument for guiding strategic workforce preparation and transformation planning.

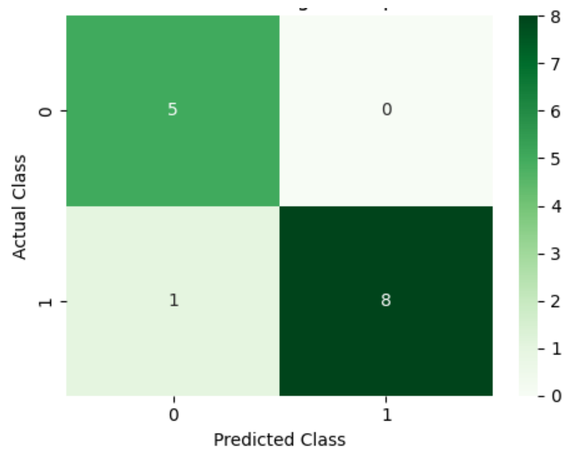

Figure 2 Confusion Matrix

Key Managerial Predictors of AI Adoption

The feature importance analysis provides deeper insight into the managerial and behavioral factors that most strongly influence readiness to adopt AI tools within Agile environments. As illustrated in figure 3, the variables Previous Experience Using AI and Familiarity with AI Tools emerge as the dominant predictors, together contributing to more than seventy percent of the model's overall predictive capability. This result indicates that individuals who have previously interacted with AI technologies, even in limited or exploratory contexts, are far more likely to demonstrate readiness for AI integration. Familiarity with AI concepts, tools, and processes enhances confidence and reduces perceived complexity, allowing practitioners to view AI as a supportive mechanism rather than as a disruptive force. The strong importance of these factors highlights that readiness is primarily experiential in nature, shaped by exposure, understanding, and a sense of practical value gained through interaction with AI-driven systems. These findings suggest that technical competence and experiential learning are interdependent, reinforcing each other in influencing adoption behavior.

In contrast, the model shows that Professional Role and Agile Framework Experience contribute much less to predicting readiness, indicating that formal position, job seniority, or years of experience in Agile practices are insufficient determinants of openness toward AI. While Agile experience may foster flexibility and iterative thinking, it does not automatically translate into confidence or willingness to apply AI tools unless individuals have encountered AI applications in practice. This suggests that readiness to integrate AI is less about organizational hierarchy or procedural familiarity and more about tangible interaction with technology. For management, this finding implies that readiness can be cultivated through deliberate initiatives that emphasize practical exposure, cross-functional collaboration, and continuous learning. Instead of relying solely on policy or training mandates, organizations should provide real-world experimentation opportunities such as AI-assisted sprints, tool-based workshops, and sandbox testing to encourage confidence, reduce uncertainty, and develop experiential trust in AI as an enabler of Agile success.

