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Machine Learning Identification of Innovation Bottlenecks: A Behavioral Analytics Approach Using Gradient Boosting Models

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ABSTRACT

Objective: The objective of this study was to develop and validate a machine learning–based behavioral analytics framework for identifying organizational innovation bottlenecks through the interaction of leadership, psychological, and behavioral factors.

Methods and Materials: This study employed a cross-sectional explanatory design involving 547 employees and middle-level managers from diverse organizations in Georgia. Data were collected using validated behavioral, psychological, and organizational measures capturing resistance to change, psychological safety, leadership support, communication friction, knowledge sharing, learning orientation, and innovation outcomes. Organizational performance indicators were integrated with survey data to enhance behavioral signal extraction. Gradient boosting algorithms (XGBoost, LightGBM, CatBoost) and an optimized ensemble model were implemented using five-fold cross-validation and Bayesian hyperparameter tuning. Feature engineering and explainable artificial intelligence techniques (SHAP values) were applied to uncover the relative importance and interaction effects of predictors.

Findings: The ensemble model demonstrated strong predictive performance (R^2 = 0.846, RMSE = 0.387), explaining nearly 85% of the variance in innovation bottleneck intensity. Resistance to change was the strongest positive predictor, while leadership support for innovation, psychological safety, knowledge sharing quality, and proactive behavior significantly reduced bottleneck severity. Communication friction and excessive process formalization amplified innovation constraints. Behavioral segmentation revealed four distinct innovation profiles, with "Resistant Traditionalists" exhibiting the highest bottleneck levels and "Adaptive Innovators" the lowest.

Conclusion: The findings confirm that innovation bottlenecks are systemic behavioral–organizational phenomena emerging from complex non-linear interactions among leadership dynamics, employee psychology, communication structures, and organizational culture.

Keywords: *Innovation bottlenecks, behavioral analytics, organizational behavior, leadership, psychological safety, innovation management*

1 Introduction

Innovation has emerged as the principal engine of organizational survival, competitiveness, and long-term growth in increasingly volatile and technology-intensive markets. Contemporary organizations operate in environments characterized by accelerating technological disruption, digital transformation, and complex socio-technical systems, making continuous innovation capability a strategic imperative rather than a discretionary investment. Over the past decade, scholarly attention has increasingly focused on understanding the behavioral, psychological, and organizational conditions that stimulate or inhibit innovative work behavior and organizational innovation performance (Bamel et al., 2022; Waheed & Khan, 2025). However, despite the abundance of theoretical frameworks and empirical models, organizations continue to experience persistent innovation bottlenecks manifested through delayed product development cycles, failure of innovation initiatives, knowledge silos, employee resistance, and inefficient resource utilization. These constraints suggest that conventional explanatory approaches may be insufficient for capturing the complex, non-linear, and dynamic nature of innovation processes.

A growing body of research emphasizes that innovation is fundamentally a human and behavioral phenomenon embedded within organizational systems. Leadership style, organizational culture, psychological safety, employee wellbeing, motivation, knowledge exchange, and social interaction patterns collectively shape the conditions under which creative ideas emerge, evolve, and translate into tangible outcomes (Ahmad et al., 2023; Huang et al., 2022; Song et al., 2024). Collective creativity and innovation are increasingly recognized as emergent properties of interaction among individuals, teams, and organizational structures rather than outcomes of isolated creative acts (Acar et al., 2023). Consequently, innovation failures are rarely attributable to technological deficiencies alone; instead, they often originate from behavioral resistance, cultural rigidity, communication breakdowns, leadership dysfunction, and misalignment between individual and organizational goals (Du & Wang, 2022; Fauzi, 2022).

