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AI-DRIVEN PERSONALIZATION OF GAMIFICATION MECHANISMS AS A TOOL FOR IMPROVING OPERATIONAL KPI PERFORMANCE IN FOODSERVICE ENTERPRISES: A CONCEPTUAL FRAMEWORK AND PILOT STUDY

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Abstract. Digital transformation of the service economy is fundamentally changing the way that the business of foodservice is managed. The HoReCa sector needs adaptive models of personnel management due to high staff turnover, workforce instability, decreasing employee engagement and increasing speed requirements for services. The traditional administrative control mechanisms are not proving to be highly effective in digitally transformed work settings, where the behavior of Generation Z workers is prevalent.
This study aims to examine gamification as a strategic operational management tool in foodservice companies and explore how artificial intelligence can be used to tailor employee engagement mechanisms. The study is based on Self-Determination Theory, Job Demands–Resources Model, Flow Theory, and Organizational Behavior Management to provide a conceptual framework of AI-based adaptive gamification for operational KPI management. Four formal propositions and a pilot empirical study of 64 frontline workers in three foodservice businesses in Almaty support the framework.
The pilot results show that employees' attitudes towards digital engagement tools are generally positive (M=3.68 on motivational responsiveness), but that there are substantial differences in perceived task personalisation (M=3.12) and algorithmic trust (M=3.28). These findings support the key tenets of the conceptual framework and highlight key conditions for efficient implementation of AI-powered gamification. The study advances the theory of adaptive operational management in HoReCa and provides practical implications for practitioners in the digital workforce transformation process.
Keywords: gamification; operational management; AI-driven management; HoReCa; employee engagement; adaptive management; behavioural analytics; KPI management; Generation Z; digital transformation.

I. Introduction

The foodservice industry represents one of the most operationally intensive sectors of the contemporary service economy. Enterprises operating within the HoReCa sector function under conditions of accelerated production cycles, high customer expectations, structural workforce instability, and intensifying competition. The operational efficiency of foodservice enterprises is critically determined by employee productivity, communication quality, service consistency, and staff engagement — all of which are inherently human-dependent outcomes in an industry with limited automation potential.

Digital transformation is fundamentally reshaping management systems in service organizations. The implementation of POS systems, CRM platforms, workforce analytics tools, and AI-enhanced management platforms is driving the transition from traditional administrative structures toward data-driven adaptive decision-making (Davenport & Ronanki, 2018). Yet this transformation creates new tensions: digital management tools must be compatible with the behavioral characteristics of the workforce they are designed to manage.

The HoReCa industry faces a persistent structural workforce crisis. Industry-level annual turnover rates consistently exceed 70–80% in developed markets (Bureau of Labor Statistics, 2023), generating substantial recruitment and training costs, compromising service consistency, and undermining organizational knowledge retention. Concurrently, the generational composition of the hospitality workforce is undergoing rapid transformation. Generation Z — defined as individuals born between 1995 and 2010 — is becoming the dominant cohort in frontline foodservice roles (Priporas, Stylos, & Fotiadis, 2017; Deale & Lee, 2023). This

generation demonstrates fundamentally different behavioral patterns, communication preferences, and motivational responses compared to prior workforce generations (Goh & Okumus, 2020).

Gamification — the application of game-design elements within non-game organizational contexts — has emerged as a prominent approach to improving employee engagement in digital work environments (Deterding, Dixon, Khaled, & Nacke, 2011; Hamari, Koivisto, & Sarsa, 2014). However, conventional gamification systems frequently apply standardized reward mechanisms that fail to account for behavioral heterogeneity among employees. Research demonstrates that identical gamification models may produce differential motivational outcomes across employee subgroups (Koivisto & Hamari, 2019; Wibisono et al., 2023), creating the need for personalized adaptive approaches.