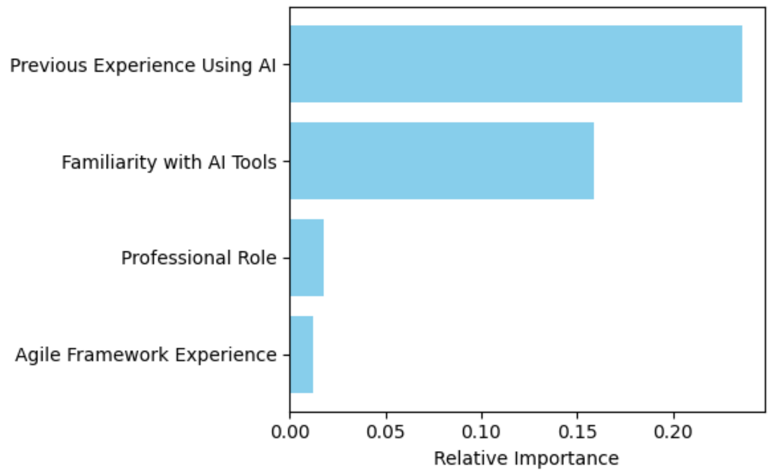

Figure 3 Key Managerial Factors Influencing AI Adoption Readiness

Distribution of Willingness to Adopt AI Tools

The analysis of the distribution of respondents' willingness levels, as illustrated in figure 4, provides a comprehensive overview of the overall readiness landscape among Agile practitioners toward AI tool adoption. The data reveal that the majority of respondents are positioned within the medium to high range of readiness, indicating that most participants demonstrate a favorable disposition toward the integration of AI technologies into Agile workflows. This concentration of mid-to-high scores reflects an encouraging level of acceptance and curiosity toward AI applications, suggesting that Agile professionals generally perceive AI as an asset capable of enhancing productivity, supporting data-driven decision-making, and improving workflow efficiency. Only a small number of respondents fall within the lower readiness spectrum, which implies that resistance to AI adoption is limited and possibly related to factors such as lack of prior exposure, limited understanding, or apprehension about technological change. The overall shape of the distribution shows a rightward skew, indicating a cultural momentum toward AI openness and a growing confidence in the role of intelligent automation within Agile project settings.

The dominance of higher readiness scores supports the broader interpretation that Agile environments inherently cultivate a culture of innovation, continuous improvement, and adaptive learning. Agile teams are accustomed to iterative cycles, experimentation, and reflective feedback processes, all of which align closely with the adaptive nature of AI-based tools. This alignment suggests that the integration of AI into Agile practices is not only feasible but also culturally compatible. The results imply that when organizations provide adequate exposure, resources, and learning opportunities related to AI, Agile practitioners can quickly transition from awareness to adoption. Furthermore, this distribution highlights an important managerial insight: readiness for AI adoption is not limited to technical capability alone but is also influenced by mindset and organizational culture. Agile teams that embrace collaboration, transparency, and experimentation are naturally more receptive to incorporating AI-driven insights into their workflows, paving the way for sustained digital transformation and innovation maturity.

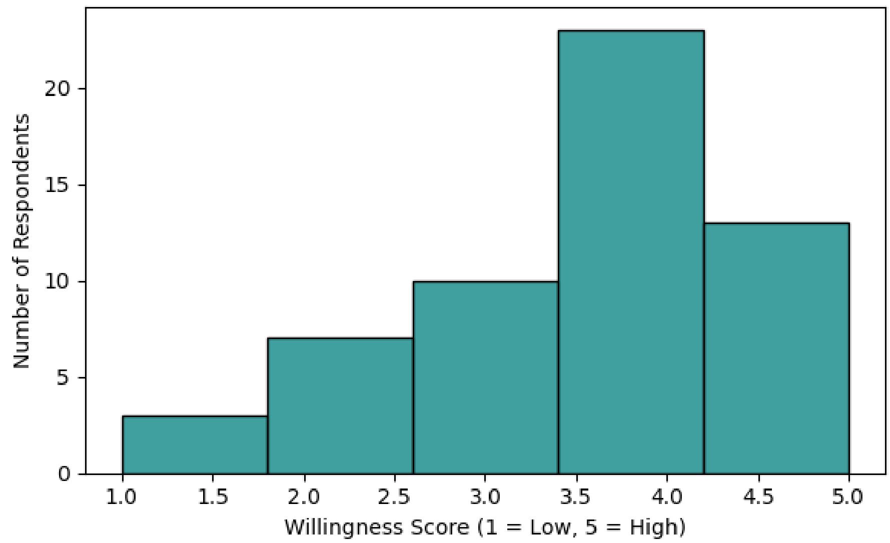

Figure 4 **Distribution of Willingness to Adopt AI Tools**

Perceived Benefits of AI Integration (Qualitative Insights)