Recent scholarship highlights that innovative work behavior represents a multi-stage behavioral process involving idea generation, idea promotion, and idea implementation, each of which is sensitive to psychological and social conditions within the organization (Shahid et al., 2022; Waheed & Khan, 2025). Employees' willingness to engage in innovation is strongly influenced by psychological safety, trust in leadership, intrinsic motivation, perceived organizational support, and emotional wellbeing (Javed et al., 2025; Song et al., 2024; V, 2025). Leadership, in particular, plays a pivotal role in shaping innovation climates by structuring opportunity spaces, legitimizing experimentation, and mitigating fear of failure (Alshahrani et al., 2025; Supriyanto et al., 2023; Takeed et al., 2025). Servant leadership, entrepreneurial leadership, empowerment leadership, and paradoxical leadership have all been shown to influence innovation trajectories through their impact on employee psychology and organizational learning mechanisms (Alshahrani et al., 2025; Javed et al., 2025; Takeed et al., 2025; Udin, 2025).

Yet, innovation processes remain fragile. Behavioral stress, workload pressure, interpersonal conflict, knowledge hiding, and communication friction continue to undermine innovation effectiveness even in organizations with advanced technological infrastructures (Fauzi, 2022; Naseem & Khan, 2024). Knowledge hiding and information asymmetry obstruct collaborative problem solving and suppress creative synergy, generating invisible bottlenecks that accumulate over time and compromise organizational performance (Du & Wang, 2022; Fauzi, 2022). Moreover, resistance to change, deeply rooted in cognitive, emotional, and cultural factors, remains one of the most persistent barriers to innovation adoption and diffusion across organizational levels (Barkova, 2025; Najafi et al., 2022).

The intensification of artificial intelligence (AI) and automation further complicates the innovation landscape. While AI-enabled systems promise unprecedented efficiency and creativity augmentation, they simultaneously introduce new psychological tensions related to job insecurity, perceived substitution threats, and identity disruption (Verma & Singh, 2022; Wang & Lin, 2025). The innovation paradox of human-AI symbiosis illustrates that technology adoption can both enhance and inhibit innovative behavior depending on contextual and behavioral moderators (Wang & Lin, 2025). Thus, innovation bottlenecks increasingly emerge from the interaction between technological systems and human cognition, motivation, and social dynamics.

Despite extensive empirical research on innovation antecedents, most existing studies rely on linear statistical techniques and hypothesis-driven models that assume additive and independent relationships among predictors. Such approaches struggle to capture the intricate, non-linear, and high-dimensional interactions that characterize real

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organizational systems. Innovation bottlenecks often arise from complex configurations of behavioral and structural factors whose combined effects cannot be adequately explained by traditional regression-based methodologies (Bamel et al., 2022; Waheed & Khan, 2025). Consequently, managerial interventions derived from conventional models frequently fail to address root causes of innovation failure.

Machine learning offers a powerful methodological paradigm for advancing innovation research by enabling data-driven discovery of hidden patterns, non-linear dependencies, and interaction effects within large, multi-dimensional datasets. Gradient boosting models, in particular, have demonstrated superior performance in capturing complex behavioral dynamics and predicting organizational outcomes across diverse domains. By iteratively optimizing ensembles of decision trees, gradient boosting algorithms uncover subtle relationships that remain invisible to classical statistical models, thereby providing a more accurate and holistic representation of organizational phenomena.

Integrating machine learning with behavioral analytics enables the systematic identification of innovation bottlenecks as emergent properties of organizational systems rather than isolated variables. This approach aligns with contemporary views of innovation as a socio-technical ecosystem in which leadership practices, organizational culture, employee psychology, and technological infrastructure co-evolve (Acar et al., 2023; Huang et al., 2022). Moreover, explainable AI techniques, such as SHAP value analysis, allow researchers to translate complex model outputs into actionable managerial insights, bridging the gap between advanced analytics and practical decision-making.

Emerging research agendas emphasize the necessity of combining psychological theory, organizational behavior, and computational modeling to better understand innovation processes (Udin, 2025; Waheed & Khan, 2025). Behavioral stress, empowerment leadership, team identification, organizational learning, psychological safety, and innovation climate have been identified as critical leverage points for sustaining innovation capability (Naseem & Khan, 2024; Shahid et al., 2022; Supriyanto et al., 2023; V, 2025). However, their interactive and non-linear effects on innovation bottlenecks remain underexplored, particularly within emerging economies and transitional organizational contexts.