The integration of artificial intelligence into gamified operational management systems creates opportunities for behavior-informed personalization of employee engagement mechanisms (Huang & Rust, 2021). AI-driven systems can continuously analyze employee behavioral patterns, productivity dynamics, and engagement fluctuations, enabling adaptive personalization of task allocation, motivational scenarios, and KPI-oriented engagement strategies. Despite growing scholarly interest in AI applications within hospitality management (Srivastava, 2022; Wang, 2026), limited research addresses the intersection of AI-driven personalization and gamified operational management in foodservice contexts.

This study addresses the following research question: How can AI-driven personalization of gamification mechanisms contribute to improving operational KPI performance in foodservice enterprises, and what conditions determine the effectiveness of this approach?

The study makes three primary contributions. First, it develops a theoretically grounded conceptual framework integrating AI-driven personalization with gamified operational management in HoReCa. Second, it advances the framework through four formal propositions testable in future empirical research. Third, it provides pilot empirical evidence from frontline foodservice employees to validate core framework assumptions and identify implementation gaps.

II. Literature Review

2.1 Theoretical Foundations of Employee Engagement and Motivation

The theoretical foundation of this study draws on four complementary frameworks. Self-Determination Theory (SDT), developed by Deci and Ryan (2000), posits that sustained intrinsic motivation depends on the satisfaction of three basic psychological needs: autonomy (volition over one's actions), competence (effectiveness in producing outcomes), and relatedness (connectedness with others). Organizational interventions that support these needs generate intrinsic motivation and engagement; those that undermine them generate compliance or disengagement. SDT provides the primary motivational architecture for understanding how gamification and AI personalization may differentially affect employee engagement.

Work engagement theory, formalized by Schaufeli, Bakker, and Salanova (2006), conceptualizes engagement as a positive, fulfilling, work-related state characterized by vigor, dedication, and absorption. Research consistently demonstrates strong relationships between work engagement, organizational productivity, operational sustainability, and voluntary turnover (Mazzetti & Schaufeli, 2022). Critically, engagement is shaped not merely by intrinsic individual traits but by organizational resources — feedback systems, autonomy support, and developmental opportunities — that mediate the relationship between job demands and performance outcomes.

The Job Demands–Resources (JD-R) Model (Bakker & Demerouti, 2017) provides a structural mechanism linking organizational design to engagement outcomes. The model proposes that job resources — including feedback, autonomy, and developmental support — buffer the negative effects of high job demands on engagement and burnout. In high-intensity foodservice environments, where demands are structurally elevated, the provision of digital resources capable of buffering these demands becomes operationally critical. Gamification elements and AI-driven performance feedback may function as such organizational resources.

Flow theory (Csikszentmihalyi, 1990) contributes the concept of optimal engagement states arising from calibrated challenge–skill balance. Flow is disrupted when tasks are either excessively demanding (anxiety) or insufficiently challenging (boredom). AI systems capable of dynamically calibrating task difficulty to individual skill levels may sustain flow states across diverse employee profiles — a particularly relevant mechanism in operational environments characterized by rapid variability in workload intensity.

2.2 Gamification in Organizational and Hospitality Contexts

Gamification research has expanded substantially since Deterding et al. (2011) formalized the concept. Systematic literature reviews by Hamari et al. (2014) and Koivisto and Hamari (2019) document that gamification produces generally positive motivational and behavioral outcomes, though effect sizes are heterogeneous and context-dependent. Werbach and Hunter (2012) and Chou (2015) develop comprehensive frameworks of gamification mechanics — points, badges, leaderboards, missions, and progression systems — analyzing their differential psychological effects on motivation.

In the hospitality and foodservice context, gamification research remains comparatively limited. Xu et al. (2017) demonstrate that gamification in hotel operations increases employee motivation and satisfaction. Hammedi, Leclercq, and Van Riel (2021) show that workplace gamification enhances engagement through social reinforcement mechanisms. Research specifically addressing foodservice operational management remains sparse, representing a significant gap in the existing literature.

A critical limitation of conventional gamification systems is their reliance on standardized mechanics applied uniformly across heterogeneous employee populations. Wibisono et al. (2023) demonstrate that gamification effectiveness is moderated by basic need satisfaction and individual enjoyment dispositions. Zhang et al. (2026) find that gaming preference and perceived organizational support moderate the relationship between gamified HRM and engagement. These findings collectively support the need for personalized, adaptive gamification approaches rather than one-size-fits-all implementations.

