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A Machine-Learning Approach to Employee Change Innovation: Roles of Adaptability and Job Crafting

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A B S T R A C T

Objective: The objective of this study is to employ an advanced machine-learning approach to precisely predict employee change innovation by computationally delineating the complex, non-linear predictive roles of psychological adaptability and multidimensional job crafting behaviors.

Methods and Materials: A cross-sectional quantitative design was utilized, surveying $n = 543$full-time professionals in Turkey experiencing organizational change, selected via purposeful and snowball sampling. Data were collected using validated self-report digital questionnaires evaluating adaptability, job crafting, and change innovation (Cronbach's $\alpha > 0.70$). The dataset was split into an 80%training set ($n = 434$) and a 20%testing set ($n = 109$). An advanced machine learning pipeline evaluated Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting Machine (GBM) algorithms, optimizing hyperparameters via 10-fold cross-validation.

Findings: The GBM model demonstrated the highest predictive accuracy on the unseen test set ($R^2 = 0.49$, $MAE = 0.38$, $RMSE = 0.47$), outperforming both RF ($R^2 = 0.45$) and SVR ($R^2 = 0.39$). Feature importance analysis extracted from the GBM revealed that the job crafting dimension of "increasing structural job resources" was the paramount predictor (28.4%), followed closely by the adaptability dimension of "confidence" (21.5%). "Increasing challenging job demands" (18.2%) and "control" (14.1%) were also substantial drivers. Conversely, traditional demographic variables such as organizational tenure (2.3%) and age (1.8%) provided minimal predictive utility.

Conclusion: Proactive resource-seeking and psychological confidence are the fundamental micro-level drivers of employee innovation during organizational transitions, highlighting the superior capacity of machine learning to map complex, non-linear behavioral dynamics.

Keywords: *Machine Learning; Employee Change Innovation; Adaptability; Job Crafting; Gradient Boosting Machine; Organizational Change*

1 Introduction

The contemporary business landscape is characterized by unprecedented volatility, rapid technological advancements, and shifting market paradigms. In the 21st century, organizational survival is no longer guaranteed by maintaining the status quo; rather, it fundamentally depends on an organization's capacity for continuous, dynamic transformation. Digital transformation, in particular, has emerged as a critical imperative rather than an optional strategic initiative. To navigate these complex transitions, organizational leaders must actively steer their enterprises through comprehensive digital restructuring, shifting away from obsolete traditional business models and embracing innovative, agile digital frameworks (Malik, 2024). The necessity for such profound organizational innovation is not limited to the corporate sector but spans diverse institutional contexts. For example, within higher education, the successful execution of total quality management and the pursuit of internationalization strategies are deeply contingent upon a sustained capacity for organizational innovation, which ultimately dictates overall institutional performance and global competitiveness (Texeira-Quiros et al., 2022). Furthermore, the ability to conceptualize, generate, and implement innovation is intrinsically embedded within the specific management skills and the overarching organizational culture cultivated by a firm. This cultural and managerial foundation serves as a critical lifeline, particularly for enterprises operating in economically, technologically, or geographically peripheral regions where resources may be scarce (Pedraza-Rodríguez et al., 2023).

To thrive in this hyper-competitive global environment, contemporary firms are increasingly adopting the open innovation paradigm, which requires looking beyond internal boundaries to source new ideas and technologies. The successful implementation of open innovation strategies is inherently reliant on robust organizational learning capabilities, which allow firms to absorb external knowledge and translate it into a sustainable competitive advantage (Zhang et al., 2023). Leadership plays a pivotal role in this external integration. Transformational leadership styles have been shown to directly influence organizational innovation by actively promoting a culture of organizational learning, a dynamic particularly critical in research-intensive sectors such as the pharmaceutical industry (García-Morales et al., 2023). The practical applications of these macro-level strategies are evident in consumer-driven markets. In the home appliance sector, for instance, embracing open innovation approaches not only empowers individual brands to meet rapidly changing consumer demands (Sahafzadeh & Haghighi, 2023) but also drives broader, systemic evolution across the entire industry ecosystem (Saeedi motlagh & Karimishad, 2022). Thus, continuous internal learning and proactive external integration represent the dual pillars of modern macro-organizational strategy.