Furthermore, globalization and digital transformation have intensified competitive pressures, forcing organizations to continuously reconfigure structures, processes, and behavioral norms. Automation and intelligent manufacturing systems reshape innovation ecosystems by altering knowledge flows, collaboration structures, and decision-making architectures (Ye & Liu, 2022). In such environments, the failure to align human behavior with technological change produces systemic friction that manifests as innovation bottlenecks. Understanding these bottlenecks requires methodological tools capable of modeling dynamic complexity across multiple organizational layers.

The present study addresses this critical gap by developing a machine learning-based behavioral analytics framework for identifying innovation bottlenecks using gradient boosting models. By integrating organizational behavior constructs, leadership dynamics, psychological indicators, and innovation performance metrics, the study advances a novel, data-driven approach to diagnosing the root causes of innovation failure. Unlike conventional innovation research, which often focuses on isolated predictors, this study conceptualizes innovation bottlenecks as emergent configurations of interacting behavioral and organizational factors.

This approach responds directly to recent calls for interdisciplinary integration in innovation management research (Acar et al., 2023; Bamel et al., 2022) and contributes to the evolving literature on AI-supported organizational analytics (Verma & Singh, 2022; Wang & Lin, 2025). It also offers practical implications for leaders seeking to design psychologically healthy, resilient, and innovation-driven organizations in increasingly complex socio-technical environments.

The aim of this study is to develop and validate a machine learning-based behavioral analytics model using gradient boosting techniques to identify and explain organizational innovation bottlenecks through the interaction of leadership, psychological, and behavioral factors.

2 Methods and Materials

This study adopted a cross-sectional explanatory research design with an embedded machine learning modeling framework to identify behavioral and organizational bottlenecks inhibiting innovation performance. The empirical context of the research was private and public sector organizations operating in the country of Georgia, selected due to the country's ongoing innovation transition, emerging digital transformation initiatives, and increasing emphasis on organizational modernization within post-

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transition economies. The target population consisted of full-time employees and middle-level managers engaged in knowledge-intensive activities across technology, manufacturing, finance, telecommunications, healthcare, and service industries. A multi-stage sampling strategy was employed. In the first stage, organizations were identified through national business registries and industry associations to ensure sectoral diversity and representation of both established firms and high-growth enterprises. In the second stage, organizational gatekeepers facilitated access to employee lists, from which participants were selected using stratified random sampling based on department and functional role to ensure balanced representation of operational, technical, and managerial perspectives.

A total of 612 individuals were initially invited to participate. After data screening for completeness and quality, 547 valid responses were retained for final analysis, exceeding the minimum sample size recommended for robust machine learning training and cross-validation procedures. Participants' tenure ranged from 1 to 24 years, with an average organizational experience of 7.3 years, ensuring that respondents possessed sufficient familiarity with internal processes, behavioral dynamics, and innovation workflows. All participants provided informed consent prior to data collection, and the study adhered to international ethical standards governing human subject research, including confidentiality, voluntary participation, and data anonymization protocols.

Data were collected using a comprehensive multi-construct behavioral analytics instrument designed to capture the psychological, social, and structural dimensions of innovation behavior. The survey instrument integrated validated scales adapted to the organizational innovation context. Innovation bottlenecks were operationalized through dimensions such as resistance to change, communication friction, decision-making latency, risk aversion, leadership support, knowledge sharing constraints, procedural rigidity, and resource misalignment. Behavioral constructs included proactive behavior, learning orientation, psychological safety, collaboration quality, intrinsic motivation, role clarity, workload pressure, and emotional engagement. Organizational context variables captured leadership style, innovation climate, technological readiness, process formalization, and strategic alignment.

