




Clustering Innovation Behaviors Using Machine Learning: Roles of Future Time Perspective and Proactive Motivation

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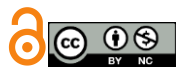
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ABSTRACT

Objective: This study aimed to identify distinct profiles of employee innovation behaviors using unsupervised machine learning and to evaluate the predictive roles of future time perspective and proactive motivation in determining membership within these empirically derived behavioral clusters.

Methods and Materials: A quantitative, cross-sectional design was utilized to collect data from a purposive sample of 458 professionals employed in various knowledge-intensive sectors across Spain. Participants completed validated self-report questionnaires assessing three core dimensions of innovation behavior (idea generation, idea promotion, and idea realization), alongside measures of future time perspective and proactive motivation. The analytical framework employed a K-means clustering algorithm to partition the multidimensional innovation scores into distinct profiles, followed by multinomial logistic regression models to evaluate the predictive capacity of the psychological variables in determining cluster categorization.

Findings: The K-means clustering analysis ($k = 3$) successfully identified three distinct behavioral profiles: “Passive Innovators” ($n = 142, 31.0\%$), “Moderate Innovators” ($n = 198, 43.2\%$), and “High Innovators” ($n = 118, 25.8\%$). The multinomial logistic regression model demonstrated robust predictive power (Nagelkerke $R^2 = .40$). A one-unit increase in future time perspective significantly increased the odds of an individual belonging to the High Innovators cluster rather than the Passive Innovators cluster ($OR = 3.48, p < .001$). Furthermore, proactive motivation emerged as an exceptionally strong differentiator; a one-unit increase in proactive motivation drastically elevated the likelihood of being classified as a High Innovator compared to the passive reference group ($OR = 8.75, p < .001$).

Conclusion: Fostering a future-oriented mindset and cultivating intrinsic proactive motivation are critical psychological catalysts for transforming passive employees into highly engaged innovators capable of driving ideas from initial conception to full realization.

Keywords: Innovation Behaviors, Machine Learning, K-means Clustering, Future Time Perspective, Proactive Motivation, Organizational Behavior.

1 Introduction

In the contemporary, hyper-competitive global marketplace, an organization's survival and sustained competitive advantage are intrinsically linked to its capacity for continuous innovation. This imperative places a profound emphasis on the micro-foundations of organizational success, specifically the innovative behaviors exhibited by individual employees. Employee innovation behavior is broadly conceptualized as a complex, multi-stage process encompassing the generation of novel and useful ideas, the promotion of these ideas to stakeholders to garner support, and the ultimate realization or implementation of these concepts into tangible products, services, or optimized organizational processes. The cultivation of such behaviors is heavily dependent on strategic human resource management and effective knowledge management processes, which collectively serve to transform human capital into a formidable competitive advantage (Shaalán et al., 2022). Furthermore, the overarching employment model adopted by a firm establishes the structural boundaries and psychological contracts that can either constrain or catalyze employees' willingness to engage in extra-role innovative tasks (Xie & Fang, 2020). To maximize this potential, organizations must foster an environment characterized by high organizational competence and deep employee commitment, as these factors are foundational to enhancing overall performance and facilitating sustained innovation (Mertiningsih et al., 2024). High-commitment human resource management systems, in particular, play a crucial role in shaping these behaviors, with their effectiveness often mediated by an employee's acceptance of organizational change and moderated by the perceived strength of the human resource system itself (You & Park, 2024).