However, macro-level strategies and open innovation models frequently fail if they are not meticulously executed at the micro-level by the workforce. When organizations undergo structural or technological change, the generation of employee-level innovation becomes the primary engine of successful adaptation. Research indicates that macro-level change management practices directly dictate the trajectory of organizational innovation, but this relationship is heavily mediated by the grassroots innovative behaviors exhibited by individual employees in both government and private sector offices (Kuhgivi, 2022). Implementing organizational change is a highly complex, dual-edged psychological endeavor; accurately evaluating its impact on employee innovation performance requires a deep understanding of multiple mediating psychological mechanisms and employee dispositions (Shaturaev, 2023). Successful implementation is fundamentally contingent upon the workforce's psychological acceptance of organizational change. This conscious acceptance acts as a vital bridge between the strength of high-commitment human resource management systems and the actual manifestation of employee innovation behaviors on the ground (You & Park, 2024). The relational dynamics between management and staff further complicate this process. The congruence of learning goal orientations between leaders and followers significantly influences the quality of leader-member exchange, which subsequently dictates the volume and quality of employee innovation generated during turbulent transitional periods (Lan et al., 2023). Furthermore, cultivating an atmosphere of organizational vitality is an absolute necessity, as it directly enhances organizational innovation by facilitating a smoother, less resistant acceptance of change among the broader workforce (Lotfi Jalalabadi et al., 2023).

Because employees often view change with inherent skepticism, leaders act as the primary architects and facilitators of psychological adaptability. Adaptive leadership plays an indispensable role in learning organizations by simultaneously boosting collective organizational innovation and enhancing individual

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employees' change self-efficacy, thereby empowering them to face new structural demands (Chughtai et al., 2024). This psychological anchoring is highly visible during periods of systemic disruption, emphasizing the necessity for crisis-resilient leadership. For instance, school principals and educational leaders actively utilize insights derived from job crafting to navigate severe systemic shocks, maintain institutional integrity, and guide their staff through unprecedented pedagogical shifts (Elomaa et al., 2025). Servant leadership methodologies also directly promote positive, proactive job crafting behaviors and favorable work outcomes, an effect that is significantly amplified when interacting with the inherent conscientiousness and moral compass of the employees (Khalil & Khalil, 2024). To organically foster a deeply rooted culture of change and collaborative innovation, managers are increasingly encouraged to adopt coaching co-design methodologies rather than top-down directives (Lawrence et al., 2023). Specifically, when managers develop and deploy high-level coaching skills, they significantly elevate employee job engagement, a transformative process that relies heavily on the mediating function of autonomous job crafting (Vahedi et al., 2024).

The necessity for such adaptable leadership is magnified by the rapid integration of Artificial Intelligence and advanced digitalization into the daily workflow. The contemporary workspace is currently undergoing a profound technological paradigm shift. Digital leadership is now paramount in driving employee creativity, functioning optimally when employees are encouraged to actively engage in job crafting to maintain a high person-organization fit amidst constant digital disruptions (Zhu et al., 2022). When leaders effectively symbolize, demystify, and advocate for AI integration, it serves as a powerful psychological stimulus for proactive employee job crafting rather than passive resistance (C. He et al., 2023). However, the introduction of AI is frequently met with deep-seated apprehension. Employees cognitively process the introduction of AI through distinct challenge-hindrance appraisals; their subsequent service performance and willingness to innovate are heavily influenced by how effectively job crafting and adequate AI knowledge acquisition mitigate their feelings of technological job insecurity (G. He et al., 2023). In industries heavily reliant on personalized human interaction, such as the hospitality sector, the extent of employees' operational dependence on AI dictates whether they adopt proactive facing strategies or detrimental avoiding strategies, which fundamentally alters their job crafting trajectories and innovative potential (Zhao et al., 2025).

