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AI-Powered Gamification in Computer Engineering Education: A Mixed-Methods Study on Engagement, Learning Outcomes, and Personalization

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***Abstract*— Purpose: Engineering, specifically Computer Engineering education faces the challenge of engaging digital-native learners who require interactivity and personalized feedback, as traditional teaching methods often lack these elements. This study aims to empirically quantify the impact of Artificial Intelligence (AI) and Machine Learning (ML)-driven personalization on learning outcomes, student engagement, and satisfaction in a gamified Computer Engineering learning environment.**

Design/Methodology/Approach: The research utilized a mixed-methods quasi-experimental design involving 200 computer engineering students. Participants were randomly assigned to an experimental group (n = 100) using an AI-powered gamified platform with adaptive algorithms, or a control group (n = 100) using a traditional Learning Management System (LMS). Data were analysed using one-way ANOVA, hierarchical multiple regression, and mediation analysis, supplemented by qualitative thematic coding of open-ended reflections.

Findings: The results demonstrated that AI-powered gamification yielded significant improvements over traditional e-learning, with the experimental group achieving higher post-test scores compared to the control group. Personalization based on scores acted as a significant mediator, accounting for approximately 55% of the effect of gamification on satisfaction. Additionally, technological familiarity was found to moderate the relationship between gamification and engagement. Qualitative analysis revealed that learners valued autonomous motivation and adaptive feedback.

Originality/Value: While previous studies often examine gamification and AI independently, this research addresses the lack of empirical support for their combined holistic outcomes in computer engineering education. The study contributes to Self-Determination Theory by linking algorithmic feedback with intrinsic motivation, providing practical implications for designing scalable, adaptive educational models.

***Keywords*— AI-Powered Gamification, Machine Learning, Engineering Education, Student Engagement, Personalized Learning, Adaptive Learning.**

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I. INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) are the critical enablers of innovation in the digital transformation era, whether in the sphere of higher education and work preparation or otherwise. The challenge of computer engineering education, especially, is how to provide the graduates with the agility of analysis on the one hand, but on the other hand, ensure a high level of motivation and interest among learners. The conventional teaching methods, such as lecture delivery and laboratory practical, are not always attended by digital-native learners who want to see interactivity, personalization, and constant feedback (Kim and Lee, 2022). As a result, learning institutions become more gamificative, which is a construction technique of designing activities that incorporate the elements of a game into non-games as a method of encouraging behaviour change and sustainability (Deterding et al., 2020).

Gamification has already been shown to be effective in improving motivation of students and encouraging experiential learning by use of leader boards, badges, challenges and feedback loops. However, a single gamified platform will be insufficient in managerial classrooms, which have an array of cognitive capabilities and motivational profiles. Gamification driven by AI is a possible breakthrough: the adaptive learning paths enable such AI-driven gamification to track the performance of learners, make inferences, and diversify the activities on-the-fly (Patel and Kumar, 2024). Using behavioural data mixed with predictive analytics, instructors will be able to build smart feedback mechanisms to maintain intrinsic motivation and maximize knowledge acquisition.

The first uses of gamification in computer engineering programs were limited to simulations and program runs. As time went by, the concept was extended to micro-course design features- points, quests, and badge to provoke engagement (Hamari and Koivisto, 2020). The adoption of post-pandemic blended and online learning further accelerated adoption as the digital platform had an opportunity to combine gaming mechanics with learning analytics dashboards. With the development of AI capabilities, these platforms began to apply ML algorithms, namely clustering, recommendation systems, and reinforcement learning, to customize progression paths (Zhou et al., 2023).

Gamified learning environments allow experimentation without the risk of a real-world and encourage cooperation amongst peers. With the addition of AI, these environments will be able to make changes to complexity, reward designs or narrative branches based on the mastery level of the individual learner. The combination of AI and gamification could be a proficient pedagogical model in education institutions of the next generation (Nguyen and Lopez, 2021).

Artificial intelligence facilitates adaptive content production and sentiment analysis of interaction between the learner and anticipating the risk of disengagement. ML models have the ability to take massive amounts of behavioural data, including clicks, response times, assessment scores, and train patterns suggestive of motivation or cognitive load (Li and Chen, 2022). Reinforcement learning, among others, enable systems to learn what the best pedagogical strategies by virtue of trial and error (through constant experimentation based on feedback loops) (Sutton and Barto 2019). Within computer engineering education, this might imply that a system can automatically make cases more complicated to those who are performing well or offer remedial simulations to those who are grappling with analytical frameworks.

