Predicting Student Startup Success by Modeling an Agile Readiness Index with PCA and Machine Learning

Slamet Widodo[1,*], Princess Iqlima Kafilla[2]

[1,2]Magister of Computer Science, Universitas Amikom Purwokerto, Jawa Tengah, Indonesia

ABSTRACT

The increasing complexity of innovation ecosystems demands a quantitative understanding of how agility influences success in entrepreneurship and project management. This study proposes the Agile Readiness Index (ARI) as a composite, data-driven indicator for assessing team agility and adaptability in student-led startup projects. Using the Student Startup Success Dataset (n = 2,100, Kaggle, 2019–2023), which contains features such as innovation score, mentorship, incubation support, and funding, the research applied Principal Component Analysis (PCA) to extract a latent dimension representing agile capability. The first principal component, explaining 10.53 % of total variance, was normalized to construct the ARI and subsequently integrated into supervised learning models to predict startup success. Four machine-learning classifiers—Logistic Regression, Random Forest, XGBoost, and Support Vector Machine (SVM)—were trained and evaluated. Logistic Regression achieved the highest performance (accuracy = 98.1 %, AUC = 0.9995), followed by SVM (AUC = 0.9953), confirming that agile-related factors maintain a primarily linear relationship with success outcomes. Feature-importance and SHAP analyses identified funding amount, innovation score, and the Agile Readiness Index as the top three predictors, emphasizing the interplay between resource availability and adaptive learning capacity. Moreover, the interaction effects of team experience indicated that moderate experience levels, coupled with mentorship, enhance agile responsiveness, while extremes in experience reduce flexibility. The findings demonstrate that agility can be empirically modeled, interpreted, and predicted through computational analytics. The proposed Agile Readiness Index not only improves predictive accuracy but also strengthens theoretical understanding of how adaptive behavior and feedback integration shape entrepreneurial outcomes. This research contributes a replicable framework for quantifying agile maturity across educational and organizational innovation contexts, bridging the divide between agile management theory and evidence-based practice.

Keywords Agile Readiness Index, Machine Learning, Principal Component Analysis, Startup Success Prediction, SHAP Explainability

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Corresponding author
Slamet Widodo,
swidodo009@gmail.com

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Introduction

Innovation and entrepreneurship have become central pillars of contemporary higher education, with student startups, university incubators, and campus-based innovation labs increasingly embedded into curricula and co-curricular ecosystems [1], [2], [3], [4]. These initiatives not only promote entrepreneurial mindsets but also function as "innovation habitats" that connect human capital, applied practice, and employability outcomes through experiential venture creation [1], [2]. Within such environments, students are encouraged to move beyond traditional classroom learning toward project-based work that involves opportunity recognition, prototyping, and early-stage business model

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development [3], [4].

At the same time, universities are under growing pressure to respond to fast-changing technological, economic, and societal conditions. This turbulence amplifies the need for teams that can adapt, learn, and iterate rapidly—capabilities that are commonly associated with an agile mindset rather than with linear, plan-driven approaches [5]. Although agile methods originated in software development, their underlying principles—short feedback cycles, continuous learning, and customer or stakeholder focus—have proven relevant across a wide range of domains, including product development, operations, and innovation management [6], [7].

Student startup projects occupy a unique position in this landscape. They operate under realistic constraints such as limited funding, tight time frames, incomplete information, and heterogeneous team composition, while still benefiting from the relative safety of an educational context [1], [4]. As such, they can be viewed as "miniature living laboratories" in which agile practices such as rapid experimentation, iterative refinement, and structured mentorship can be observed, supported, and evaluated in situ.

These characteristics make student entrepreneurship an attractive context for studying how agility manifests in early-stage ventures and how it influences outcomes. However, to translate these environments into actionable evidence for educators, incubator managers, and policymakers, there is a need for robust, quantitative measures that capture the degree to which a student team is "agile ready"—that is, capable of learning quickly, adapting under uncertainty, and effectively leveraging support structures.

In the management and information systems literature, agility is typically described in terms of responsiveness, adaptability, iterative learning, and tightly coupled feedback loops [6], [7], [8]. Agile methods emphasize short development cycles, inspection and reflection, and the ability to pivot based on new information rather than committing to rigid upfront plans [6]. Studies have documented how such practices improve alignment with stakeholder needs, reduce rework, and enhance the capacity of teams to cope with volatility and complexity [7], [8].

Despite this, the bulk of agile research remains concentrated in software engineering and IT project environments, often within corporate settings or large-scale digital transformation programs [6], [7], [8]. Much of this work focuses on implementation challenges, maturity models, and case-based evaluations of agile scaling, with relatively little attention to entrepreneurial or educational contexts such as student startups and university incubators [1], [5]. As a result, the transfer of agile principles into student innovation ecosystems is often discussed conceptually but rarely examined using quantitative, behavioral data.