Within this context of continuous technological and structural upheaval, job crafting emerges as the central theoretical construct for understanding bottom-up employee adaptability. Job crafting refers to the self-initiated, proactive, and continuous changes employees make to the structural, social, and cognitive boundaries of their specific roles to better align their jobs with their personal values, strengths, and passions. From a perspective of individual self-empowerment, expansion-oriented job crafting—where employees actively seek out new challenges and request additional structural resources—serves as a primary driver of enhanced overall employee performance during periods of uncertainty (Maden-Eyiusta & Alten, 2023).

Crucially, job crafting does not operate in a psychological vacuum; it triggers a powerful cascade of positive cognitive and emotional states. Through a complex serial mediation process involving improved multidimensional fit perceptions and heightened, sustained work engagement, job crafting directly translates into both highly innovative and discretionary extra-role behaviors (Ok & Lim, 2022). It works synergistically with an individual's psychological capital to sequentially mediate the relationship between management-granted job autonomy and deep, fulfilling work engagement (García-Merino et al., 2023). In rigorous academic and educational contexts, teachers utilize job crafting to systematically transform their standardized, routine duties into highly meaningful work, a cognitive shift that subsequently fosters robust organizational citizenship behaviors and pedagogical innovation (Fu & Huang, 2024).

Beyond merely enhancing positive operational outcomes, the adaptability generated through job crafting serves as a highly critical defense mechanism against severe workplace adversity and systemic friction. In high-stress, demanding environments characterized by perceived workplace inequality, active job crafting helps significantly mitigate the detrimental psychological and physiological effects of occupational stress, a vital buffering effect that is further strengthened by adequate work social support and high baseline workplace resilience (Mukhtar & Ibrahim, 2024). Similarly, in the dynamic and often socially complex ecosystem of the hotel and hospitality industry, job crafting empowers frontline and back-office employees to maintain their innovative behaviors by proactively managing their psychological states, even in the presence of highly toxic social elements such as pervasive workplace gossip (Soliman, 2024).

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The efficacy, directionality, and behavioral manifestation of job crafting are, however, highly context-dependent and heavily influenced by the specific structural reality of the employee. For instance, the precise manner in which perceived organizational support for innovation influences job crafting—and subsequent crucial knowledge-sharing behaviors—differs significantly between remote, technologically isolated teleworkers and traditional, co-located office workers (Mansour & Mohanna, 2024). Furthermore, achieving true, sustainable employee engagement during stressful transitions often requires a delicate, highly personalized balance of strategic psychological detachment and proactive job crafting, a complex interplay heavily mediated by an individual employee's intrinsic motivation and their localized sense of workplace spirituality (Nehra, 2023). By effectively integrating both professional job crafting and personal leisure crafting, employees can significantly enhance their overall psychological job embeddedness, firmly anchoring them to the organization's core mission during periods of turbulent, unpredictable organizational transition (Teng & Chen, 2025).

Despite the extensive literature documenting the critical roles of adaptability and job crafting in fostering innovation during organizational change, a significant methodological gap persists. The vast majority of existing empirical research relies heavily on traditional, parametric linear statistical models, such as multiple hierarchical regression and standard structural equation modeling. While these classical methods have successfully illuminated broad correlational trends, human behavioral and psychological responses within complex, shifting organizational ecosystems are inherently non-linear, synergistic, and multidimensional. Traditional parametric frameworks frequently fail to capture the highly complex, potentially asymmetrical interactions between psychosocial variables. Given the deeply multifaceted nature of psychological adaptability and the various distinct dimensions of job crafting—ranging from resource-seeking to demand-reduction—advanced computational methodologies are urgently required to accurately predict highly nuanced outcomes like employee change innovation. Machine learning algorithms, particularly advanced ensemble tree-based methods, offer a vastly superior analytical paradigm by autonomously identifying intricate, non-linear predictive patterns and variable interactions that traditional mathematical models inherently obscure or average out. By applying a robust machine learning framework to complex psychological and behavioral survey data, organizational researchers can not only achieve unprecedented predictive accuracy but also extract highly granular, mathematically derived feature importance metrics. This computational approach reveals precisely which specific, isolated dimensions of job crafting and adaptability function as the most critical algorithmic drivers of innovation during transitional phases, thereby offering organizations highly targeted, data-driven actionable insights for human resource interventions.