The intricate relationship between the organizational environment and employee innovation is further nuanced by psychological and cultural dimensions. Cultivating an organizational psychology and culture that supports risk-taking and psychological safety is essential, particularly within new ventures where the structural uncertainty requires a high degree of employee adaptability and proactive innovation (Du & Wang, 2022). The modern workplace also demands an appreciation for diversity and cultural intelligence, which acts as a critical antecedent to sustainable innovation behavior, especially when this relationship is nurtured through active knowledge sharing and a supportive, inclusive organizational culture

(Hernawati, 2024). Fundamentally, the intersection of personality psychology and the immediate working environment dictates how new ventures and established firms alike extract innovative performance from their workforce (Yang & Wu, 2021). Intrinsic motivation stands out as a paramount psychological driver in this context; knowledge-based employees in the modern industrial era rely heavily on their internal drive and a collaborative environment of knowledge sharing to successfully execute innovative behaviors (Yu, 2021). Furthermore, an employee's specific goal orientation—whether focused on mastery, performance, or avoidance—significantly shapes their approach to complex problem-solving and subsequent innovation outcomes (Mei-rong et al., 2022). These psychological frameworks are equally vital in academic and highly specialized contexts, where the initiative for scientific research and innovation among postgraduates can be thoroughly understood and predicted through the lens of the theory of planned behavior (Wang et al., 2022).

A vast and highly influential stream of research within organizational behavior underscores the pivotal role of leadership in either stifling or stimulating employee innovation. Leadership acts as the primary conduit through which organizational culture and strategic objectives are communicated to employees. Authentic and transformational leadership paradigms have been extensively linked to increased employee innovation. By leading with transparency and a compelling vision, these leaders build the psychological capital of their subordinates, providing the necessary emotional and cognitive resources required to engage in complex service innovation behaviors (Markus et al., 2018). This dynamic is particularly evident at the executive level; the transformational leadership of a Chief Executive Officer creates an overarching alignment of vision that directly cascades down to enhance the innovation behavior of specialized roles, such as designers (Liu & Niu, 2020). In specialized, fined, peculiar, and innovative small and medium-sized enterprises, authentic leadership proves vital in simultaneously elevating work engagement and driving the practical generation of innovative solutions (Zhang et al., 2023). Moreover, within high-stress environments like healthcare, entrepreneurial leadership is critical for encouraging frontline staff, such as nurses, to challenge the status quo and engage in behaviors that improve patient care and operational efficiency (Bagheri & Akbari, 2018). The relational dynamics between a leader and a subordinate, captured by the concept of leader-member exchange, also form a critical foundation for innovation.

When professionals, such as university lecturers, perceive a high-quality relationship characterized by trust and support from their superiors, they are significantly more inclined to invest discretionary effort into innovative academic behaviors (Zhu & Tsai, 2024).

Beyond transformational and authentic frameworks, contemporary research highlights the importance of ethical, environmental, and shared leadership models in addressing specific types of innovation. Ethical leadership is fundamental in establishing a moral compass for the organization, which unexpectedly plays a critical role in service innovation; however, the effectiveness of ethical leadership in promoting innovation is highly contingent upon the employees' psychological well-being, such as their sleep quality, highlighting a complex dual-path model of influence (Rasheed et al., 2024). In response to growing global environmental concerns, leadership models have evolved to specifically target ecological outcomes. Environmental leadership directly boosts employees' green innovation behaviors by clearly articulating sustainability goals and modeling environmentally responsible actions (Xu et al., 2022). Similarly, ethical leadership has been shown to positively impact green innovation by fostering a climate of responsibility and ethical stewardship (Yang & Liu, 2022). The push for sustainability is also highly relevant in industries with massive environmental footprints, such as the construction sector, where understanding the mechanisms that influence green technology innovation is imperative for future industry viability (Li et al., 2022). Furthermore, as organizations pivot towards decentralized structures, shared leadership—where decision-making and influence are distributed among team members—has gained prominence. Interestingly, shared leadership can influence unconventional forms of creativity, including employees' deviant innovation behaviors (Chen & Ma, 2025). Deviant innovation, where employees secretly pursue new ideas in defiance of formal organizational directives, represents a complex game of risk and reward that can ultimately yield significant, albeit unpredictable, organizational innovation performance (Han et al., 2024).