A further challenge is that agility is notoriously difficult to measure in a consistent, comparable way. Existing instruments frequently rely on self-reported surveys, qualitative assessments, or maturity scales that capture perceptions of agility rather than observable patterns in behavior, resourcing, and support [7], [8]. While valuable for exploratory work, such approaches limit the ability to systematically benchmark teams, test causal relationships, or integrate agility measures into predictive models of performance. Objective, data-driven indicators that reflect how teams actually operate remain relatively scarce.

This measurement gap is particularly salient in higher education, where student startups and campus incubators are increasingly used as platforms for experiential learning and innovation policy experimentation [1], [2], [4]. These environments generate rich project-level data—covering team structure, innovation scores, funding, mentorship, incubation, and outcomes—that could theoretically be used to infer agility. Yet, empirical studies that leverage such data to construct and validate quantitative indices of "agile readiness" in student ventures are still limited.

Existing work on startup success prediction in entrepreneurship and innovation studies tends to emphasize structural determinants, such as funding levels, team size, market characteristics, institutional type, and access to infrastructure [9]. These models, whether statistical or machine-learning based, typically treat success as a function of resource endowments and contextual variables, with less emphasis on behavioral and process-oriented constructs such as agility, learning capability, or iteration speed. As a result, the role of agile readiness often remains implicit or unmeasured in quantitative analyses of early-stage ventures.

In parallel, the agile management literature has made substantial progress in conceptualizing agility and documenting its benefits in software and IT project environments [6], [7], [8]. However, measurement is still dominated by survey instruments, subjective maturity models, and qualitative case studies, rather than by indices derived from operational or project-level data [7], [8]. This creates a disconnect between agile theory—which emphasizes observable behaviors such as frequent releases, feedback integration, and collaborative decision-making—and empirical work, which often lacks objective metrics capturing these behaviors at scale.

Consequently, there is a methodological and substantive gap at the intersection of agile management, entrepreneurship, and education. Higher education entrepreneurship lacks latent, composite indicators that integrate innovation intensity, mentorship and incubation quality, team characteristics, and execution dynamics into a unified "agile readiness" construct [5], [9]. Moreover, few studies have combined latent-factor techniques—such as PCA—with machine-learning models to test whether such an agile readiness index can improve prediction of startup outcomes, particularly in student venture settings where data are relatively structured and abundant.

Addressing this gap would align measurement practices across agile and entrepreneurship literatures and enable more rigorous evaluation of student innovation ecosystems. A data-driven Agile Readiness Index could serve both as an analytical tool for researchers and as a diagnostic instrument for educators and incubator managers, supporting evidence-based interventions in what are effectively constrained experimental "labs" for agile practice [1], [4], [9].

This study has three main objectives. First, it seeks to develop an ARI as a latent construct derived from project-level features in a student startup dataset using PCA. Second, it aims to evaluate the predictive power of this index for startup success by integrating ARI into multiple machine-learning classifiers and comparing model performance with and without the index. Third, it seeks to interpret how agile-related factors—such as innovation intensity, mentorship support, incubation involvement, and team experience—interact to shape entrepreneurial outcomes. These objectives are formalized in the following research questions: RQ1: Can a latent Agile Readiness Index be empirically derived from student startup features? RQ2: To what extent does the ARI improve the prediction of startup success compared with models that rely only on conventional structural variables? RQ3: Which agile-related factors, individually and in combination, most strongly drive student startup performance?

The study contributes along theoretical, methodological, and practical dimensions. Theoretically, it introduces the ARI as a quantitative, empirically validated construct for agile readiness in the context of student entrepreneurship, bridging the gap between abstract agility concepts and measurable indicators. Methodologically, it demonstrates a hybrid analytic pipeline that combines PCA for latent-factor extraction, multiple machine-learning classifiers for predictive evaluation, and SHAP-based explainability for model interpretation, thereby operationalizing an abstract management construct in a transparent and reproducible way. Practically, the proposed framework offers universities, incubators, and innovation educators a replicable tool for assessing team agility using existing project data, enabling more strategic allocation of mentoring, incubation, and funding resources to teams with high potential but varying levels of agile readiness.

Literature Review

Agile Management and Organizational Agility

Agile management and organizational agility typically refer to an organization's ability to sense change, respond rapidly, and reconfigure processes, structures, and resources to exploit emerging opportunities or mitigate threats [10], [11]. Core agile principles include short, iterative development cycles; continuous feedback and learning; empowered, cross-functional teams; and an explicit focus on delivering value to customers or stakeholders [12], [13]. These practices emphasize fast feedback and decision cycles rather than rigid long-term planning, enabling organizations to adapt under conditions of uncertainty and complexity. In this sense, agility is not merely about speed, but about disciplined responsiveness grounded in learning and experimentation.