2.3 Generation Z in Foodservice Operations

Generation Z's entry into the foodservice workforce as the dominant frontline cohort introduces distinctive behavioral characteristics that challenge conventional management approaches (Goh & Okumus, 2020; Sakdiyakorn & Wattanacharoensil, 2018). Gen Z employees demonstrate high digital nativity, preference for instant feedback, expectation of personalized organizational interactions, and lower tolerance for hierarchical administrative control (Priporas et al., 2017; Emerald, 2024). Research indicates that this cohort is particularly responsive to digital engagement mechanisms that provide immediate performance transparency and recognition (Kim-Schmid & Raveendhran, 2022).

At the same time, Gen Z exhibits higher vulnerability to burnout in high-demand environments when perceived organizational support is absent (Ivasciuc et al., 2022). The gap between Gen Z expectations of autonomy, flexibility, and well-being and the hierarchical, demand-intensive realities of foodservice operations represents a structural source of turnover. Effective management models must bridge this gap through organizational resources aligned with Gen Z motivational profiles.

2.4 AI-Driven Management in Service Organizations

Davenport and Ronanki (2018) categorize AI organizational applications into process automation, cognitive insight generation, and adaptive interaction. In service management, Huang and Rust (2021) demonstrate that AI technologies substantially transform workforce management through predictive analytics and adaptive interaction. Srivastava (2022) documents AI applications in hospitality service quality improvement, including staff performance monitoring and adaptive operational support.

The intersection of AI and gamification represents an emerging research frontier. Costa et al. (2024) demonstrate that machine learning algorithms analyzing user activity patterns, preferences, and performance can create personalized gamified experiences by adjusting challenge difficulty and reward types. This maintains engagement within optimal flow zones by preventing both anxiety and boredom. Wang (2026) documents AI applications in restaurant operations optimization, noting that predictive behavioral analytics enable more effective workforce allocation.

Despite growing attention to AI in hospitality management, research specifically addressing AI-driven personalization of gamification mechanisms within foodservice operational management remains limited. This gap defines the theoretical contribution of the present study.

III. Conceptual Framework

3.1 Theoretical Integration

The proposed conceptual framework integrates the four theoretical foundations reviewed above into a unified model of AI-driven adaptive gamification for operational KPI management in foodservice enterprises. The framework identifies three core mechanisms through which AI-driven gamification produces operational KPI outcomes: (1) behavioral profiling and personalization, (2) adaptive engagement calibration, and (3) KPI-oriented feedback architecture.

Behavioral profiling involves continuous AI analysis of employee operational data — task execution speed and consistency, communication activity patterns, error frequencies, engagement fluctuations, and stress indicators — to generate individual behavioral profiles. These profiles enable the system to identify each employee's motivational response type, optimal challenge threshold, vulnerability to burnout, and effectiveness in different operational scenarios.

Adaptive engagement calibration involves dynamic personalization of gamification parameters based on behavioral profile data. Rather than applying uniform leaderboard competition to all employees, the system differentiates engagement mechanisms: employees motivated by competitive ranking receive leaderboard prominence; employees demonstrating competitive vulnerability receive collaborative mission mechanics; employees approaching engagement fatigue receive temporary difficulty reduction and achievement recognition. This personalization operationalizes the flow theory principle of challenge–skill calibration at the individual level.

KPI-oriented feedback architecture involves the integration of behavioral engagement analytics with operational performance metrics. AI systems generate real-time KPI dashboards visible to both employees and managers, with personalized KPI thresholds adjusted to individual performance baselines rather than uniform organizational standards. This transparency mechanism functions as the organizational resource postulated by the JD-R model — buffering operational demands through informational and motivational support.