The landscape of employee innovation is also undergoing a profound transformation driven by rapid technological advancements and shifting workplace dynamics. The integration of digital human resource management systems is revolutionizing how organizations identify, cultivate, and manage innovative talent. In highly dynamic sectors, such as the Information and Communication Technology industry, digital human resources directly impact employee

innovation behavior, a process that is crucially mediated by the organization's capacity for continuous, technology-facilitated learning (Alrifae, 2025). The synergistic effect of accumulating human capital and fostering organizational learning is a proven pathway to elevating both innovation behavior and the overall performance of employees in knowledge-intensive sectors like banking (Isa & Muafi, 2022). However, the influx of technology presents a complex duality. The implementation of Artificial Intelligence assistants in the workplace operates as a double-edged sword; while Artificial Intelligence can significantly augment the technical capacity for idea generation, it may simultaneously disrupt traditional cognitive workflows and alter the fundamental nature of employees' innovation behaviors (Yin et al., 2024). Concurrently, the social environment of the workplace remains a powerful determinant of innovation. Negative social interactions, particularly workplace ostracism, trigger a detrimental chain of mediating psychological effects that severely inhibit an employee's psychological safety and, consequently, their willingness to engage in any form of innovative endeavor (Xing & Li, 2022).

While the existing body of literature provides profound insights into the organizational, leadership, and contextual antecedents of innovation, a significant methodological and theoretical gap remains. The vast majority of prior studies have approached employee innovation behavior from a variable-centered perspective. Techniques such as multiple linear regression and structural equation modeling treat innovation as a continuous, homogenous variable, essentially measuring the aggregate relationship between an independent variable and an innovation score across an entire sample. This approach implicitly assumes that employees are a monolithic group and that the process of innovation is uniformly experienced. However, human behavior in the workplace is rarely uniform; it is highly heterogeneous. Employees likely cluster into distinct, naturally occurring profiles based on how they engage with the three stages of innovation: idea generation, promotion, and realization. For instance, some employees may excel at generating ideas but completely lack the drive to promote them, while others may be passive observers, and a select few may consistently drive ideas from inception to full execution.

To uncover these latent behavioral profiles, a person-centered analytical approach is necessary. Unsupervised machine learning, particularly algorithms like *K* – *means* clustering, offers a mathematically rigorous

methodology for partitioning multidimensional behavioral data into distinct groups. By deploying machine learning, researchers can move beyond average effects to map the true topographical landscape of innovation behaviors within an organization. Identifying whether an employee belongs to a “Passive Innovator,” “Moderate Innovator,” or “High Innovator” cluster provides far more actionable insight for targeted management interventions than a simple aggregate score.

Furthermore, while broad psychological constructs like intrinsic motivation have been studied, there is a critical need to evaluate specific, future-oriented psychological predictors that drive membership into these high-performing clusters. Future time perspective—an individual’s cognitive bias toward anticipating and valuing long-term future outcomes over immediate gratification—is theoretically vital for innovation, given that realizing a new idea often requires enduring significant short-term uncertainty and effort. Similarly, proactive motivation—the self-starting, change-oriented drive to alter one’s environment—is essential for pushing an idea through the inevitable organizational resistance encountered during the promotion and realization phases. Understanding how a future-oriented mindset and a proactive motivational state distinguish highly innovative employees from their passive counterparts will provide organizations with precise psychological targets for recruitment and development. This study aimed to identify distinct profiles of employee innovation behaviors using unsupervised machine learning and to evaluate the predictive roles of future time perspective and proactive motivation in determining membership within these empirically derived behavioral clusters.

2 Methods and Materials

The present study utilized a quantitative, cross-sectional design to investigate the clustering of innovation behaviors among professionals and to determine the predictive roles of future time perspective and proactive motivation. The target population comprised individuals employed in various knowledge-intensive sectors across Spain. A purposive sampling technique was employed to recruit a diverse yet representative cohort of professionals who are regularly exposed to work environments requiring problem-solving and innovative thinking. Following the distribution of the survey through professional networking platforms and direct email invitations to several Spanish enterprises, a total of 458 valid responses were collected and retained for the final

analysis. The sample included participants from diverse demographic backgrounds, encompassing different age groups, educational levels, and professional tenures, thereby ensuring a comprehensive capture of innovation behaviors across multiple organizational contexts within the Spanish workforce. Informed consent was obtained from all participants prior to their involvement, and all procedures were conducted in strict adherence to ethical guidelines concerning anonymity, data protection, and voluntary participation.