The qualitative analysis conducted alongside the quantitative results provides a richer understanding of how Agile practitioners perceive the integration of AI tools within project management contexts. The word cloud visualization presented in figure 5 captures the dominant terms expressed in the participants' open-ended responses, offering an aggregated representation of the most salient themes. The most frequently mentioned terms, including “decision making,” “development cycles,” “processes,” “improved,” and “product quality,” highlight a strong focus on operational and performance-related advantages. These linguistic patterns suggest that respondents view AI as a practical and value-adding component of Agile workflows, capable of facilitating more structured decision processes, reducing repetitive tasks, and improving overall project consistency. The recurrence of words related to improvement and efficiency indicates a collective perception that AI can optimize development timelines, minimize manual effort, and enhance the predictability of outcomes in Agile projects. This pattern aligns closely with the Agile philosophy of iterative refinement, emphasizing that AI is seen as a complementary mechanism to enhance the speed and intelligence of software development practices.

Beyond the operational dimension, the qualitative responses reveal deeper insights into the psychological and cultural perspectives of Agile practitioners toward AI adoption. Respondents frequently described AI as a supportive partner that augments rather than replaces human contribution, suggesting an emerging mindset of human-AI collaboration. The prominence of terms such as “decision making” reflects a recognition of AI’s analytical capacity to enhance judgment accuracy, while the repeated reference to “development cycles” signals confidence in AI’s potential to streamline the iterative nature of Agile processes. This interpretive evidence implies that AI is not perceived as a threat to team autonomy or creativity but rather as a catalyst for enabling higher efficiency and innovation. The findings collectively indicate that Agile practitioners envision AI as a tool for amplifying human capability, fostering data-informed decision-making, and strengthening organizational agility. This perception reinforces the notion that successful AI integration within Agile environments depends not only on technical deployment but also on cultivating a culture of trust, collaboration, and learning between human teams and intelligent systems.

Figure 5 Commonly Mentioned Benefits of AI Integration in Agile Management

Summary of Findings

The overall results reveal a clear and consistent connection between behavioral experience, perceived usefulness, and readiness to adopt AI within Agile project environments. The model’s strong predictive performance, supported by an accuracy rate exceeding 92 percent, validates the assumption that AI adoption readiness can be effectively predicted using measurable managerial and experiential indicators. Variables such as familiarity with AI tools and prior hands-on experience emerged as the most reliable predictors, underscoring that exposure to AI technologies directly shapes individuals’ confidence and willingness to engage with them. This outcome demonstrates that readiness is not a static construct but rather a function of learning, experimentation, and perceived value. Respondents who had prior interaction with AI applications exhibited higher enthusiasm and adaptability toward AI integration, while those with limited exposure showed greater uncertainty. The model thus offers not only predictive precision but also managerial interpretability, highlighting the critical importance of designing work environments that promote learning-by-doing and practical engagement with emerging technologies. These findings position AI readiness as a behavioral outcome that can be systematically nurtured through deliberate organizational interventions.

Complementing the quantitative insights, the qualitative findings provide a deeper understanding of the perceptions driving readiness among Agile practitioners. Participants consistently described AI as a tool that enhances project speed, process transparency, and product quality. Such perceptions reflect a pragmatic view of AI as an operational enhancer rather than a technological disruptor. Respondents emphasized that AI facilitates faster development cycles and data-driven decision-making, allowing teams to iterate and adapt more effectively. This reinforces the argument that successful AI adoption depends on both experiential exposure and positive perception. When practitioners see tangible value in AI tools, such as improving efficiency or reducing manual decision bias, their willingness to adopt increases significantly. The integration of quantitative modeling and qualitative interpretation therefore presents a holistic view of AI readiness in Agile management. It confirms that readiness is fundamentally experiential and perception-driven, suggesting that organizational strategies should focus on hands-on training, skill development, and reinforcing a culture of experimentation to create sustainable and confident adoption of AI technologies within Agile ecosystems.