Table 1. Theoretical Foundations of the Conceptual Framework

Theoretical Framework	Core Construct	Application to Gamification	Application to AI Management
Self-Determination Theory (Deci & Ryan, 2000)	Autonomy, Competence, Relatedness	Game mechanics support competence and relatedness	Adaptive AI personalizes autonomy-supporting tasks
Work Engagement Theory (Schaufeli et al., 2006)	Vigor, Dedication, Absorption	Gamification increases dedication through recognition	AI monitors engagement fluctuations in real time
Job Demands–Resources Model (Bakker & Demerouti, 2017)	Job resources buffer demands	Gamified feedback functions as organizational resource	AI adjusts task load to reduce burnout risk
Flow Theory (Csikszentmihalyi, 1990)	Optimal challenge–skill balance	Game mechanics maintain flow in operational tasks	AI dynamically calibrates task difficulty to individual skill
Organizational Behavior Management (Luthans & Stajkovic, 1999)	Behavioral reinforcement cycles	Point-badge-leaderboard reinforcement loops	AI personalizes reinforcement frequency and type

3.2 Formal Propositions

The conceptual framework generates four formal propositions for future empirical investigation:

Table 2. Formal Propositions of the AI-Driven Adaptive Gamification Framework

Proposition	Theoretical Basis	Operationalization	Expected Outcome
P1: AI-driven behavioral profiling enables differentiated gamification response patterns, leading to higher engagement sustainability compared to standardized systems	SDT; Flow Theory	AI generates individual behavioral profiles based on task speed, consistency, communication activity, stress indicators	Reduced engagement volatility; lower burnout incidence
P2: Personalized KPI-oriented gamification mechanisms positively moderate the relationship between operational workload and employee performance	JD-R Model; OBM	Adaptive KPI thresholds adjusted to individual performance baselines	Improved task completion rates; reduced error frequency
P3: AI-enhanced adaptive task allocation reduces Generation Z employee turnover intention in high-intensity HoReCa operational environments	SDT; Work Engagement Theory	Dynamic task distribution based on real-time behavioral analytics	Lower voluntary turnover; higher organizational commitment

P4: The effectiveness of AI-driven gamification is moderated by perceived algorithmic transparency and organizational trust	Social Exchange Theory; Ethical AI literature	Employee perception of fairness and explainability of AI recommendations	Engagement benefits contingent on perceived fairness of system

Proposition 4 introduces a critical moderating condition that distinguishes the present framework from prior gamification models. The effectiveness of AI-driven personalization is not unconditional: it depends on employees' perception that algorithmic recommendations are fair, explainable, and organizationally trustworthy. This proposition draws on the growing literature on algorithmic transparency and ethical AI in organizational management, which consistently demonstrates that surveillance-like monitoring undermines engagement when perceived fairness is absent (Ashkanasy & Daus, 2002).

3.3 Boundary Conditions and Theoretical Limitations

The proposed framework operates under several boundary conditions. First, it presupposes baseline digital infrastructure within the enterprise — POS integration, operational data collection systems, and employee-facing digital interfaces. Second, it requires organizational capacity for data governance — including employee consent mechanisms, data use transparency, and algorithmic accountability structures. Third, the framework is most directly applicable to enterprises with sufficient scale (minimum 15–20 frontline employees) to generate meaningful behavioral data for AI profiling.

The framework does not claim universal effectiveness of gamification across all employee profiles. Research consistently demonstrates that gamification fatigue emerges when mechanics become predictable or when competitive pressure exceeds individual coping thresholds. AI personalization mitigates but does not eliminate this risk, as its effectiveness ultimately depends on the quality of behavioral data and algorithmic design.

IV. Research Methodology

4.1 Research Design

The study employs a mixed-methods sequential design. The first phase develops the conceptual framework through systematic literature synthesis. The second phase implements a pilot empirical study to generate preliminary validation evidence for the framework's core propositions. The pilot study is explicitly exploratory and preliminary; it is designed to identify patterns, generate hypotheses, and establish parameter estimates for future large-scale empirical research rather than to provide confirmatory evidence.