To empirically assess the constructs of interest, a structured questionnaire comprising well-established psychometric scales was administered to the participants. Innovation behaviors were evaluated using a multidimensional scale designed to capture the distinct phases of the innovation process, specifically idea generation, idea promotion, and idea realization. Participants rated the frequency of their engagement in these behaviors on a five-point Likert-type scale, providing a robust continuous measure for subsequent machine learning applications. Future time perspective was measured utilizing a validated adaptation of the Zimbardo Time Perspective Inventory, focusing specifically on the future orientation subscale. This instrument assesses the degree to which individuals anticipate, plan for, and are influenced by future outcomes and goals, with higher scores reflecting a stronger future-oriented mindset. Proactive motivation was captured through a comprehensive inventory that measures self-starting, proactive, and persistent work behaviors. This scale evaluates the internal drive of employees to anticipate future problems or opportunities and take self-directed action to bring about meaningful change. All instruments were translated into Spanish using a rigorous forward and backward translation protocol to ensure linguistic equivalence and cultural relevance, and they demonstrated high internal consistency and reliability within the current sample.

The analytical framework for this study was executed in several systematic phases utilizing advanced computational environments and machine learning techniques. Initially, data preprocessing was conducted to handle missing values, standardize the continuous variables to a mean of 0 and a standard deviation of 1, and ensure the dataset was optimized for unsupervised learning algorithms. To identify distinct profiles of innovation behaviors, an unsupervised machine learning approach, specifically the K-means clustering algorithm, was applied to the multidimensional innovation behavior scores. The optimal number of clusters

was determined by evaluating multiple internal validation metrics, including the silhouette coefficient and the within-cluster sum of squares through the elbow method, ensuring that the resulting groupings were both mathematically rigorous and theoretically meaningful. Following the successful categorization of participants into distinct innovation behavior clusters, supervised learning and inferential statistical methods were deployed to examine the roles of future time perspective and proactive motivation. Specifically, multinomial logistic regression models and decision tree classifiers were utilized to assess the predictive capacity of these psychological variables in determining cluster membership. This allowed for a detailed understanding of how varying levels of future-oriented thinking and proactive drive correspond to specific profiles of innovative engagement. Furthermore, feature importance analyses were conducted to quantify the relative contribution of each motivational construct in delineating the boundaries between the identified behavioral clusters.

3 Findings and Results

Initial descriptive statistics and Pearson bivariate correlations were computed to examine the fundamental relationships among the three dimensions of innovation behaviors (idea generation, idea promotion, and idea realization), future time perspective, and proactive motivation. As anticipated, the correlational analysis revealed significant positive associations among all the study variables. Future time perspective demonstrated a strong positive correlation with proactive motivation ($r = .52, p < .001$) and all three dimensions of innovation behavior. Similarly, proactive motivation was highly correlated with idea generation ($r = .61, p < .001$), idea promotion ($r = .58, p < .001$), and idea realization ($r = .64, p < .001$). These initial results provided a robust foundation for the subsequent clustering and predictive modeling, indicating that future-oriented and proactive individuals generally report higher engagement in all stages of the innovation process. Table 1 presents the means, standard deviations, and correlation coefficients for the primary study variables.

Table 1

Descriptive Statistics and Pearson Correlations Among Study Variables

Variable	<i>M</i>	<i>SD</i>	1	2	3	4	5
1. Idea Generation	3.54	0.88	–				
2. Idea Promotion	3.22	0.94	.72**	–			
3. Idea Realization	3.15	0.96	.68**	.75**	–		
4. Future Time Perspective	3.81	0.75	.45**	.41**	.47**	–	
5. Proactive Motivation	3.68	0.82	.61**	.58**	.64**	.52**	–

Following the correlational analysis, a K-means clustering algorithm was applied to the standardized scores of the three innovation behavior dimensions to identify distinct behavioral profiles within the sample. To determine the optimal number of clusters (k), the within-cluster sum of squares (WCSS) was calculated across multiple values of k (from 1 to 10) using the elbow method. The visual inspection of the elbow plot suggested an inflection point at $k = 3$. This was further corroborated by calculating the silhouette scores, which assess how similar an object is to its own cluster compared to other clusters. The three-cluster solution yielded the highest average silhouette score (0.64), indicating a strong and distinct cluster structure.