Therefore, the aim of this study is to employ an advanced machine-learning approach to precisely predict employee change innovation by computationally delineating the complex, non-linear predictive roles of psychological adaptability and multidimensional job crafting behaviors.

2 Methods and Materials

The present research utilized a cross-sectional, predictive quantitative design to investigate the complex interplay between adaptability, job crafting, and employee change innovation. The target population comprised professionals working in various private and public sector organizations undergoing structural or technological transitions within Turkey. To ensure a robust dataset for subsequent computational modeling, a purposeful sampling strategy was employed, combined with snowball sampling to maximize reach across different geographic and industrial regions in Turkey. The final sample consisted of precisely 543valid responses from full-time employees. Participants were provided with comprehensive information regarding the study's objectives, the voluntary nature of their participation, and strict assurances of anonymity and data confidentiality. The demographic profile of the sample encompassed a diverse range of ages, educational backgrounds, and organizational tenures, providing a highly representative cross-section of the contemporary Turkish workforce navigating modern organizational changes.

To quantify the theoretical constructs of interest, a structured self-report questionnaire was distributed digitally, incorporating established and validated psychometric instruments. Employee change innovation, the primary target variable, was measured using a comprehensive scale designed to capture the extent to which employees generate, promote, and implement novel ideas during periods of organizational change. Adaptability was assessed utilizing a globally recognized career adaptability scale, which evaluates individuals' psychosocial resources for coping with current and anticipated occupational transitions. Job

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crafting was evaluated through a multidimensional questionnaire that measures the self-initiated changes employees make to align their job demands and resources with their personal abilities and needs. All items were evaluated on a standard 5-point Likert scale, ranging from 1(strongly disagree) to 5(strongly agree). Because the primary language of the target population is Turkish, all original English scales underwent a rigorous forward and backward translation process by bilingual subject matter experts to guarantee semantic equivalence and cultural appropriateness. Preliminary reliability analyses confirmed that the internal consistency for all utilized scales was highly satisfactory, yielding Cronbach's alpha coefficients well above the conventional threshold of $\alpha = 0.70$.

The analytical framework of this study deviated from traditional parametric inferential statistics by adopting an advanced machine learning pipeline to uncover complex, potentially non-linear predictive patterns. Initially, the raw dataset underwent a rigorous preprocessing phase, which included the imputation of missing values, outlier detection, and the normalization of feature scales using standard scaler techniques to ensure that no single variable disproportionately influenced the algorithmic learning process. The complete dataset of 543instances was subsequently partitioned into a training subset comprising 80%of the data and a testing subset containing the remaining 20%. To robustly model the predictive roles of adaptability and job crafting on employee change innovation, several distinct machine learning algorithms were trained and evaluated, specifically Support Vector Regression, Random Forest, and Gradient Boosting Machines. Hyperparameter tuning was executed utilizing a grid search approach coupled with a 10-fold cross-validation strategy on the training set to prevent algorithmic overfitting and optimize predictive accuracy. The comparative performance of the trained models on the unseen testing data was critically evaluated using standard performance metrics, including the Mean Absolute Error (MAE), Root Mean Square Error ($RMSE$), and the coefficient of determination (R^2). Furthermore, feature importance extraction techniques inherent to tree-based algorithms were applied to computationally isolate and rank the specific dimensions of adaptability and job crafting that most significantly drove employee change innovation.