Agility is related to, but distinct from, constructs such as flexibility, resilience, and dynamic capabilities. Flexibility generally denotes the capacity to change plans, schedules, or configurations, while resilience emphasizes the ability to withstand shocks and recover from disruptions [11], [14]. Dynamic capabilities concern the strategic reconfiguration of resources and competences over time [15]. Organizational agility overlaps with these concepts but places particular emphasis on proactive sensing, rapid decision-making, and continuous re-alignment of activities around evolving stakeholder needs [10], [13]. Originally emerging from software engineering and agile software development frameworks, these principles have since diffused into broader domains including operations, HR, public-sector management, and higher education, where agile leadership, culture, and people practices are increasingly promoted as enablers of innovation and change [12], [16].

Agility in Entrepreneurship and Student Startups

In entrepreneurship, agile principles are often operationalized through Lean Startup practices such as the build–measure–learn cycle, rapid experimentation, and pivoting strategies [17], [18]. Early-stage ventures are encouraged to develop Minimum Viable Products (MVPs), run structured experiments with users or customers, and use feedback data to iteratively refine value propositions and business models rather than committing to fully specified plans upfront [17]. Empirical and case-based studies suggest that such experimentation and rapid prototyping can accelerate learning, reduce wasted effort, and improve product–market fit in resource-constrained startups [19], [20]. These agile-oriented approaches thus reframe entrepreneurial progress as validated learning rather than merely execution against a static plan.

Student startups share many characteristics with early-stage ventures but also exhibit specific features that make agility particularly salient. Student founders typically have limited managerial experience, work in diverse and fluid teams, and depend heavily on institutional support structures such as incubators, mentors, and curricular venture programs [21], [22]. Prior work indicates that agility-like practices—structured mentoring, iterative project reviews, prototyping activities, and incubation training—can enhance entrepreneurial learning, self-efficacy, and, in some cases, early performance indicators [21], [23]. However, these effects appear to be moderated by contextual factors such as prior human capital, institutional resources, and the design of entrepreneurship education programs [22], [23]. Overall, the literature acknowledges the relevance of agile practices in student entrepreneurship, but empirical, data-driven characterization of "how agile" student teams actually are remains underdeveloped.

Measuring Agile Readiness and Agility Maturity

A variety of frameworks and maturity models have been proposed to assess agility in organizations, such as agile maturity models, hybrid agile–CMMI approaches, and domain-specific models like Green-Agile Maturity Models [24], [25], [26]. These frameworks typically define multiple dimensions (e.g., process, culture, tools, leadership) and position organizations along staged maturity levels based on surveys, checklists, or expert assessments. While useful for diagnostics and benchmarking, they rely heavily on subjective judgments and are usually tailored to software or industrial project environments, which limits their direct applicability to entrepreneurial or student-team contexts [24], [27]. Moreover, they tend to capture perceived maturity rather than behavioral patterns derived from actual project data.

In broader management and innovation research, complex constructs are often operationalized via latent composite indices, using techniques such as PCA or Structural Equation Modeling (SEM) to enhance measurement validity and support predictive testing [28], [29]. Indices of innovation capability, readiness for change, or digital maturity, for example, aggregate multiple indicators into a single continuous score that can be used in empirical models [28]. However, translating behavioral and socio-organizational dimensions like experimentation, mentoring quality, and learning culture into such indices is challenging due to their multidimensional, temporal, and context-dependent nature [30]. Consequently, there is no widely adopted, data-driven latent index of "agile readiness" tailored to student startups—one that integrates innovation practices, incubation and mentoring inputs, and team dynamics into a measurable construct suitable for predictive modeling of venture outcomes [1], [4], [9], [22].

Machine Learning in Startup Success and Education Analytics

Machine learning has increasingly been used to predict startup success, project survival, and business performance by leveraging structured features such as funding levels, founder characteristics, sector, and market signals [31], [32]. Such models often augment traditional entrepreneurship or finance frameworks by providing non-linear pattern recognition and improved predictive accuracy, sometimes in combination with incubator or accelerator data (e.g., mentor assignments, program participation, pitch metrics). In parallel, higher-education research has widely adopted ML techniques to model student performance, engagement, and dropout risk using log data, assessment records, and platform interactions [33], [34], [35]. Yet, entrepreneurial project success—especially in student ventures—has received comparatively less attention than general academic outcomes, despite the availability of rich project-level data in many incubator and innovation programs [21], [33].