The three identified clusters were theoretically and practically meaningful. Cluster 1 ($n = 142, 31.0\%$) was labeled “Passive Innovators,” characterized by the lowest

mean scores across idea generation, promotion, and realization. Cluster 2 ($n = 198, 43.2\%$) was designated as “Moderate Innovators,” representing individuals with average scores across all three dimensions. Finally, Cluster 3 ($n = 118, 25.8\%$) was named “High Innovators,” comprising professionals who exhibited exceptionally high engagement in all phases of the innovation process. To confirm the distinctiveness of these clusters, a multivariate analysis of variance (MANOVA) was conducted. The results demonstrated a significant main effect of cluster membership on the combined innovation behavior variables, Wilks’ $\Lambda = 0.21, F(6,906) = 175.43, p < .001, \eta_p^2 = .54$. Post hoc analyses using Tukey’s HSD confirmed that all three clusters differed significantly from one another on every dimension of innovation behavior ($p < .001$). Table 2

details the centroid profiles (means and standard deviations) for the three clusters.

Table 2

Cluster Profiles: Means and Standard Deviations of Innovation Behaviors by Cluster

Variable	Cluster 1: Passive Innovators (<i>n</i> = 142)	Cluster 2: Moderate Innovators (<i>n</i> = 198)	Cluster 3: High Innovators (<i>n</i> = 118)	<i>F</i> (2, 455)
	<i>M</i> (<i>SD</i>)	<i>M</i> (<i>SD</i>)	<i>M</i> (<i>SD</i>)	
Idea Generation	2.55(0.58)	3.62(0.45)	4.58(0.38)	524.12**
Idea Promotion	2.21(0.52)	3.35(0.42)	4.22(0.49)	488.75**
Idea Realization	2.08(0.49)	3.28(0.46)	4.20(0.44)	562.33**

In the final analytical phase, a multinomial logistic regression model was constructed to evaluate the predictive roles of future time perspective and proactive motivation in determining cluster membership. The “Passive Innovators” (Cluster 1) served as the reference category. The overall model was statistically significant, $\chi^2(4) = 198.45$, $p < .001$, indicating that the inclusion of future time perspective and proactive motivation significantly improved the model’s fit compared to the null model. The pseudo- R^2 values (Cox and Snell = .35, Nagelkerke = .40) indicated a substantial proportion of variance in cluster membership was explained by the predictors.

The parameter estimates revealed that both psychological constructs uniquely and significantly predicted the likelihood of belonging to a higher-level innovation cluster. Specifically, a one-unit increase in future time perspective significantly increased the odds of belonging to the

“Moderate Innovators” cluster relative to the “Passive Innovators” ($OR = 2.15$, $p = .002$). This effect was even more pronounced when predicting membership in the “High Innovators” cluster ($OR = 3.48$, $p < .001$). Similarly, proactive motivation emerged as a powerful predictor. For every one-unit increase in proactive motivation, the odds of being classified as a “Moderate Innovator” rather than a “Passive Innovator” increased by a factor of 3.92 ($p < .001$). Furthermore, higher proactive motivation drastically increased the likelihood of being categorized as a “High Innovator” compared to the passive reference group ($OR = 8.75$, $p < .001$). The results highlight that while both variables are critical, proactive motivation serves as a particularly strong catalyst for differentiating top-tier innovators from their passive counterparts. Detailed results of the multinomial logistic regression are presented in Table 3.