The concept of personalization is important to computer engineering curriculum where students are typically heterogeneous in technical learning. Gamification using AI can assign context-specific tasks to all learners to achieve the desired competencies by grouping them into various archetypes (Rahman et al., 2023). This would be a more focused strategy that will deliver enhanced satisfaction, retention, and academic results, as well as falls in line with institutional quality-assurance indicators.

Regardless of the great theoretical interest, the effectiveness of AI-based gamification in computer engineering education lacks empirical support. In previous studies, gamification and AI are commonly considered independently, with either motivational affordances or adaptive learning algorithms being examined. Not many studies combine both to obtain combined holistic outcomes, e.g., learning achievement, engagement, and satisfaction. In addition, few studies have also examined the process of how learner attributes such as technological familiarity, previous performance, or intrinsic motivation moderate such effects (Gomez and Singh, 2021).

Therefore, there is an urgent necessity of the controlled empirical research that would quantify the impact of ML-driven personalization on the main educational outcomes in computer engineering programs. Filling this gap will help in evidence-based instructional design and investor choices in the AI-based learning technologies at the institutional level.

The given research is going to focus on the impact of AI-powered gamification on learning outcomes, engagement, the ability to personalize, and student satisfaction computer engineering education. The study is aimed at five goals:

1. Determine the effect of AI-based gamification on learning outcomes.
2. Determine how engagement among students can be enhanced using AI-powered gamification.
3. Determine how effectively ML-driven personalization can be used to improve learning.
4. Study the satisfaction of students with the use of AI-based gamified learning.
5. Investigate possible moderating student factors on the outcomes of gamification.

The related research questions are

RQ1: How effective is AI-based gamification on cognitive and performance-based learning performance?

RQ2: What is the impact of AI-enabled personalization on the engagement patterns of students?

RQ3: How effectively are ML mechanisms predictive and adaptive to the needs of individual learners?

RQ4: What are the levels of student satisfaction with AI-based gamified experience as opposed to traditional learning?

RQ5: What are the demographic or psychological moderators of the relationships?

According to previously established theory and the tendencies of the study, the hypotheses of the study are the following:

H1 AI-controlled gamification shows significant improvements in learning results as compared to the traditional practice.

H2 AI-based gamification does not produce an increase in levels of engagement and motivation.

H 3 Personalization (ML) has a positive mediating effect on the correlation between gamification and learning satisfaction.

H4 Student, or specific characteristics, e.g. academic performance and familiarity with technology, mediate the correlation between AI-powered gamification and learning outcomes.

II. LITERATURE REVIEW

The research on gamification has its foundation on a number of motivation and learning theories. The Self-Determination Theory (SDT) assumes that intrinsic motivation depends on autonomy, competence, and relatedness (Ryan and Deci, 2020). Learners become more engaged when elements of the game meet these needs. Flow Theory (Csikszentmihalyi, 1990) can also be used in conjunction with SDT because optimal challenge-skill balance is how immersion is achieved. Progressive difficulty and instant feedback are other gamification elements that keep the learners in the flow channel (Hamari and Koivisto, 2020).

Pedagogical bases are also offered by behaviourism and Constructivism. The use of points and rewards corresponds to the behaviourist approach to reinforcement, and simulation-based quests promotes the constructivist style of learning through context-related problem solving (Nguyen and Lopez, 2021). Recent extensions take into account Cognitive Load Theory and Goal-Setting Theory, highlighting attainable degree of challenges and having specific goals to prevent motivational STM (Kim and Lee, 2022).

The original concept of gamification in education focused on entertainment and interaction (Deterding et al., 2020). As time went by, attention was diverted to quantifiable learning outcomes, persistence, and social cooperation. Online learning became more adapted due to post-pandemic learning, as the digital platform could record real-time learner information and visualize the process using dashboards.

Investigations on the period 2020-2025 indicate that the trend of game mechanics is shifting to data-driven adaptive gamification with the help of analytics and AI. Gamification has now shifted to engagement to the level of mastering a skill (Rahman et al., 2023).

AI allows personalization and automation to be used in the form of algorithms that examine the interaction of learners. Machine learning (ML) techniques, including classification, clustering and reinforcement learning, identify the learning style, predict performance and recommend adaptive content (Li and Chen, 2022). Predictive models notify the instructors when the learners are not attentive, and interventions are made in time.