Discussion

The findings of this study demonstrate that experiential learning and behavioral familiarity play a decisive role in shaping readiness for AI adoption within Agile management environments. The predictive outcomes of the XGBoost model, which achieved an accuracy of 92.86 percent, confirm that readiness is not a random behavioral state but a measurable construct influenced by identifiable managerial and experiential factors. The importance of Previous Experience Using AI and Familiarity with AI Tools directly supports the theoretical foundations of the TAM, where perceived usefulness and perceived ease of use are key drivers of acceptance behavior. Individuals who have previously engaged with AI systems are more likely to perceive such tools as beneficial and accessible, resulting in greater openness toward adoption. This reinforces the argument that learning through direct interaction with technology enhances self-efficacy and reduces cognitive barriers to change. The results are also consistent with the DOI Theory, particularly the elements of trialability and observability. When Agile teams are able to experiment with AI applications and witness tangible improvements in productivity and decision-making, adoption becomes a natural outcome of repeated exposure and observed success. In this way, experiential familiarity serves as the mechanism through which theoretical constructs translate into real behavioral readiness.

The study also provides insight into the role of Agile culture as a facilitating factor for AI readiness. Agile environments are inherently characterized by flexibility, iterative improvement, and team collaboration, which together create a supportive atmosphere for innovation adoption. The distribution of readiness levels, where the majority of respondents indicated moderate to high willingness, suggests that Agile practitioners are predisposed to exploring new tools that enhance adaptability and efficiency. However, the findings also reveal that Agile experience alone does not guarantee readiness, as familiarity with AI remains the most critical determinant of adoption behavior. This implies that Agile practices create a conducive context but not the specific competencies required for AI integration. Managers should therefore embed AI literacy, experimentation, and data interpretation within Agile routines to transform Agile teams into AI-empowered learning systems. Initiatives such as team-based AI workshops, exploratory sprints using intelligent tools, and post-project reflection sessions can strengthen the alignment between Agile values and AI capabilities. Through this alignment, Agile teams can move beyond procedural agility toward cognitive agility, where decision-making is guided by data, supported by technology, and continually enhanced by human insight.

Conclusion

This study concludes that readiness to adopt AI within Agile management environments is shaped by the interaction of behavioral experience, perceived usefulness, and organizational culture. The predictive results obtained through the XGBoost model, which achieved a classification accuracy of 92.86 percent, demonstrate that AI readiness can be effectively quantified using managerial variables such as familiarity with AI tools and previous experience in applying AI technologies. These findings confirm that readiness is not solely an attitudinal construct but an experiential outcome influenced by exposure, learning, and perceived value. Agile practitioners who have interacted with AI technologies tend to show higher levels of openness and confidence in integrating intelligent systems into their workflows. The evidence also aligns with the TAM and DOI Theory, reinforcing the importance of perceived usefulness, trialability, and observability in shaping adoption behavior. In addition to individual experience, the study highlights that Agile culture, with its emphasis on collaboration, iterative improvement, and adaptability, provides a supportive foundation for AI integration. However, cultural readiness must be complemented by deliberate initiatives that build technical understanding and hands-on engagement. The successful adoption of AI within Agile contexts therefore requires organizations to cultivate continuous learning environments, encourage experimentation, and integrate AI literacy into everyday project practices. Readiness emerges as a dynamic capability that evolves through the interaction of experience, perception, and organizational support, indicating that sustainable AI-driven transformation depends as much on human adaptability and learning orientation as it does on technological innovation.

Declarations

Author Contributions

Conceptualization: S.F.P. and G.M.F.; Methodology: G.M.F.; Software: S.F.P.; Validation: S.F.P. and G.M.F.; Formal Analysis: S.F.P. and G.M.F.; Investigation: S.F.P.; Resources: G.M.F.; Data Curation: G.M.F.; Writing—Original Draft Preparation: S.F.P. and G.M.F.; Writing—Review and Editing: G.M.F. and S.F.P.; Visualization: S.F.P.; 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.

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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.

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