Table 3

Multinomial Logistic Regression Predicting Innovation Cluster Membership

Predictor	<i>B</i>	<i>SE</i>	Wald χ^2	<i>p</i>	Odds Ratio (<i>Exp</i> (<i>B</i>))	95% CI for <i>Exp</i> (<i>B</i>)
Moderate Innovators (Cluster 2) vs. Passive Innovators (Cluster 1)						
Intercept	-5.62	0.88	40.81	<.001	—	—
Future Time Perspective	0.76	0.24	10.03	.002	2.15	[1.34, 3.45]
Proactive Motivation	1.36	0.22	38.18	<.001	3.92	[2.54, 6.04]
High Innovators (Cluster 3) vs. Passive Innovators (Cluster 1)						
Intercept	-9.45	1.25	57.15	<.001	—	—
Future Time Perspective	1.24	0.31	16.01	<.001	3.48	[1.89, 6.39]
Proactive Motivation	2.16	0.32	45.56	<.001	8.75	[4.67, 16.38]

4 Discussion

The primary objective of this research was to leverage unsupervised machine learning to uncover distinct profiles

of employee innovation behaviors and to assess how future time perspective and proactive motivation predict membership within these empirically derived clusters. Utilizing a K – meansclustering algorithm ($k = 3$), the multidimensional data analysis successfully segmented the

sample of 458 professionals into three distinct behavioral profiles: “Passive Innovators” ($n = 142$, 31.0%), “Moderate Innovators” ($n = 198$, 43.2%), and “High Innovators” ($n = 118$, 25.8%). Furthermore, the multinomial logistic regression model demonstrated substantial predictive capacity (Nagelkerke $R^2 = .40$). The results revealed that both future time perspective ($OR = 3.48$, $p < .001$) and proactive motivation ($OR = 8.75$, $p < .001$) significantly increase the likelihood of an employee belonging to the High Innovators cluster compared to the Passive Innovators reference group.

The identification of three heterogeneous innovation profiles supports the contemporary conceptualization of innovation as a complex, multifaceted construct rather than a uniform trait distributed evenly across the workforce. The High Innovators group, comprising 25.8% of the sample, represents individuals who consistently engage across all stages of the innovation lifecycle: generating novel concepts, actively promoting them to stakeholders, and ensuring their practical realization. This finding aligns with organizational studies suggesting that comprehensive innovation behavior is contingent upon a supportive organizational psychology and culture that inherently encourages risk-taking (Du & Wang, 2022). Conversely, the presence of a substantial Passive Innovators cluster (31.0%) highlights the inhibiting effects of certain workplace dynamics. For instance, employees experiencing negative social interactions, such as workplace ostracism, often withdraw from voluntary innovative efforts due to diminished psychological safety and a disrupted chain of mediating cognitive processes (Xing & Li, 2022). The Moderate Innovators profile (43.2%) likely represents employees who possess the capacity to generate ideas but lack the systemic support or personal drive to promote and implement them. The transition from moderate to high innovation often necessitates robust knowledge management processes and high-commitment human resource systems that facilitate employee acceptance of change and strengthen the structural capacity for realization (Shalan et al., 2022; You & Park, 2024).

The statistical finding that future time perspective significantly predicts membership in the High Innovators cluster ($OR = 3.48$) underscores the critical temporal dynamics inherent in the innovation process. Innovation inherently requires the deferral of immediate gratification in favor of long-term organizational benefits and problem-solving. Employees with a strong future time perspective are better equipped to tolerate the ambiguity and potential short-term failures associated with developing new ideas. This