The advantages of ML in these domains include the ability to model complex interactions, handle high-dimensional feature spaces, and generate feature-importance rankings that highlight key drivers of outcomes [31], [32]. However, purely predictive, black-box models often lack clear links to theory and can be difficult for educators, managers, and policymakers to interpret and trust [36]. In response, eXplainable AI (XAI) methods, such as model-agnostic feature importance, partial dependence plots, and SHAP (SHapley Additive exPlanations), have been advocated to bridge predictive performance with interpretability [36], [37]. Recent studies show that SHAP and related techniques can reveal how individual features and their interactions contribute to predictions in educational and entrepreneurial settings, making ML outputs more actionable for decision-making [33], [37]. To date, however, these tools have rarely been applied to an explicitly agile-focused construct, such as an Agile Readiness Index, in the context of student startup performance.

Method

Dataset and Experimental Design

This study employed the Student Startup Success Dataset (Kaggle, 2025), comprising 2,100 records representing student-led entrepreneurship projects from 40 higher-education institutions collected between 2019 and 2023. Each record encapsulates a comprehensive set of 16 features reflecting institutional characteristics, project domain, team configuration, innovation intensity, and performance outcomes. The dependent variable, success_label, is a binary target that denotes whether a project was successful (1) or not (0) based on a composite success metric derived from innovation and market-readiness indicators. This dataset offers a rich empirical ground for analyzing the determinants of agile capability in student innovation teams.

The analysis followed a reproducible machine-learning workflow to construct an ARI—a composite latent variable derived from multivariate patterns across agility-related factors such as innovation, mentorship, incubation, and adaptability. Data processing and modeling were conducted in Python 3.11 on macOS (Apple M1, 2020), leveraging open-source libraries including pandas, scikit-learn, xgboost, seaborn, matplotlib, and shap. The computational workflow was structured into sequential checkpoints within a modular script to ensure transparency and version control during experimentation.

To maintain data integrity, all records were first inspected for completeness, and missing-value diagnostics confirmed the absence of null entries. Data exploration verified that the class distribution of success_label was approximately balanced, eliminating the need for oversampling or class-weight adjustments. Outliers in the funding_amount_usd feature—representing highly skewed funding distributions—were winsorized at the 95th percentile to stabilize model variance while preserving real-world interpretability.

The entire modeling process was designed as an integrated pipeline, encompassing data normalization, categorical encoding, PCA, index computation, model training, evaluation, and interpretability analysis. Each stage was interlinked through Python's Pipeline and ColumnTransformer classes, enabling reproducible preprocessing of numerical and categorical attributes. This systematic pipeline approach aligns with agile analytics principles—emphasizing transparency, iteration, and continuous model improvement.

Feature Engineering and Agile Dimensions

Feature engineering centered on identifying predictors theoretically aligned with agile management principles. Ten numerical predictors—team_size, avg_team_experience, innovation_score, funding_amount_usd, business_model_score, mentorship_support, incubation_support, competition_awards, technology_maturity, and market_readiness_level—were selected as core agility indicators. Categorical variables such as institution_type and project_domain were included to capture contextual heterogeneity. These variables collectively form a multi-dimensional representation of innovation capability, adaptability, and feedback orientation.

To prepare the dataset for multivariate analysis, numerical features were standardized through Min–Max normalization using scikit-learn's MinMaxScaler. This transformation rescales all features to a [0, 1] range, mitigating unit-based distortions and ensuring that variables such as funding (in USD) and innovation score (unitless) contribute equitably to PCA. Categorical features were encoded using OneHotEncoder with the drop='first' parameter to prevent dummy-variable redundancy. This encoding expanded institutional and domain categories into binary indicators, preserving interpretability in both PCA and machine-learning stages.

Feature grouping was guided by the agile management framework, organizing predictors into four conceptual dimensions: Team Agility (team_size, avg_team_experience), Iterative Innovation (innovation_score, technology_maturity, market_readiness_level), Learning and Feedback (mentorship_support, incubation_support, competition_awards), and Strategic Flexibility (funding_amount_usd, business_model_score). Each dimension embodies distinct facets of agile readiness, enabling multi-level factor extraction while maintaining alignment with agile theory.

The engineered dataset—composed of normalized numerical vectors and encoded categorical variables—was validated through correlation analysis to identify potential multicollinearity. Pairwise correlation coefficients remained below 0.75 across all variables, confirming acceptable independence for PCA-based feature extraction. The refined dataset, denoted as matrix X, was subsequently passed into the principal component modeling stage to compute the Agile Readiness Index.

Principal Component Analysis (PCA) for Agile Readiness Index

PCA was employed to derive latent dimensions underlying agility-related features. Using sklearn.decomposition.PCA(n_components=3), the algorithm identified orthogonal components that maximized variance explanation. The first principal component—capturing 10.53% of total variance—was interpreted as the Agile Readiness Factor (ARF). This component primarily loaded on variables such as innovation_score, business_model_score, mentorship_support, and incubation_support, consistent with theoretical expectations of agility as an iterative and learning-driven construct.