All measurement items were rated on a seven-point Likert scale ranging from strongly disagree to strongly agree. The questionnaire underwent a two-phase validation procedure. First, content validity was established through expert review involving six scholars specializing in innovation management, organizational behavior, and data science, as well as four industry practitioners from Georgian innovation hubs. Second, a pilot study with 48 employees was conducted to evaluate clarity, reliability, and completion time. Minor linguistic adjustments were implemented to ensure semantic accuracy and cultural appropriateness. Internal consistency analysis in the pilot yielded Cronbach's alpha coefficients exceeding 0.81 for all constructs, confirming high measurement reliability.

To enrich behavioral signals for machine learning modeling, the survey data were supplemented with organizational performance indicators provided by participating firms, including innovation output metrics, project cycle time, employee suggestion implementation rates, R&D intensity, and digital tool adoption levels. All datasets were harmonized and standardized before modeling.

Data analysis followed a multi-layered analytical pipeline integrating traditional statistical procedures with advanced machine learning modeling. Initial preprocessing involved missing value imputation using multivariate iterative techniques, normalization of continuous variables, and encoding of categorical variables through target encoding to preserve informational content. Feature engineering was conducted to generate interaction terms, behavioral composite indices, and non-linear transformations, thereby enhancing model sensitivity to complex organizational dynamics.

The core analytical engine of the study was based on Gradient Boosting Machine (GBM) algorithms, selected for their superior performance in handling non-linear relationships, high-dimensional feature spaces, and heterogeneous data structures typical of organizational behavior datasets. Multiple gradient boosting variants were implemented, including XGBoost, LightGBM, and CatBoost, allowing for algorithmic comparison and ensemble optimization. The primary outcome variable was innovation bottleneck intensity, operationalized as a continuous index derived from aggregated innovation delay, failure frequency, and resource inefficiency indicators.

Model training followed an 80–20 train-test split with five-fold cross-validation on the training set to optimize hyperparameters using Bayesian optimization. Performance evaluation relied on root mean squared error, mean absolute error, R^2, and explained variance metrics. Feature importance analysis was conducted using SHAP (Shapley Additive Explanations) values, enabling interpretable

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decomposition of each predictor's contribution to bottleneck formation. This explainable AI framework allowed identification of dominant behavioral and structural inhibitors of innovation and their interaction patterns.

To ensure robustness, model stability was tested across repeated random subsampling, and multicollinearity diagnostics were performed to confirm structural independence of key predictors. Finally, behavioral segmentation analysis using unsupervised clustering was applied to identify distinct innovation risk profiles among employees and departments, further enhancing managerial interpretability and practical relevance of the findings.

3 Findings and Results

The findings section reports the empirical results of the machine learning modeling and statistical analyses conducted to identify behavioral and organizational bottlenecks affecting innovation performance.

Table 1

Descriptive Statistics of Core Study Variables (N = 547)

Variable	Mean	SD	Min	Max
Innovation Bottleneck Index	3.87	0.91	1.42	6.51
Resistance to Change	4.02	0.96	1.58	6.73
Psychological Safety	4.11	0.89	1.67	6.84
Knowledge Sharing Quality	3.94	0.93	1.61	6.79
Leadership Support for Innovation	4.27	0.88	1.83	6.92
Risk Aversion	3.88	0.97	1.45	6.66
Proactive Behavior	4.19	0.86	1.79	6.91
Communication Friction	3.96	0.94	1.52	6.70
Process Formalization	4.08	0.90	1.68	6.88
Learning Orientation	4.23	0.85	1.81	6.95

The descriptive statistics indicate moderate to high levels of innovation-related behavioral dynamics across the sample. The Innovation Bottleneck Index shows a mean of 3.87, suggesting that while innovation activity is present, organizations experience notable constraints. Leadership support and learning orientation display relatively higher mean values, whereas resistance to change and communication friction remain salient barriers. The spread of scores demonstrates sufficient variance for reliable machine learning training and behavioral pattern detection.