result is strongly supported by literature emphasizing the role of goal orientation and long-term vision in driving employee innovation behavior (Mei-rong et al., 2022). Leadership plays a crucial role in cultivating this forward-looking mindset. Transformational and authentic leaders enhance employees' psychological capital, thereby fostering a future-oriented perspective that is critical for sustained service innovation and overall work engagement (Markus et al., 2018; Zhang et al., 2023). Even top-down executive influence, such as a Chief Executive Officer's transformational leadership, relies on instilling a shared, future-focused vision among like-minded cooperators (Liu & Niu, 2020). The necessity of a long-term perspective is especially pronounced in specialized domains such as green innovation. Employees engaging in green technology innovation must conceptualize the long-term environmental impacts of their actions, a mindset often stimulated by environmental leadership that explicitly values future ecological outcomes over immediate financial gains (Li et al., 2022; Xu et al., 2022). Furthermore, an ethical leadership framework, which inherently prioritizes long-term moral considerations over short-term expediency, provides the normative foundation required for employees to engage confidently in forward-thinking innovation (Yang & Liu, 2022). Thus, a future time perspective acts as a cognitive bridge linking overarching leadership visions to the individual execution of innovative behaviors.

The exceptional predictive strength of proactive motivation ($OR = 8.75$) in differentiating High Innovators from Passive Innovators highlights the absolute necessity of self-initiated, change-oriented drive. Idea realization, the final and most challenging stage of the innovation process, demands a high degree of proactivity to overcome bureaucratic inertia, secure resources, and navigate organizational resistance. This aligns closely with research demonstrating that intrinsic motivation and a proactive disposition are paramount for knowledge-based employees navigating complex industrial environments (Yu, 2021). Proactive motivation is deeply intertwined with how employees leverage their working environment and personality psychology to drive performance, particularly in new ventures (Yang & Wu, 2021). In highly dynamic sectors, proactive individuals are more likely to utilize digital human resource tools and actively participate in organizational learning, thereby significantly enhancing their innovative output (Alrifae, 2025; Isa & Muafi, 2022).

Interestingly, intense proactive motivation can sometimes manifest in unconventional or rule-breaking ways, such as

deviant innovation behavior. Highly driven employees may circumvent formal organizational constraints or utilize shared leadership dynamics to independently pursue promising ideas that leadership has not formally sanctioned (Chen & Ma, 2025; Han et al., 2024). The capacity to channel this profound proactive drive into constructive, officially recognized organizational outcomes requires a delicate balance of supportive management. Cultivating a high-quality leader-member exchange provides professionals, such as university lecturers, with the autonomy and trust necessary to execute their proactive academic and scientific initiatives within the framework of planned behavior (Wang et al., 2022; Zhu & Tsai, 2024). Furthermore, while technological advancements like artificial intelligence can assist in the technical aspects of idea generation, it is the employee's proactive human motivation that remains the irreplaceable catalyst for navigating the complex social and organizational hurdles required to bring an idea to fruition, thereby mitigating the double-edged nature of technological integration (Yin et al., 2024).

The ability of proactive motivation and future time perspective to translate into high innovation is also heavily moderated by the broader employment model and cultural environment. The overarching organizational culture and the level of cultural intelligence present within the workforce act as vital conduits for knowledge sharing and sustainable innovation (Hernawati, 2024). An employment model that strategically aligns with employees' proactive tendencies by offering autonomy will naturally see a higher concentration of individuals within the High Innovators cluster (Xie & Fang, 2020). Furthermore, maintaining the psychological and physiological well-being of employees is critical; even the most proactive individuals cannot sustain high innovation behaviors if they are fundamentally depleted, highlighting the need for restorative factors like adequate sleep quality to complement ethical leadership and intrinsic drive (Rasheed et al., 2024). Ultimately, transforming raw organizational competence into tangible employee performance requires treating innovation not just as a random outcome, but as a critical intervening variable driven by proactive psychological states (Mertiningsih et al., 2024). In specialized, high-stakes environments like healthcare, entrepreneurial leadership is specifically required to trigger this proactivity, empowering frontline staff to challenge existing protocols and drive behavioral change (Bagheri & Akbari, 2018).