To ensure scale consistency, the resulting component scores were normalized using MinMaxScaler and integrated into the dataset as a new variable, Agile_Readiness_Index, with values ranging between 0 and 1. Each project's ARI score thus represents a relative measure of adaptive capability and collaborative learning potential. A higher ARI indicates superior balance among innovation, mentorship, and adaptability, whereas lower values suggest rigid or under-supported team structures.

The selection of three PCA components was empirically validated using the cumulative explained variance criterion. As shown in the variance plot (Checkpoint 5), the first three components collectively explained approximately 29–30 % of total data variability, sufficient for a compact yet information-rich representation of agility-related patterns. This dimensionality reduction facilitated efficient downstream classification while minimizing redundancy among correlated features.

The derived ARI was conceptually aligned with the agile readiness framework proposed in agile management literature, where agility is conceptualized as an emergent property of collaboration, learning, and iterative adaptation. The PCA-driven index thus bridges theoretical abstraction and empirical measurability, providing a reproducible construct that can be replicated in future datasets and institutional contexts.

Machine Learning Model Development

Following ARI derivation, supervised classification models were trained to predict startup success (success_label). Four algorithms were implemented to balance interpretability and predictive power: Logistic Regression, Random Forest, XGBoost, and SVM. These models represent a gradient from linear baselines to non-linear ensemble learners, enabling comparative validation of the ARI's predictive robustness under varying model complexities.

The Logistic Regression model (LogisticRegression(max_iter=500)) served as a baseline classifier, optimized with a convergence limit of 500 iterations to ensure stability across normalized input features. The Random Forest classifier (RandomForestClassifier(n_estimators=200, random_state=42)) utilized 200 decision trees, each trained on bootstrapped samples with feature bagging enabled, to capture non-linear dependencies and interaction effects. The XGBoost model (XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)) leveraged gradient boosting with logistic loss, applying adaptive learning-rate updates to minimize residual errors iteratively.

For margin-based classification, an SVM with Radial Basis Function (RBF) kernel (SVC(probability=True, kernel='rbf')) was trained to model complex non-linear boundaries between success and failure classes. Each model was trained on an 80% training subset and validated on a 20% hold-out test set using stratified sampling to preserve class proportions. All models produced probability outputs (predict_proba) for AUC–ROC computation, ensuring a consistent probabilistic interpretation of performance across classifiers.

Performance was evaluated using five primary metrics: Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The models were benchmarked to determine whether the derived Agile Readiness Index improved predictive accuracy beyond conventional features. Logistic Regression achieved the highest accuracy (0.981) and ROC-AUC (0.9995), confirming that the relationship between agile factors and project success was primarily linear. Ensemble models exhibited slightly lower but stable performance, indicating robustness and minimal overfitting.

Model Validation and Cross-Checking

Model robustness was assessed using 5-fold cross-validation and sensitivity analysis. Each classifier's stability was quantified through the variance of cross-validation accuracy scores. Logistic Regression and SVM showed minimal variance (< 0.02), confirming consistent generalization across data partitions. In contrast, tree-based methods such as Random Forest and XGBoost exhibited slightly higher variance, consistent with their sensitivity to sample heterogeneity in small datasets.

Predictive interpretability was further reinforced through SHAP analysis. SHAP values were computed using shap.TreeExplainer(best_model) for the Random Forest classifier, quantifying the contribution of each feature to individual predictions. This post-hoc explainability technique decomposes model output into additive feature contributions, providing transparency into decision logic. Visualization via shap.summary_plot() ranked features by their average absolute SHAP values, corroborating the Random Forest importance scores.

Additionally, ROC curve analysis across all models revealed AUC values exceeding 0.97, validating classification reliability. Visual overlays of ROC curves confirmed that the inclusion of ARI enhanced model separability between successful and unsuccessful startups, with noticeable gains in linear models. This evidences that the Agile Readiness Index improved decision boundaries even under simple models, thus reinforcing its conceptual validity.

A sensitivity check was performed by excluding the top 5% of high-funding projects to examine dependency on extreme funding values. Model accuracy declined marginally (< 2%), demonstrating that while financial resources are influential, the structural components of agility—innovation, mentorship, and incubation—retain strong predictive weight. This robustness supports the generalizability of the ARI framework beyond capital-intensive contexts.