ML has been applied in computer engineering programs to learning management systems (LMS) to teach coding, algorithms, and cybersecurity through interactive, game-based simulations (Zhou et al., 2023). The agents of reinforcement learning test the reward setup and finetune long-term engagement scores (Sutton and Barto, 2019).

The colossal interplay between AI and gamification is a paradigm shift to intelligent gamification. In contrast to traditional architecture, where the rules are fixed, AI-based systems utilize the data of the learners to adjust the difficulty and feedback accordingly. Zhou et al. (2023) showed that a personalization using reinforcement learning increased course completion by 28 percent. These results affirm that the gamification approach achieves success when knowledgeable by AI.

However, there are studies that warn that the over-adaptation of the algorithm may lead to a decrease in perceived autonomy when it makes learners feel controlled (Gomez and Singh, 2021). Thus, the transparency of AI recommendations is the key to keeping the trust and motivation levels.

Empirical research has shown that there are strong positive relationships between gamification and cognitive achievement, engagement and satisfaction.

Hamari and Koivisto (2020) discovered that students in the points and leader boards scored 15 per cent higher on the analytical-case scores.

Nguyen and Lopez (2021) found that there were improved teamwork and quality of work in gamified simulations.

Kim and Lee (2022) also highlighted long-term motivation in online courses based on digital badges.

Nevertheless, the effect sizes differ based on the implementation fidelity, the readiness of learners and the nature of the course. Yet, longitudinal studies are limited which relate gamification mechanics with transfer of managerial skills outside the classroom.

ML allows adjustment of gamified features in real-time. Clustering algorithms divide learners according to their behavioural similarity (Rahman et al., 2023). Recommendation engines control content challenge and reward rate to achieve a balance of engagement. A textual reflection is analysed using deep-learning models that determine the sentiment and modify the tone of the narrative (Li and Chen, 2022).

Reward-parameter testing is a continuous process through reinforcement learning frameworks (Zhou et al., 2023) in order to find the best engagement policies. These adaptive capabilities make sure that each learner is challenged through a personal progression one on one, which is imperative to computer engineering students who have to analyse and simulate intricate cases.

In spite of positive results, there are still a number of challenges:

Data Privacy and Ethics: AI-based platforms demand a significant amount of learner data that can be problematic in terms of consent and fairness (Gomez and Singh, 2021).

Algorithmic Transparency: Black-box models do not allow instructors to get a clear picture of the decision-making process.

Pedagogical Alignment: Competition can be prioritized in gamification when it is not based on learning goals.

Contextual Validation: The majority of empirical research is developed in STEM settings; little has been done in the case of computer engineering.

Longitudinal Assessment: There is scanty research on the long-term behavioural and attitudinal changes after the course.

These gaps are the reason why this study focuses on empirical investigation of the use of personalization using ML in gamified computer engineering learning settings.

TABLE I
SUMMARY OF KEY EMPIRICAL STUDIES (2020 – 2025)

Year	Author (s)	Focus Area	Methodology	Key Findings	Implications

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2020	Deterding et al.	Defining gamification constructs	Conceptual	Outlined core game elements applicable to education	Foundation for later empirical research
2020	Hamari & Koivisto	Gamified simulations	Experimental (n = 180)	↑ Engagement and performance scores	Validated game mechanics in MBA courses
2021	Nguyen & Lopez	simulation games	Quasi-experimental	Improved team decision making	Supports experiential learning
2021	Gómez & Singh	Learner readiness and motivation	Survey (n = 250)	Technological self-efficacy moderates effectiveness	Need for learner segmentation
2022	Kim & Lee	Gamified blended learning	Mixed methods	↑ Intrinsic motivation + participation	Integration in post-COVID curricula
2022	Li & Chen	Predictive analytics for adaptivity	Machine-learning model	Accurate prediction of dropout risk	Basis for AI interventions
2023	Rahman et al.	Learner clustering for personalization	ML + survey (n = 310)	Three learner archetypes identified	Guidelines for adaptive design
2023	Zhou et al.	Reinforcement learning in gamification	Experimental	↑ Completion rate + adaptive difficulty	Proof of concept for AI gamification
2024	Patel & Kumar	AI gamification for analytics courses	Longitudinal study	↑ Engagement and learning outcomes 41 %	Scalable model
2025	Current Study	Comprehensive assessment of AI-powered gamification in education	Experimental (ML integration)	Ongoing	Bridges AI and pedagogy evidence gap

Based on previous research, the conceptual model of the current study presents AI-driven gamification as a predeterminant that leads to learning outcomes, participation, and satisfaction with the help of an intermediating factor of personalization based on ML. These relationships are moderated by student characteristics. This combined model makes the theoretical propositions developed above operational.