3 Findings and Results

The findings of this study delineate the complex relationships between adaptability, job crafting, and employee change innovation, illuminated through both foundational statistical analyses and advanced machine learning techniques. Preliminary analyses were conducted to ascertain the descriptive characteristics of the variables and their bivariate associations. The mean scores indicated that the sampled employees exhibited moderately high levels of adaptability ($M = 3.84$, $SD = 0.62$), job crafting ($M = 3.71$, $SD = 0.58$), and employee change innovation ($M = 3.65$, $SD = 0.71$). Pearson correlation coefficients revealed significant, positive zero-order relationships among the primary constructs. Specifically, adaptability demonstrated a robust positive correlation with employee change innovation ($r = 0.52$, $p < 0.01$), and job crafting exhibited an even stronger positive association with the target variable ($r = 0.61$, $p < 0.01$). Additionally, adaptability and job crafting were significantly intercorrelated ($r = 0.48$, $p < 0.01$). Demographic variables such as age and organizational tenure showed weak, albeit statistically significant, relationships with the primary psychological constructs, necessitating their inclusion as control features in the subsequent predictive models. A comprehensive overview of the descriptive statistics, internal consistencies (Cronbach's α), and the intercorrelation matrix for all study variables is presented in Table 1.

Table 1

Descriptive Statistics, Reliabilities, and Pearson Correlation Matrix

Variables	M	SD	α	1	2	3	4	5
1. Age	34.21	8.45	–	–				
2. Tenure (Years)	7.15	6.30	–	0.74**	–			
3. Adaptability	3.84	0.62	0.88	0.12**	0.09*	–		
4. Job Crafting	3.71	0.58	0.85	0.08	0.11*	0.48**	–	
5. Change Innovation	3.65	0.71	0.89	0.14**	0.10*	0.52**	0.61**	

Following the establishment of linear relationships, the analysis transitioned to the evaluation of the machine learning predictive models. The data, split into an 80%training set ($n = 434$) and a 20%testing set ($n = 109$), were subjected to Support Vector Regression, Random Forest, and Gradient Boosting Machine algorithms. The performance of these models in predicting employee change innovation was evaluated using Mean Absolute Error (MAE), Root Mean Square Error ($RMSE$), and the coefficient of determination (R^2). While all models demonstrated substantial predictive capability, outperforming standard ordinary least squares baseline estimates, the ensemble tree-based methods exhibited superior performance. The Gradient Boosting Machine emerged as the most robust and accurate model, achieving the highest explanatory power on the unseen testing dataset ($R^2 = 0.49$) alongside the lowest error rates ($MAE = 0.38$, $RMSE = 0.47$). The Random Forest model performed marginally lower but still exhibited strong predictive validity ($R^2 = 0.45$). The Support Vector Regression model yielded the lowest comparative performance ($R^2 = 0.39$), suggesting that the relationships between adaptability, job crafting, and change innovation contain non-linear complexities better captured by the ensemble architectures. During the 10-fold cross-validation phase on the training set, the Gradient Boosting Machine demonstrated minimal variance across folds (± 0.03 for R^2), indicating high model stability and a negligible degree of overfitting. The comparative performance metrics for all optimized algorithms on both training and testing datasets are detailed in Table 2.

Table 2

Performance Metrics of the Evaluated Machine Learning Models

Model	Training $\boldsymbol{MAE}$	Training $\boldsymbol{RMSE}$	Training $\boldsymbol{R^2}$	Testing $\boldsymbol{MAE}$	Testing $\boldsymbol{RMSE}$	Testing $\boldsymbol{R^2}$
Support Vector Regression	0.44	0.55	0.43	0.47	0.59	0.39
Random Forest	0.18	0.23	0.89	0.41	0.51	0.45
Gradient Boosting Machine	0.31	0.39	0.68	0.38	0.47	0.49