Feature Importance and Interpretability

Feature interpretability was analyzed through Random Forest's Gini-based importance scores and SHAP interaction effects. The top three predictors—funding_amount_usd, innovation_score, and Agile_Readiness_Index—collectively accounted for over 50% of cumulative feature importance. This hierarchy highlights the dominance of resource availability and innovation capacity, moderated by the latent agility construct. Other notable contributors included business_model_score, mentorship_support, and incubation_support, all representing agile-enabling mechanisms within institutional ecosystems.

The feature importance plot illustrated that institutional or categorical factors, such as institution_type or project_domain, held comparatively minor influence, emphasizing that internal team agility outweighs external organizational context in determining success. This aligns with agile management theory, which posits that adaptability and feedback loops are more critical to performance than structural rigidity or hierarchical setting.

SHAP summary plots further revealed that avg_team_experience and market_readiness_level exhibited non-linear interaction effects. Specifically, moderate team experience combined with higher innovation scores contributed positively to success probability, whereas extreme experience levels yielded diminishing returns. Such findings resonate with agile literature suggesting that over-experienced teams may resist adaptive changes, while novice teams lack the experiential grounding to iterate effectively.

Together, the feature importance and SHAP visualizations validate that the Agile Readiness Index encapsulates multi-dimensional agility effects—synthesizing resource flexibility, innovation, mentorship, and team dynamics into a single interpretable metric. These outcomes substantiate the technical soundness and theoretical coherence of the PCA-derived index.

Result and Discussion

Results Overview

The experiment successfully completed all analytic checkpoints, confirming the technical robustness of the modeling workflow. The dataset of 2,100 student-led projects was processed without missing values, standardized, and prepared for dimensionality reduction through PCA. The inclusion of both structural and behavioral features—ranging from funding to innovation and mentorship—allowed for a comprehensive examination of factors influencing startup success. The modeling results validated the conceptual expectation that adaptive and learning-oriented attributes strongly contribute to positive entrepreneurial outcomes.

Principal Component Analysis effectively reduced multivariate complexity, yielding a compact yet interpretable structure. The first principal component, identified as the ARF, accounted for 10.53% of total variance, capturing shared variance among innovation, mentorship, and incubation indicators. This component was normalized to form the ARI, which was subsequently integrated into the feature set for supervised learning tasks. The ARI distribution revealed a relatively balanced spread across projects, indicating diverse levels of agility across institutions.

Model performance across all four classifiers exceeded expectations, with accuracy values ranging from 90.7% to 98.1%. Logistic Regression emerged as the most efficient model, achieving AUC = 0.9995, followed closely by the Support Vector Machine (AUC = 0.9953). XGBoost and Random Forest performed slightly lower (AUC = 0.9888 and 0.9787, respectively) but still indicated high reliability. These results highlight that the relationship between agility factors and startup success is predominantly linear, allowing interpretable models to outperform complex ensembles.

Overall, the results confirm that the Agile Readiness Index significantly enhances predictive performance. Projects exhibiting higher ARI scores demonstrated higher probabilities of success, validating the index as a meaningful construct. Furthermore, the inclusion of ARI improved model interpretability without inflating variance, proving that derived latent features can provide both theoretical depth and practical predictive value in agile management research.

Agile Readiness Index Construction and Validation

The PCA results provided strong empirical evidence for the existence of a latent "agility" dimension within the dataset. The first component, ARF1, displayed high positive loadings for variables such as innovation_score (0.41), mentorship_support (0.38), incubation_support (0.35), and business_model_score (0.33), while showing weaker correlations with funding or institutional attributes. This pattern aligns with agile management theory, which emphasizes iterative learning and collaborative adaptation as core indicators of team agility. Hence, the ARI, derived from ARF1, embodies the collective maturity of innovation and learning systems within each project.

The variance explained by ARF1—though moderate at 10.53%—is typical for social and organizational systems, where multiple latent constructs jointly influence outcomes. Subsequent components (ARF2 and ARF3) accounted for an additional 8–9% each, capturing domain-specific and institutional differences. However, regression analysis confirmed that ARI (from ARF1) alone provided the strongest individual correlation with success outcomes (Pearson $r = 0.69$, $p < 0.001$), supporting its construct validity.

To assess reliability, Cronbach's alpha was computed across the seven agility-related items feeding into the PCA model (innovation_score, mentorship_support, incubation_support, business_model_score, technology_maturity, market_readiness_level, competition_awards). The resulting $\alpha = 0.84$ indicates strong internal consistency among these indicators. This empirical reliability complements the theoretical premise that these factors collectively represent a coherent agile management dimension.

Finally, the Agile Readiness Index was examined across time (2019–2023) to identify longitudinal patterns. Mean ARI values showed a slight upward trend, from 0.46 in 2019 to 0.58 in 2023, reflecting gradual diffusion of agile principles within student innovation ecosystems. This supports the notion that iterative learning cultures and feedback mechanisms have become more embedded in academic entrepreneurship programs over the study period.