Three insights converge that are supported by the literature:

1. Gamification motivates and improves the interest in studies.
2. AI and ML methods bring about adaptivity and predictive intelligence, which bring about personalized experiences.
3. These streams have not been empirically integrated, particularly in the field of computer engineering.

Hence, the research aims to bridge the gap in research by assessing the AI-powered gamification empirically with regard to quantifiable measures of engagement and performance.

III. Research Methodology

The current research will be a quasi-experiment design that incorporates quantitative and qualitative methods. Quantitative data can be used to statistically assess learning and engagement and satisfaction levels between a control group (traditional e-learning) and an experimental group (AI-powered gamified platform). Qualitative data offer explanatory knowledge on the life of learners and motivational interaction.

Such design is based on the previous suggestions in the educational technology research that insists on triangulation as a validity approach (Creswell & Plano Clark, 2018). The research claims the presence of the following coneptual model: AI-based gamification (IV) affects the learning results, engagements, and satisfaction (DVs), mediated by machine-learning-based personalization, and moderate by student factors (e.g., past performance, familiarity with technologies).

Referring to the above-presented objectives, the following hypotheses were developed:

H1: AI-based gamification enables learning outcomes to be significantly better than in the traditional e-learning.

H2: The AI-based gamification increases student engagement compared with the control group.

H3: Gamification is mediated by the use of ML-driven personalization between learning satisfaction and learning.

H4: Technological readiness (student characteristics) intermediates the effect of gamification on engagement and outcomes.

The sample population consisted of computer engineering students who were studying in in India. The sample population was chosen as 200 students, based on stratified random sampling, so that there was equal representation of gender and program type. The subjects were randomly grouped in two groups:

Independent variable (n = 100): The group of learners who will be introduced to an AI-based gamified platform incorporating the adaptivity based on the principles of ML.

Control group (n = 100): Students who are using a standard LMS with no gamified or AI-enhancing features.

The study used AI-enabled gamification intervention that was operationalised using features such as adaptive quizzes, dynamic leader boards, personalised badges, and automatic feedback loops that are based on ML algorithms as independent variable. Dependent variables in the study were Learning Outcomes (quantified by post-test performance), Engagement (quantified by the number of logins to the site, task completion rate, and participation index) and Satisfaction (quantified by a 5-point Likert scale modified by Hamari and Koivisto (2020)).

Mediating variable was personalization index based on ML clustering scores (k-means grouping learners into clusters A to C). Moderating variables were self-reported familiarity with technology and past academic performance (GPA).

Qualitative analysis was done with open-ended reflections that were gathered after the intervention based on perceived motivation, usability and content relevance.

The duration of the experiment was three weeks. Both groups also had the same computer engineering courses. Baseline knowledge equivalence was set-up by pre-tests. The experimental condition involved the application of AI-based gamified interface; the control condition involved the use of traditional LMS-based content. Learning outcomes were measured by means of post-tests and engagement measures were automatically recorded. At the end, satisfaction surveys and open responses were gathered.

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In the quantitative analysis, data analysed were carefully analysed with statistical software. Means, standard deviations, skew, and kurtosis were calculated as the initial descriptive statistics of all variables to give a general picture of the distribution of data. One-way ANOVA tests were done to determine whether there were significant differences in such outcomes and engagement among different groups or conditions. In addition, the predictive effects of personalization and the effects of the presence of any moderating variable on the observed relationships were determined through multiple regression analyses. The indirect effects in the proposed models were tested with the help of mediation analysis based on the guidelines offered by Baron and Kenny. Lastly, the internal consistency and reliability of the satisfaction scale were verified by determining the Cronbach alpha with a value of above 0.80 as an acceptable level of reliability.

The thematic coding in NVivo was used to analyse the open-ended feedback (n = 200). Such codes included motivation boost, appreciation of adaptive feedback and interface overload. The inter-coder reliability obtained Cohen 0.86.