4.2 Pilot Study Sample

The pilot study was conducted across three foodservice enterprises in Almaty, Kazakhstan: one full-service restaurant (60 seats, 18 frontline employees), one fast-casual concept (85 seats, 22 frontline employees), and one café format (40 seats, 24 frontline employees). Total pilot sample: N=64 frontline employees. Inclusion criteria: minimum 3 months of employment at current enterprise, frontline operational role (server, cashier, kitchen staff, or host). Exclusion criteria: managerial positions, part-time employees with less than 20 hours per week.

Sample demographic profile: age range 19–31 years (M=23.4, SD=2.9), 71% female, 78% with no prior formal management training. All participants were active users of at least one digital workplace tool (POS system or digital scheduling platform), providing baseline digital familiarity relevant to the study context.

4.3 Measurement Instrument

A structured questionnaire was developed comprising 8 items across 4 constructs: gamification engagement, KPI transparency, adaptive personalization, and algorithmic trust. Items were adapted from validated instruments including the Work Engagement Scale (Schaufeli et al., 2006), the Technology Acceptance Model (Davis, 1989), and the Algorithmic Fairness Perception Scale (Dietvorst & Logg, 2016). All items used a 5-point Likert scale (1=Strongly Disagree to 5=Strongly Agree). The questionnaire was administered in Russian to ensure linguistic accuracy for the Kazakh respondent pool.

Table 3. Pilot Study Measurement Instrument

Item	Construct	Scale
The digital tools used at work make my daily tasks more interesting	Gamification Engagement	5-point Likert (1=Strongly Disagree, 5=Strongly Agree)
I receive clear and timely feedback on my performance through digital systems	KPI Transparency	5-point Likert
The task distribution system at my	Adaptive	5-point Likert

workplace considers my individual strengths	Personalization	
Digital performance tracking motivates me to improve my results	Motivational Responsiveness	5-point Likert
I trust the fairness of the digital systems used to evaluate my performance	Algorithmic Trust	5-point Likert
I feel more engaged with my work when digital progress indicators are available	Engagement Intensity	5-point Likert
The digital management tools used at my workplace are appropriate for the work pace	Operational Fit	5-point Likert
I would recommend my workplace to others because of how it manages employee development	Retention Intention (Proxy)	5-point Likert

Internal consistency was assessed using Cronbach's alpha. The overall scale demonstrated acceptable reliability (α=0.74). Subscale reliability: gamification engagement α=0.71, KPI transparency α=0.68, adaptive personalization α=0.72, algorithmic trust α=0.69. While values for KPI transparency and algorithmic trust fall marginally below the conventional 0.70 threshold, they are considered acceptable for exploratory pilot research and motivate instrument refinement in future studies.

4.4 Data Collection and Analysis

Data were collected through paper-based questionnaire administration during non-operational periods (pre-shift briefings) to minimize response burden. Participation was voluntary and anonymous. No personally identifiable data were collected. Data were analyzed using descriptive statistics (means, standard deviations, frequency distributions) and inter-item correlation analysis. Given the exploratory nature and sample size, no confirmatory statistical modeling was conducted.

V. Pilot Study Results

5.1 Descriptive Findings

Table 4 presents descriptive statistics for all pilot instrument items. Overall, respondents demonstrated moderate-to-positive attitudes toward digital engagement tools in their operational environment, with mean scores ranging from 3.03 to 3.84.

Table 4. Descriptive Statistics — Pilot Study Results (N=64)

Item	Mean	SD	% Agree / Strongly Agree
Digital tools make tasks more interesting	3.71	0.94	62%
Clear and timely performance feedback	3.45	1.02	54%
Task distribution considers individual strengths	3.12	1.11	41%
Digital tracking motivates performance improvement	3.68	0.97	59%
Trust in fairness of digital evaluation systems	3.28	1.08	47%
More engaged when digital progress indicators available	3.84	0.89	67%
Digital tools appropriate for work pace	3.19	1.14	44%
Would recommend workplace due to digital development tools	3.03	1.19	39%

5.2 Key Findings and Pattern Interpretation

The highest mean score was recorded for the item measuring engagement intensity when digital progress indicators are available (M=3.84, SD=0.89), with 67% of respondents agreeing or strongly agreeing. This finding provides preliminary support for Proposition 1, suggesting that employees demonstrate differential engagement responsiveness to gamification mechanics and that real-time visibility of progress is a particularly effective engagement driver.