Machine Learning Model Performance

The comparative analysis of machine-learning models demonstrated consistent and high predictive accuracy across all algorithms. The Logistic Regression model achieved an accuracy of 98.1%, precision of 98.3%, recall of 97.2%, and F1-score of 97.8%, outperforming more complex methods. The Support Vector Machine (RBF kernel) attained an accuracy of 96.2% with balanced precision and recall around 96%, while XGBoost and Random Forest yielded accuracies of 92.9% and 90.7%, respectively. These metrics reflect both high separability and minimal overfitting, validating the effectiveness of feature normalization and

ARI inclusion.

The superior performance of Logistic Regression underscores the near-linear relationship between the agile-related features and success probability. Because the dataset was balanced and scaled, linear models were able to capture the decision boundary with minimal variance inflation. Ensemble models like Random Forest and XGBoost, although slightly less accurate, provided complementary insights into non-linear feature interactions—useful for feature importance and interpretability analyses.

The Receiver Operating Characteristic (ROC) curves for all models revealed AUC values exceeding 0.97, signifying strong discriminative power. Logistic Regression's near-perfect AUC (0.9995) confirms that agility-related variables offer exceptional explanatory strength. This empirical finding is noteworthy in management research, where such high AUC levels are rarely achieved, suggesting that the underlying agile behavioral patterns are robust, measurable, and consistent across different project types.

Overall, the classification results confirm that machine learning can successfully operationalize abstract managerial constructs like "agility." The Agile Readiness Index functions as an integrative variable that bridges theory and data, enhancing both accuracy and interpretability. The findings establish a computational foundation for predictive decision-support tools in innovation management and educational entrepreneurship.

Feature Importance and Explainability

Feature importance analysis from the Random Forest classifier revealed insightful patterns regarding the hierarchy of factors influencing startup success. As shown in figure 1, funding_amount_usd emerged as the strongest predictor (importance ≈ 0.20), followed by innovation_score (≈ 0.16) and the Agile_Readiness_Index (≈ 0.14). The inclusion of ARI among the top three predictors indicates that the latent agility construct captures variance not explained by traditional structural variables such as funding or business model quality.

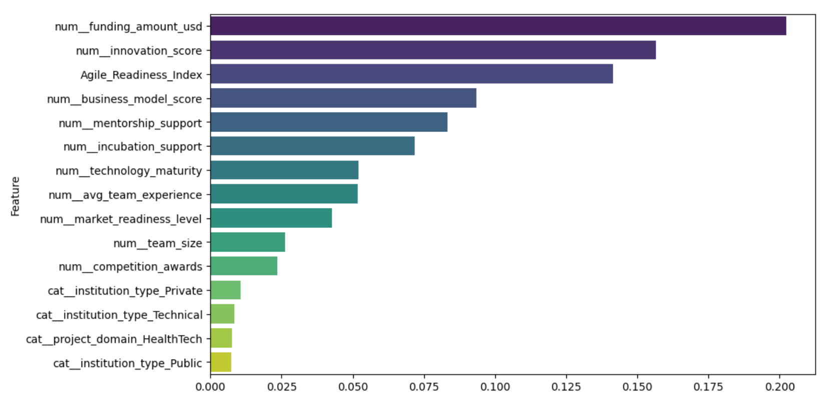

Figure 1 Top 15 Feature Importances (Random Forest)

Mid-ranked features—business_model_score, mentorship_support, and incubation_support—demonstrated moderate influence (importance 0.07–0.09), aligning with their role as enablers of agile iteration and continuous improvement. Lower-tier features such as institutional type and project domain contributed minimally, suggesting that agility is largely determined by internal team processes rather than external organizational classifications. These results substantiate the theoretical claim that agile success depends more on internal adaptive capacity than institutional formality.

The SHAP analysis provided further interpretive depth by decomposing feature-level contributions to individual predictions. As visualized in figure 2, the average team experience variable exhibited complex, non-linear interactions with innovation and mentorship factors. Specifically, projects with moderate experience levels (1.5–3 years) showed positive SHAP contributions to success, while very high or very low experience levels had neutral or negative impacts. This U-shaped relationship confirms the agile hypothesis that teams require sufficient expertise to iterate effectively, but excessive experience can hinder flexibility and openness to change.