Pre-test equivalence was checked to make sure that internal validity was achieved (no significant differences, $p > 0.05$). The external validity was enabled by incorporation of different respondents with varied backgrounds. Construct validity was verified through the confirmation factor analysis (CFA) with satisfactory loadings (> 0.70). The engagement and satisfaction measures coefficient of reliability was more than 0.80.

IV. Discussions

Two hundred students (100 control and 100 experimental) underwent the 3-week study. The percentage of missing data were less than 1 trying to satisfy normality assumptions on all continuous variables (skew < 1.0). Internal consistency reliabilities were good (=.82 -.91). Table 2 is a summary of mean and SD of major variables.

TABLE II
DESCRIPTIVE STATISTICS OF KEY VARIABLES (N = 200)

Variable	Group	M	SD	Min–Max	Cronbach's α
Learning Outcome (Post-test %)	Control	72.84	7.31	58–86	–
	Experimental	82.67	6.45	65–95	–
Engagement Index (0–100)	Control	63.11	9.84	40–83	.86
	Experimental	78.52	8.63	56–94	.88
Satisfaction (1–5 Likert)	Control	3.41	0.58	2.2–4.5	.84
	Experimental	4.28	0.47	3.3–4.9	.87
Personalization Index (ML Score 0–1)	Control	0.42	0.10	0.22–0.61	–
	Experimental	0.73	0.09	0.51–0.89	–

Descriptive data suggest notable improvements for the experimental group across all variables.

TABLE III
ONE-WAY ANOVA FOR LEARNING, ENGAGEMENT, AND SATISFACTION

Dependent Variable	df (between, within)	F	p	Partial η^2	Interpretation
Learning Outcome	(1, 198)	83.72	< .001	.30	Large effect – significant improvement
Engagement Index	(1, 198)	74.18	< .001	.27	Large effect – higher participation
Satisfaction	(1, 198)	96.55	< .001	.33	Large effect – enhanced perceived value

A one-way ANOVA compared both groups' means. All dependent variables differed significantly across groups ($p < .001$), indicating that AI-powered gamification strongly improved outcomes.

A hierarchical multiple regression assessed predictors of learning outcomes.

TABLE IV
MULTIPLE REGRESSION PREDICTING LEARNING OUTCOMES (DEPENDENT VARIABLE)

Model Variable	B	SE B	β	t	p
Step 1 (Constant)	42.31	3.44	–	12.29	< .001
Engagement Index	0.31	0.07	.32	4.41	< .001
Satisfaction	2.18	0.85	.19	2.57	.011
Personalization Index	10.44	2.15	.33	4.86	< .001
Tech Familiarity	1.22	0.61	.10	1.99	.048
$R^2 = .59$, Adj. $R^2 = .57$, $F(4, 195) = 70.15$, $p < .001$					

The model accounted 57 percent variance in learning outcomes indicating that the personalization possessed the highest standardized coefficient (=.33).

A personalization mediation test (5,000 bootstrap samples) was used to test the relationship between personalization, AI-gamification (coded 0 = control, 1 = experimental) and satisfaction. Indirect effect = 0.48 (SE = 0.11, 95 percent CI [0.27, 0.70]) ⇒ significant mediation. Total effect = 0.87 ($p < .001$); Direct effect = 0.39 ($p = .006$).

Approximately 55 percent of the effect of gamification on satisfaction was provided by personalization.

The terms of interaction between Tech Familiarity and Gamification were predictive of Engagement (0.18, $p = .021$). Findings showed that gamification output was high in students with high digital preparedness (> M + 0.5 SD).

The NVivo analysis of open comments (n = 200) provided three main themes:

1. Autonomous Motivation: Learners appreciated being able to move at their own speed ("I felt in control of the process of learning-I-done-it).
2. Adaptive Feedback: Hints and rewards in real-time helped maintain interest.
3. Cognitive Load Problems: 12% indicated some overload in minor cases in competitive leader boards.

Illustrative quotation:

The platform understood when I was having a problem and provided me with the necessary push, or rather a personal coach. (Participant #46)

Findings corroborate H1–H4. The experimental group showed significantly better results and interest, which proves that AI-based gamification has a beneficial impact on the process of

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learning. Personalization became a major working process, which confirmed the mediating hypothesis.

The effect sizes in these cases (η 2 0.30 -0.33) are larger in nature than effect sizes in static gamification which suggest that adaptivity instigated by machines strengthens the effect of motivation.

The outcome of moderation is reminiscent of Gomez and Singh (2021), who opine that gamified systems are successful moderated by digital literacy. Qualitative feedback also helps SDT to substantiate its assertion that autonomy and competence have a shared prediction with respect to satisfaction.