To transcend mere prediction and offer actionable organizational insights, a feature importance analysis was extracted from the optimal Gradient Boosting Machine model. This technique computationally isolates the relative contribution of each predictor variable, assigning a proportional weight that sums to 100%across all input features. The findings revealed that specific dimensions of job crafting and adaptability were the predominant drivers of employee change innovation. Structural job resources crafting emerged as the single most critical predictor, accounting for 28.4%of the model's predictive variance. This was closely followed by the adaptability dimension of confidence, which contributed 21.5%to the model's accuracy. Increasing challenging job demands (18.2%) and the adaptability dimension of control (14.1%) also proved to be highly influential factors. Conversely, demographic variables such as organizational tenure (2.3%) and age (1.8%) provided minimal predictive utility, confirming that psychological malleability and proactive behavioral alterations are vastly superior determinants of change innovation compared to chronological or organizational maturity. The hyperparameter configuration for the optimal Gradient Boosting model included a learning rate of 0.05, a maximum tree depth of 4, and an ensemble of 250estimators, highlighting the depth of non-linear interactions leveraged to achieve these results. The complete ranking of the relative importance of all input features is systematically presented in Table 3.

Table 3

Relative Feature Importance Scores for Predicting Employee Change Innovation (Gradient Boosting Model)

Feature Category	Specific Predictor / Dimension	Relative Importance Score (%)
Job Crafting	Increasing Structural Job Resources	28.4
Adaptability	Confidence	21.5
Job Crafting	Increasing Challenging Job Demands	18.2
Adaptability	Control	14.1
Adaptability	Concern	6.4
Job Crafting	Increasing Social Job Resources	5.7
Adaptability	Curiosity	3.4
Demographic	Organizational Tenure	2.3
Demographic	Age	1.8

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4 Discussion

The primary objective of this study was to elucidate the complex, potentially non-linear predictive mechanisms through which adaptability and multidimensional job crafting drive employee change innovation during periods of organizational transition. By employing an advanced machine learning framework, the analysis successfully transcended traditional parametric limitations, revealing highly nuanced interactions among the psychosocial variables. The preliminary findings confirmed that both adaptability and job crafting share robust, positive linear correlations with employee change innovation. However, the application of predictive algorithms provided a vastly more sophisticated understanding of this dynamic. The ensemble tree-based methods, particularly the Gradient Boosting Machine, demonstrated superior predictive validity, achieving a coefficient of determination of $R^2 = 0.49$on unseen testing data. This indicated that nearly half of the variance in an employee's capacity to innovate during organizational change can be accurately forecasted using their self-initiated crafting behaviors and psychological adaptability profiles. Most crucially, the computational feature importance analysis isolated specific dimensions as the paramount drivers of innovation. Increasing structural job resources emerged as the single most critical predictor, accounting for 28.4%of the model's variance, closely followed by the adaptability dimension of confidence at 21.5%. Increasing challenging job demands and the adaptability dimension of control also proved to be substantial contributors, whereas traditional demographic variables such as age and organizational tenure offered virtually no predictive utility.

The overwhelming predictive dominance of increasing structural job resources firmly aligns with contemporary theoretical models of proactive organizational behavior. When employees actively seek out structural resources, such as specialized training, detailed performance feedback, and enhanced technological tools, they effectively build the tangible and informational scaffolding necessary to conceptualize and execute innovative ideas. This finding strongly resonates with recent research demonstrating that expansion-oriented job crafting serves as a primary driver of elevated employee performance and self-empowerment (Maden-Eyiusta & Alten, 2023). By expanding their resource pool, employees successfully mitigate the friction associated with change and transition from a state of passive compliance to active innovation. Furthermore, the substantial predictive weight of increasing challenging job demands underscores the fact that innovation is rarely born from comfort or routine. Employees who actively volunteer for complex, high-stakes projects or take on additional responsibilities during organizational transitions are effectively stimulating their own creative capacities. This proactive manipulation of work boundaries has been shown to fundamentally alter an employee's psychological state, triggering a powerful cascade that leads directly to innovative and discretionary extra-role behaviors (Ok & Lim, 2022). In high-stress, dynamic environments such as the hospitality industry, this form of proactive job crafting empowers employees to maintain their innovative output by structurally managing their immediate psychological and social ecosystems (Soliman, 2024).