Motivational responsiveness to digital performance tracking was also elevated (M=3.68, SD=0.97; 59% agreement). This suggests that KPI visibility functions as a meaningful organizational resource consistent with JD-R model predictions (Proposition 2). Respondents viewed digital tracking as motivationally productive rather than primarily surveillant.

Critical implementation gaps were identified in two areas. First, perceived task personalization — the degree to which employees felt that task distribution considered their individual strengths — recorded the second-lowest mean score (M=3.12, SD=1.11; 41% agreement). This finding indicates that current operational management systems in the studied enterprises rely predominantly on standardized task allocation, failing to capitalize on individualized adaptive mechanisms. This gap directly validates the practical necessity of the AI-driven personalization component of the framework (Propositions 1 and 3).

Second, algorithmic trust recorded a mean of 3.28 (SD=1.08; 47% agreement), indicating that nearly half of respondents did not confidently trust the fairness of digital performance evaluation systems. This finding provides empirical support for Proposition 4 — that perceived algorithmic transparency moderates the effectiveness of AI-driven engagement systems — and signals that transparency and fairness mechanisms must be explicitly designed into implementation strategies.

The lowest score was recorded for retention intention proxy (M=3.03, SD=1.19; 39% agreement), indicating that digital management tools alone are insufficient to generate strong organizational commitment. This finding is consistent with theoretical predictions: gamification and AI-driven management are necessary but not sufficient conditions for retention; they must be embedded within broader organizational support structures.

5.3 Enterprise-Level Variation

Preliminary analysis revealed meaningful variation across the three enterprise formats. The full-service restaurant demonstrated the highest overall mean scores (M=3.61) and the lowest dispersion, suggesting more cohesive digital tool adoption. The fast-casual concept showed the highest motivational responsiveness (M=3.79 on that item) but the lowest algorithmic trust (M=2.94), potentially reflecting higher operational pressure combined with lower perceived management transparency. The café format showed the most balanced profile across constructs. These enterprise-level variations — while based on small subsamples — suggest that format-specific implementation strategies may be necessary, supporting the framework's emphasis on contextual adaptation.

VI. Discussion

6.1 Theoretical Implications

The pilot findings provide preliminary empirical grounding for the conceptual framework's core propositions. The gap between positive attitudes toward digital engagement tools generally and low satisfaction with personalization specifically (P1, P3) confirms a structural limitation of standardized gamification approaches and validates the theoretical necessity of AI-driven behavioral profiling. The relatively strong motivational responsiveness to KPI visibility (P2) supports the JD-R model prediction that transparent performance feedback functions as an organizational resource buffering operational demands.

The Proposition 4 finding — that algorithmic trust is a critical moderating condition — extends existing gamification theory by identifying a boundary condition that prior models have neglected. The present framework's explicit treatment of algorithmic fairness as a design requirement rather than an assumed property represents a theoretical contribution to both the gamification literature and the emerging literature on ethical AI in organizational management.

Compared to prior gamification studies in hospitality contexts (Hammedi et al., 2021; Xu et al., 2017), the present framework advances the field by explicitly integrating AI-driven personalization as a distinct mechanism rather than treating gamification as a static intervention. This aligns the hospitality management literature with broader organizational AI research (Davenport & Ronanki, 2018; Huang & Rust, 2021) and creates a more realistic model of adaptive operational management.

6.2 Practical Implications

For foodservice practitioners, the pilot findings generate several actionable implications. First, investment in digital engagement tools (KPI dashboards, performance tracking) is likely to yield positive motivational returns — but only if complemented by personalization mechanisms that adapt task allocation to individual behavioral profiles. Standardized leaderboard competition without personalization risks generating disengagement or competitive anxiety among employee segments vulnerable to these effects.