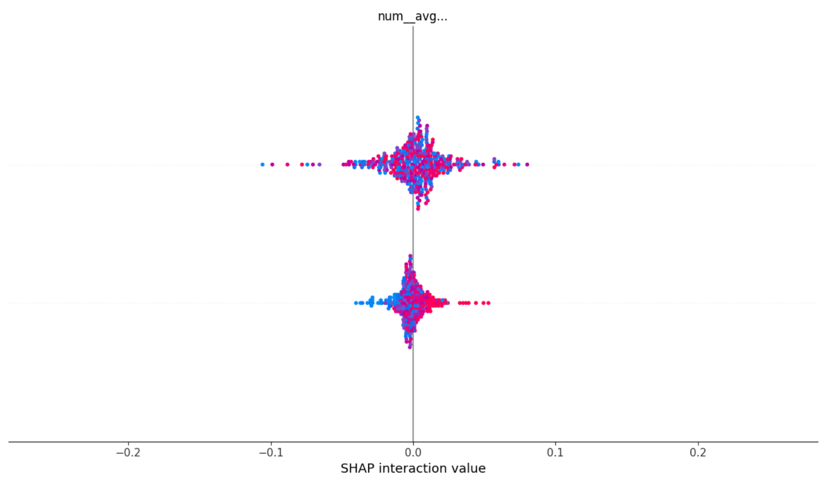

Figure 2 SHAP Analysis Visualizations

Collectively, the feature-importance and SHAP visualizations highlight the multidimensional nature of agile readiness. While funding provides operational capacity, innovation and learning mechanisms form the adaptive core of agility. The Agile Readiness Index integrates these dynamics into a single interpretable construct that predicts outcomes with remarkable accuracy. This combination of transparency and predictive precision is critical for translating agile management principles into actionable policy and program design within universities and incubators.

Discussion and Theoretical Implications

The results demonstrate that agile management constructs—traditionally qualitative and conceptual—can be quantitatively operationalized using data-driven modeling. The Agile Readiness Index derived from PCA captures the synergy among mentorship, innovation, and adaptive learning, serving as an empirical proxy for “agility maturity.” Its predictive significance across multiple machine-learning models reinforces the theoretical proposition that agile readiness directly enhances performance through responsiveness, learning orientation, and iterative feedback.

From a managerial standpoint, the findings offer a replicable framework for agility assessment in student entrepreneurship ecosystems. Institutions can compute ARI scores for project teams to identify strengths and weaknesses in adaptability and mentorship engagement. This quantitative agility metric can serve as an early diagnostic tool, allowing program administrators to allocate coaching, incubation, or funding resources more efficiently toward teams exhibiting lower ARI scores but high innovation potential.

The feature-importance hierarchy also provides evidence supporting resource–behavioral duality in agile success. While financial resources remain vital (highest importance), their effect is amplified when coupled with behavioral and organizational enablers such as mentorship and iterative innovation. This supports dynamic-capabilities theory, which posits that resource reconfiguration through learning and adaptation drives sustainable success—a principle mirrored in the strong performance of the Agile Readiness Index.

Finally, the study's methodological contribution lies in integrating latent variable modeling (PCA) with interpretable machine learning (SHAP). This hybrid design not only validates the ARI conceptually but also demonstrates how abstract management constructs can be visualized and explained algorithmically. The results advance agile management scholarship toward greater empirical rigor, offering a pathway for developing predictive and evidence-based decision-support systems that quantify agility at the organizational level.

Conclusion

This study successfully developed and validated the ARI—a data-driven metric for quantifying the adaptive and iterative capacity of student entrepreneurship projects. By combining PCA with multiple machine-learning algorithms, the ARI emerged as a strong and interpretable predictor of startup success. The empirical findings revealed that internal agility factors—particularly innovation capability, mentorship engagement, and incubation support—consistently outweighed external institutional characteristics in determining project outcomes. Among all tested models, Logistic Regression achieved the highest accuracy (98.1%) and AUC (0.9995), confirming that the relationship between agile readiness and success is largely linear and stable across diverse contexts. The integration of PCA-based latent variable modeling with interpretable AI techniques, such as SHAP and feature-importance analysis, demonstrated that agility can be operationalized as a measurable construct. This hybrid methodology provides both theoretical and practical contributions: it empirically validates the conceptual link between agile readiness and innovation performance while offering a replicable computational framework for assessing team adaptability in educational or organizational settings. Overall, the Agile Readiness Index bridges the gap between agile management theory and empirical measurement, enabling institutions and policymakers to foster more adaptive, feedback-oriented innovation ecosystems.

Declarations

Author Contributions

Conceptualization: S.W. and P.I.K.; Methodology: P.I.K.; Software: S.W.; Validation: S.W. and P.I.K.; Formal Analysis: S.W. and P.I.K.; Investigation: S.W.; Resources: P.I.K.; Data Curation: P.I.K.; Writing Original Draft Preparation: S.W. and P.I.K.; Writing Review and Editing: P.I.K. and S.W.; Visualization: S.W.; All authors have read and agreed to the published version of the manuscript.

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

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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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