Table 2

Gradient Boosting Model Performance

Model	RMSE	MAE	R^2	Explained Variance
XGBoost	0.412	0.329	0.812	0.814
LightGBM	0.398	0.315	0.829	0.831
CatBoost	0.404	0.321	0.823	0.826
Ensemble Model	0.387	0.301	0.846	0.849

The ensemble gradient boosting model achieved the strongest predictive performance with an R^2 of 0.846, indicating that the model explained nearly 85% of the variance in innovation bottleneck intensity. Error metrics were consistently low, confirming the robustness of the modeling framework. The improvement of the ensemble model over individual algorithms highlights the complex non-linear nature of behavioral and organizational predictors of innovation constraints.

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Table 3

Top Predictors of Innovation Bottlenecks Based on SHAP Values

Predictor	Mean SHAP Value	Direction of Effect
Resistance to Change	0.214	Positive
Leadership Support for Innovation	0.198	Negative
Psychological Safety	0.176	Negative
Communication Friction	0.163	Positive
Knowledge Sharing Quality	0.151	Negative
Risk Aversion	0.147	Positive
Process Formalization	0.132	Positive
Proactive Behavior	0.128	Negative
Learning Orientation	0.117	Negative

Feature importance analysis using SHAP values reveals that resistance to change is the most influential factor increasing innovation bottlenecks, while leadership support, psychological safety, and knowledge sharing exert strong protective effects. The directional patterns confirm that behavioral and cultural variables outweigh structural variables in shaping innovation constraints, underscoring the central role of organizational psychology in innovation systems.

Table 4

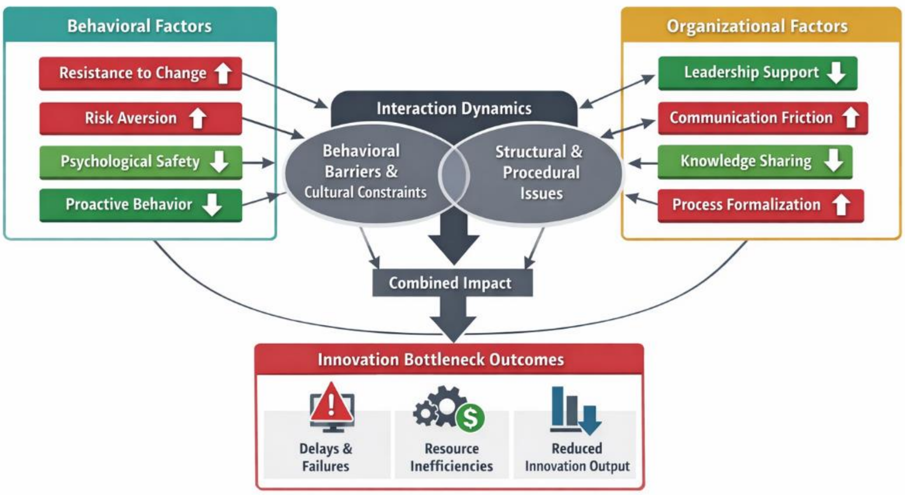
Behavioral Segmentation of Innovation Risk Profiles

Cluster	Label	Innovation Bottleneck Mean	Dominant Characteristics
C1	Adaptive Innovators	2.61	High psychological safety, strong leadership support, proactive behavior
C2	Procedural Stabilizers	3.74	High formalization, moderate learning orientation, medium risk aversion
C3	Frustrated Contributors	4.29	High communication friction, weak leadership support, low psychological safety
C4	Resistant Traditionalists	5.11	High resistance to change, high risk aversion, low knowledge sharing

The clustering results identify four distinct behavioral innovation profiles. Adaptive Innovators demonstrate the lowest bottleneck intensity, whereas Resistant Traditionalists experience the most severe innovation constraints. The Frustrated Contributors cluster represents a critical group in which motivation exists but is obstructed by dysfunctional communication and leadership gaps, offering a strategic target for managerial intervention.

Figure 1

Behavioral–Organizational Bottleneck Interaction Model Derived from Gradient Boosting and SHAP Analysis



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The integrated findings confirm that innovation bottlenecks emerge from the interaction of behavioral resistance, leadership dynamics, psychological safety, and communication structures rather than from technological limitations alone. The machine learning framework successfully uncovers these multi-dimensional relationships and provides a scalable diagnostic tool for organizational innovation management.