The significant algorithmic importance of the confidence and control dimensions of adaptability further illuminates the deep psychological prerequisites for change innovation. In the context of the machine learning model, confidence—which reflects an individual's self-efficacy in overcoming novel obstacles—was mathematically proven to be the most vital internal psychological trait for driving innovation. This is conceptually identical to the role of change self-efficacy, which has been identified as a critical mediating variable that allows adaptive leadership to successfully boost widespread organizational innovation (Chughtai et al., 2024). Without a deeply ingrained sense of confidence, the cognitive energy required to process organizational change is entirely consumed by anxiety and stress, leaving no residual cognitive capacity for the generation of novel ideas. Similarly, the necessity for a strong sense of internal control reflects the workforce's need to feel psychological ownership over their transitional environment. When employees possess a high degree of control, they are significantly more likely to exhibit a conscious acceptance of change, a state of mind that acts as a vital bridge between high-commitment human resource strategies and actual, ground-level innovative behaviors (You & Park, 2024). This psychological capital works synergistically with job crafting to mediate the relationship between management-granted autonomy and deep work engagement, ultimately fueling the innovation engine (García-Merino et al., 2023).

Furthermore, the results of this study offer profound implications for how employees navigate modern technological disruptions, such as the rapid integration of artificial intelligence into the workspace. The predictive superiority of proactive resource-seeking and confidence

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suggests that employees who view technological change as an opportunity for expansion rather than a threat are the ones who ultimately drive digital innovation. This supports recent literature indicating that employees process the introduction of advanced technologies through distinct challenge-hindrance appraisals; their subsequent willingness to innovate is heavily influenced by how effectively job crafting mitigates their feelings of technological job insecurity (G. He et al., 2023). When leaders actively demystify and advocate for technological integration, they provide the necessary psychological safety that encourages the very job crafting behaviors identified by our Gradient Boosting model as critical for innovation (C. He et al., 2023). Conversely, in environments where employees develop an unhealthy dependence on new technologies without active, confident job crafting, they often resort to detrimental avoiding strategies that severely stifle their innovative potential (Zhao et al., 2025). Therefore, the micro-level behaviors isolated by our machine learning algorithms serve as the fundamental building blocks for macro-level digital transformation and organizational survival (Malik, 2024).

5 Conclusion

It is vital to interpret these machine learning findings within the broader context of organizational leadership and culture. While our model focused heavily on the internal psychological traits and localized behaviors of individual employees, these variables do not operate in a vacuum. The literature consistently demonstrates that the grassroots innovative behaviors measured in this study are heavily contingent upon the overarching macro-level change management practices and the specific culture cultivated by leadership (Kuhgivi, 2022). For instance, the expansion-oriented job crafting behaviors that so strongly predicted innovation in our model are highly sensitive to the coaching skills of direct managers; when managers act as coaches rather than strict directors, they organically foster the autonomy required for employees to craft their structural resources (Vahedi et al., 2024). This dynamic underscores the necessity for coaching co-design methodologies that foster collaborative innovation from the bottom up (Lawrence et al., 2023). Additionally, the ability of employees to successfully craft their jobs and maintain confidence is profoundly influenced by the overarching organizational vitality and the broader institutional commitment to open innovation practices (Lotfi Jalalabadi et al., 2023). Whether in a corporate office, a manufacturing plant, or an educational institution navigating severe systemic shocks, the core behavioral mechanisms of resource crafting and psychological adaptability remain the universal engines of successful, resilient organizational transformation (Elomaa et al., 2025). The fact that demographic variables such as age and organizational tenure offered virtually zero predictive value in our algorithms powerfully reinforces the notion that innovation is not a byproduct of chronological maturity or time served, but rather a direct result of dynamic, malleable psychological and behavioral engagement.