5 Conclusion

In conclusion, this study successfully leverages advanced unsupervised machine learning techniques to move beyond traditional variable-centered approaches, offering a nuanced, person-centered understanding of workplace innovation. By identifying distinct behavioral profiles—specifically the Passive, Moderate, and High Innovators—the research empirically validates that employee innovation is not a uniform trait but a dynamic spectrum of engagement spanning idea generation, promotion, and realization. The findings underscore the profound psychological mechanisms that differentiate these groups, highlighting the critical predictive roles of future time perspective and proactive motivation. Individuals possessing a strong future-oriented mindset are significantly more likely to engage in the heavy lifting of innovation because they possess the cognitive capacity to value long-term strategic benefits over the immediate comfort of routine tasks. However, vision alone is insufficient; the staggering predictive power of proactive motivation demonstrates that the internal drive to self-start and persist through organizational friction is the ultimate catalyst for high-level innovative behavior. Consequently, this research provides compelling evidence that transforming a passive workforce into a cohort of high innovators requires more than structural opportunities or basic creative prompts. It necessitates a deep psychological cultivation of both foresight and initiative. Organizations aiming to thrive in increasingly competitive environments must systematically integrate these insights into their talent management strategies. By selecting for, developing, and rewarding employees who naturally anticipate future needs and proactively drive change, businesses can sustainably foster a dynamic environment where complex ideas are not only generated but successfully realized. Ultimately, understanding and nurturing these specific cognitive and motivational profiles serves as a foundational step toward unlocking the full innovative potential of the modern workforce.

Despite the robust findings derived from the machine learning analysis, several limitations within this study must be acknowledged. First, the cross-sectional nature of the research design precludes the establishment of definitive causal relationships between the psychological predictors and the resulting innovation behavioral profiles. While future time perspective and proactive motivation strongly predict cluster membership statistically, it is plausible that successful, ongoing engagement in innovation reciprocally

reinforces these psychological states over time, creating a bidirectional feedback loop that cannot be captured in a single timeframe. Second, the reliance on self-reported questionnaire data introduces the potential for common method bias and social desirability effects. Participants may overestimate their actual engagement in idea generation, promotion, and realization to align with perceived organizational ideals or self-enhancement motives. Third, the sample was purposively drawn from professionals within specific knowledge-intensive sectors in Spain, which restricts the broad generalizability of the findings. The manifestation of innovation behaviors, and the specific thresholds determining the three derived clusters, may vary significantly across different cultural contexts, less knowledge-intensive industries, or organizations with differing structural hierarchies.

To build upon the foundation established by this study, future research should prioritize longitudinal designs to capture the dynamic, evolving nature of employee innovation behaviors. Tracking employees over multiple time points would clarify the directional causality between psychological variables and shifts between the passive, moderate, and high innovator profiles. Furthermore, researchers should incorporate objective measures of innovation, such as supervisor ratings, verified patent filings, or the documented successful implementation of new operational protocols, to mitigate the biases inherent in self-report surveys. Exploring these behavioral clusters across diverse international and macro-cultural contexts would also yield valuable insights into how societal norms influence the micro-foundations of workplace proactivity and future orientation. Methodologically, future studies could expand beyond *K – means* clustering by employing sophisticated supervised machine learning algorithms, such as Random Forests or Support Vector Machines, to identify complex, non-linear interactions among a much broader array of psychological, environmental, and demographic predictors that drive high-level innovation behaviors.

From a practical standpoint, the identification of distinct innovation profiles offers organizations a strategic blueprint for targeted human resource management. Rather than applying a uniform, one-size-fits-all approach to innovation training, managers should tailor their interventions based on an employee's specific cluster classification. For passive innovators, interventions must focus on building foundational psychological safety and actively removing structural barriers to participation. For moderate innovators, organizations must provide robust platforms for idea

promotion and dedicate tangible resources to help them navigate the complex realization phase. Crucially, the profound predictive power of future time perspective and proactive motivation suggests that these specific traits should be actively cultivated by leadership. Human resource departments can implement specialized training programs designed to enhance forward-thinking cognitive framing and intrinsic proactivity among the workforce. Furthermore, recruitment and selection processes could be highly optimized by incorporating validated assessments of future time perspective and proactive motivation, enabling organizations to systematically acquire talent with the inherent psychological disposition required to populate the high innovator cluster and drive sustained, competitive organizational success.

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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