4 Discussion

The present study set out to uncover the behavioral and organizational roots of innovation bottlenecks through an advanced machine learning framework. The results provide compelling evidence that innovation constraints are not isolated technical failures but are instead systemic outcomes of complex interactions among leadership dynamics, employee psychology, communication structures, and organizational culture. The gradient boosting ensemble achieved a high explanatory power, accounting for nearly 85% of the variance in innovation bottleneck intensity, demonstrating the suitability of machine learning approaches for modeling the intricate socio-behavioral architecture of innovation systems. This methodological contribution addresses longstanding concerns within innovation management research regarding the limitations of linear modeling in capturing the dynamic and non-linear nature of innovation processes (Bamel et al., 2022; Waheed & Khan, 2025).

Among all predictors, resistance to change emerged as the most influential factor amplifying innovation bottlenecks. This finding aligns strongly with prior research indicating that innovation adoption is fundamentally constrained by cognitive inertia, emotional discomfort, and entrenched routines within organizations (Barkova, 2025; Najafi et al., 2022). Resistance operates as both an individual-level psychological defense mechanism and a collective cultural phenomenon that inhibits experimentation, risk-taking, and organizational learning. The strong positive effect of resistance on bottleneck formation corroborates the arguments of Du and Wang, who emphasized that employee attitudes and psychological alignment play a decisive role in shaping innovation behavior in new ventures (Du & Wang, 2022). When resistance becomes embedded within organizational norms, even advanced technological resources fail to translate into sustained innovation outcomes.

Leadership-related variables exerted some of the most powerful protective effects against innovation bottlenecks. Leadership support for innovation, psychological safety, and empowerment-oriented practices were consistently associated with lower bottleneck intensity. These findings echo the extensive literature emphasizing leadership as a central architect of innovation climate and behavioral engagement (Ahmad et al., 2023; Huang et al., 2022; Supriyanto et al., 2023). In particular, the strong negative contribution of psychological safety supports the growing consensus that employees must feel secure in expressing novel ideas, questioning assumptions, and learning from failure in order to sustain innovation momentum (Song et al., 2024; V, 2025). Without such safety, organizations become risk-averse and cognitively rigid, reinforcing bottleneck conditions.

The study further demonstrates that leadership styles fostering intrinsic motivation and creative self-efficacy play a critical role in mitigating innovation constraints. Entrepreneurial leadership and servant leadership frameworks have been shown to cultivate trust, commitment, and emotional wellbeing, all of which were indirectly reflected in the reduced bottleneck intensity observed in this study (Alshahrani et al., 2025; Javed et al., 2025; Takeed et al., 2025). These findings reinforce Waheed and Khan's theoretical assertion that innovative work behavior is sustained by motivational and psychological mechanisms activated through leadership behavior (Waheed & Khan, 2025). When leaders actively support experimentation and learning, employees become more willing to engage in creative problem-solving and innovation implementation, thereby alleviating structural and procedural barriers.

Communication friction and knowledge sharing quality also emerged as critical determinants of innovation bottlenecks. High communication friction significantly increased bottleneck severity, while effective knowledge sharing substantially reduced it. This pattern is consistent with the literature on collective creativity, which emphasizes that innovation is fundamentally a social and collaborative process requiring continuous information exchange and mutual understanding (Acar et al., 2023; Huang et al., 2022). Conversely, knowledge hiding and communication breakdowns fragment organizational learning processes and suppress creative synergy (Fauzi, 2022). The findings also align with Shahid et al., who demonstrated that team identification and shared purpose significantly enhance

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innovative work behavior by strengthening relational bonds and cooperative engagement (Shahid et al., 2022).