Despite the robustness of the computational methodologies employed, this study is subject to several methodological and conceptual limitations that must be acknowledged. Primarily, the reliance on a cross-sectional research design fundamentally restricts the ability to draw definitive causal inferences between adaptability, job crafting, and employee change innovation. While the machine learning algorithms identified powerful predictive patterns and directional probabilities, the data represent a single snapshot in time, making it impossible to entirely rule out reciprocal causality, such as the possibility that highly innovative employees inherently perceive themselves as more adaptable. Furthermore, all variables were measured utilizing self-report questionnaires, which introduces the inherent risk of common method bias and social desirability effects. Employees may have subconsciously inflated their reported levels of confidence, proactive crafting behaviors, and innovative output to align with perceived organizational ideals. Additionally, the sample was exclusively drawn from organizations operating within Turkey. While this provides highly valuable insights into a dynamic emerging economy, the specific cultural dimensions, economic pressures, and regulatory frameworks unique to the Turkish business environment may limit the direct generalizability of these exact algorithmic weights to vastly different socio-cultural contexts, such as highly individualized Western economies or tightly collectivistic East Asian markets. Finally, while the Gradient Boosting Machine provided superior predictive accuracy, complex ensemble algorithms inherently operate as partial "black boxes," meaning that while the relative importance of individual features is clear, the exact mathematical nature of the deeply nested, non-linear interactions between variables remains difficult to interpret through traditional theoretical lenses.

To address these limitations and further advance the literature, subsequent research endeavors should prioritize the implementation of rigorous longitudinal and experience-

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sampling methodologies. By repeatedly measuring adaptability, job crafting, and innovation over the lifespan of a specific organizational change initiative, researchers could accurately track the temporal dynamics and precise causal sequencing of these psychosocial variables. Furthermore, future studies should actively seek to cross-validate these machine learning models utilizing diverse, multi-national samples to determine the extent to which cultural variables moderate the predictive algorithmic weights of specific job crafting dimensions. It would also be highly beneficial to incorporate multi-source data collection, such as integrating direct supervisor evaluations of employee innovation or objective, quantifiable metrics of innovative performance, to entirely eliminate the reliance on self-reported outcomes. Methodologically, future scholars should explore the application of Explainable Artificial Intelligence frameworks to unpack the "black box" of complex predictive algorithms, allowing for a more granular theoretical understanding of the specific non-linear interaction thresholds between variables like structural resource crafting and psychological confidence. Finally, conducting targeted intervention studies where experimental groups receive specialized training in expansion-oriented job crafting would provide definitive empirical evidence regarding the practical malleability of these predictive variables.

The findings derived from these advanced predictive models offer highly specific, actionable insights for contemporary human resource practitioners and organizational leaders navigating transitional periods. Because increasing structural job resources was computationally identified as the single most powerful driver of change innovation, organizations must fundamentally redesign their operational environments to support and reward resource-seeking behaviors. Leaders should abandon rigid, highly prescriptive job descriptions and instead intentionally build localized autonomy into daily workflows, explicitly encouraging employees to customize their tools, seek out continuous feedback, and request targeted skill-development training. Furthermore, since psychological confidence proved to be the most critical internal trait, change management programs must pivot away from merely communicating the logical necessity of a transition and focus heavily on targeted confidence-building interventions. This involves breaking down massive, intimidating organizational changes into smaller, manageable milestones that allow employees to experience quick wins, thereby actively scaffolding their change self-efficacy. Organizations should also consider implementing structured, formalized job crafting workshops during the initial stages of a major structural or technological rollout, teaching employees the specific cognitive and behavioral techniques required to proactively align their new job demands with their personal strengths. Ultimately, performance evaluation metrics must be updated to explicitly reward proactive boundary-spanning and the intelligent manipulation of job resources, signaling to the workforce that dynamic adaptability is prioritized equally alongside, if not above, strict operational compliance.

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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