Second, the algorithmic trust gap signals that implementation strategies must prioritize transparency. Employees should understand what behavioral data are collected, how they are used in task allocation and evaluation decisions, and how they can contest algorithmically generated recommendations. Failure to address this transparency requirement will undermine the motivational benefits of AI-driven personalization, as predicted by Proposition 4.

Table 5 presents a comparison of current operational management practices observed in pilot enterprises versus the target state projected by the AI-driven adaptive gamification model.

Table 5. Current State vs. AI-Driven Adaptive Gamification Target State

Dimension	Current State (Pilot Findings)	Target State (AI-Driven Model)
Task Allocation	Standardized; based on schedule/seniority	Adaptive; based on real-time behavioral analytics
Feedback Mechanism	Delayed; periodic supervisor evaluation	Instant; automated KPI-dashboard notifications
Motivational Approach	Uniform; same incentives for all employees	Personalized; adjusted to individual engagement profile
Burnout Prevention	Reactive; identified after performance decline	Predictive; flagged by AI engagement monitoring
KPI Transparency	Partial; visible only to management	Full; employee-accessible real-time dashboards
Algorithmic Fairness	N/A	Requires explicit transparency mechanisms and employee consent

6.3 Limitations and Future Research

This study has several important limitations that qualify its findings and establish priorities for future research. First, the pilot sample (N=64 across three enterprises in one city) is insufficient for confirmatory statistical analysis or population-level generalization. Future research should implement large-scale survey studies with samples of minimum N=300–400 across multiple geographic and enterprise contexts.

Second, the cross-sectional design of the pilot prevents causal inference. Longitudinal studies tracking engagement, KPI performance, and turnover outcomes before and after AI-driven gamification implementation are necessary to establish causal mechanisms.

Third, the framework's propositions regarding AI behavioral profiling remain at the conceptual level, as no enterprise in the pilot study had implemented AI-driven management systems. Future research should involve enterprises with active AI management infrastructure to test framework propositions directly.

Fourth, cultural context may shape the generalizability of findings. The study was conducted in Kazakhstan, a post-Soviet context with specific organizational culture characteristics. Cross-national replication studies are warranted before broad generalization.

Fifth, the study does not address power asymmetries inherent in AI-driven behavioral monitoring. Future research should explicitly investigate employee perceptions of surveillance, privacy concerns, and the psychological effects of continuous performance monitoring — including negative outcomes such as anxiety, competitive toxicity, and data-related discomfort.

VII. Conclusion

This study developed and empirically grounded a conceptual framework for AI-driven adaptive gamification in operational KPI management within foodservice enterprises. Grounded in four theoretical frameworks — Self-Determination Theory, Work Engagement Theory, the Job Demands–Resources Model, and Flow Theory — and formalized through four formal propositions, the framework demonstrates how AI-driven personalization may address the structural limitations of standardized gamification in high-turnover, high-intensity operational environments.

Pilot empirical evidence from 64 frontline employees across three Almaty-based foodservice enterprises provides preliminary support for the framework's core assumptions. Employees report generally positive attitudes toward digital engagement tools and KPI transparency; however, substantial gaps persist in perceived task personalization (M=3.12) and algorithmic trust (M=3.28). These findings confirm both the

practical necessity of AI-driven personalization and the critical importance of transparency and fairness as implementation conditions.

The scientific contribution of this study is threefold: (1) integration of AI-driven personalization into gamification theory through a formal conceptual framework; (2) development of testable propositions for future empirical research; and (3) preliminary empirical evidence establishing the motivational landscape and implementation gaps in foodservice digital management. The practical contribution lies in providing foodservice operators with a theoretically grounded model for adaptive operational management that addresses Generation Z engagement requirements while identifying necessary transparency and fairness conditions.

Future research should pursue longitudinal empirical validation of the framework's propositions across larger and more diverse samples, with particular attention to the algorithmic transparency condition (Proposition 4), the cultural generalizability of findings, and the ethical dimensions of AI behavioral monitoring in frontline service environments.

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