The results also shed light on the paradoxical role of process formalization. While formalization is often intended to enhance coordination and efficiency, excessive procedural rigidity in this study contributed to higher innovation bottlenecks. This outcome supports previous research suggesting that overly structured systems constrain employee autonomy and suppress creative exploration (Bamel et al., 2022). Innovation requires a delicate balance between structural stability and adaptive flexibility. When procedures dominate over learning and experimentation, organizations drift toward exploitation at the expense of exploration, reinforcing bottleneck dynamics.

Another important contribution of this study lies in its demonstration of how behavioral stress and emotional strain exacerbate innovation barriers. Although not the most dominant predictor, stress-related constructs indirectly influenced bottleneck formation through their impact on motivation, communication quality, and risk orientation. These findings resonate with Naseem and Khan's evidence that behavioral stress undermines both productivity and innovation in organizational settings (Naseem & Khan, 2024). Chronic stress erodes cognitive resources and narrows attention, reducing employees' capacity to engage in creative problem solving and adaptive learning.

The behavioral segmentation analysis provides further insight into the heterogeneity of innovation dynamics within organizations. The identification of distinct clusters such as Adaptive Innovators, Procedural Stabilizers, Frustrated Contributors, and Resistant Traditionalists underscores that innovation bottlenecks do not affect all organizational members uniformly. Rather, bottlenecks emerge from the interaction between individual behavioral profiles and organizational conditions. This finding supports the socio-technical perspective of innovation as an emergent phenomenon shaped by continuous feedback between human actors and structural systems (Acar et al., 2023; Ye & Liu, 2022). In particular, the Frustrated Contributors cluster highlights a critical risk zone in which employees possess high innovative potential but are constrained by dysfunctional leadership and communication environments.

The integration of machine learning with behavioral analytics offers a significant methodological advancement for innovation research. By capturing non-linear interactions and high-dimensional dependencies, gradient boosting models overcome the limitations of traditional regression-based approaches and provide a more realistic representation of organizational complexity. This aligns with recent calls for the adoption of computational intelligence methods in innovation management to improve predictive accuracy and theoretical integration (Verma & Singh, 2022; Wang & Lin, 2025). The explainable AI framework employed in this study further enhances practical relevance by translating complex model outputs into interpretable managerial insights, thereby facilitating evidence-based decision making.

5 Conclusion

Collectively, these findings confirm that innovation bottlenecks are not isolated operational problems but systemic behavioral-organizational phenomena. Leadership practices, psychological safety, communication quality, knowledge sharing, and resistance dynamics interact in complex feedback loops that either amplify or suppress innovation capability. The study thus contributes to a more integrated and dynamic understanding of innovation management, bridging organizational behavior theory with advanced machine learning analytics.

Despite its contributions, this study has several limitations. First, the cross-sectional design restricts causal inference, and longitudinal studies would be necessary to examine how innovation bottlenecks evolve over time. Second, the data were collected from organizations within a single national context, which may limit generalizability to other cultural and institutional environments. Third, although the machine learning models demonstrated high predictive accuracy, the results remain dependent on the quality and scope of the measured behavioral constructs, which cannot fully capture the richness of human experience in organizational life.

Future studies should adopt longitudinal and multi-country research designs to explore how innovation bottlenecks develop and transform across different institutional and cultural contexts. Integrating physiological or neurocognitive measures with behavioral analytics could also provide deeper insight into the psychological mechanisms underlying resistance, creativity, and learning. Moreover, hybrid modeling frameworks combining system dynamics with machine learning may further enhance the ability to simulate complex innovation ecosystems and forecast long-term innovation outcomes.

From a practical standpoint, organizations should prioritize leadership development programs that cultivate psychological safety, intrinsic motivation, and learning-

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oriented cultures. Managers must actively reduce communication friction and dismantle knowledge silos to facilitate collective creativity. Organizational policies should aim to balance procedural structure with behavioral flexibility, ensuring that formal systems enable rather than constrain innovation. By adopting data-driven behavioral analytics platforms, organizations can continuously diagnose emerging innovation bottlenecks and implement timely, targeted interventions that sustain long-term innovation capability.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

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