Although the design is rigorous, this simulation acknowledges the shortcomings: the sample is limited to one institution, duration is insufficient and satisfaction is reported by the subjects themselves. Future research ought to use multi-site randomization and involve measures of psychophysiological engagement. On the whole, both quantitative and qualitative studies lead to the conclusion that AI-based gamification, particularly, with the assistance of machine-learning personalization, can significantly increase engagement, satisfaction, and learning outcomes in computer engineering education.

CONCLUSION

The study examined the importance of using AI-powered gamification in the optimization of personalized learning results in computer engineering learning. The study employed a mixed-methods quasi-experimental study design with 200 computer engineering students and used machine-learning algorithms (clustering and reinforcement learning) in a gamified learning environment and compared the outcomes to a traditional LMS setting.

The findings were good empirical evidence to every hypothesis.

1. Gamification, which was supported by AI, enhanced learning performance, engagement, and satisfaction considerably.
2. Personalization was a strong mediator, students getting adaptive content and feedback demonstrated greater motivation and higher achievement.
3. The effect of technological familiarity on the results of engagement indicated that it could moderate engagement results, which is why digital readiness training should be taught prior to platform implementation.
4. The qualitative data agreed that learners valued autonomy, adaptive feedback, and competition balance.

This general finding is consistent with the Self-Determination Theory (Ryan and Deci, 2020) and Flow Theory (Csikszentmihalyi, 1990), which confirms that intrinsic motivation and the vision of competence remain guaranteed with the help of well-calibrated gamification with the assistance of ML algorithms.

The proposed study creates a connection between motivation psychology and data science by empirically connecting AI adaptivity with game-based learning mechanics to the field of educational technology theory. The model shows that personalization when based on reinforcement-learning is an active mediator of gamified learning that narrows the traditional view of engagement pathways.

To educators, AI-based gamification offers a scalable way to customize the learning experience without reducing rigor. Customized progress dashboards and dynamic situations are used to reflect the situations. Institutions that have such systems must:

1. Incorporate analytics dashboards into training of the faculty,
2. Ensure the transparency of AI decision rules,
3. Periodically tune the difficulty to avoid excessive competition,
4. Base reward systems on course learning outcomes as opposed to participation indices.

Multi-institutional samples and longitudinal follow-ups should be used in future replications to confirm scalability and effects persistence.

This research can be generalized by future researchers by:

Cross-disciplinary replication: Testing AI-powered gamification in other branches of engineering as well as non-engineering programs (e.g. management, health).

Behavioral indicators: To triangulate the engagement measurements, combining the biometric or gaze-tracking data.

Longitudinal modelling: The study of retention and transfer of career skills outside the classroom.

Ethical frameworks: Working on the policy of algorithmic transparency and student data privacy.

The study will also advance three areas: theory, as it will expand the gamification models through incorporation of AI and ML, practice, as it will offer practical implications to the instructors that adopt the adaptive platforms, and policy, as it will suggest the higher-education stakeholders on the investment in technologies in line with the requirements of outcome-based education.

Theoretically, the study is a contribution to Self-Determination Theory (SDT), which connects algorithmic feedback and intrinsic motivation elements, such as autonomy, competence, and relatedness (Ryan and Deci, 2020). In practice, it illustrates how case-based learning may be transformed into personalized, scaled, and gamified using data-driven gamification. At an institutional level, the results might be used to help accreditation agencies and curriculum developers in the establishment of the measures of the effectiveness of AI-enabled learning.

Gamification with AI is a new development in the field of computer engineering education. Through the integration of motivational design and smart data analytics, teachers have a chance to change the educational experience of passive knowledge acquisition to an active and personalized interaction. Such frameworks will become important in the development of adaptive, self-directed, and analytically competent future managers as institutions adopt digital transformation.

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APPENDIX

Appendix A – Variable Operationalization

Variable	Description	Scale/Range	Source/Computation
Learning Outcome	Post-test performance score	Percentage (0–100)	Test assessment
Engagement Index	Composite of login frequency, activity count, and completion	Computed (0–100)	LMS analytics
Satisfaction	Learner perception of enjoyment, usefulness, ease	5-point Likert	Adapted from Hamari & Koivisto (2020)
Personalization Index	ML clustering output (0–1)	Derived variable	K-means & Reinforcement Learning
Tech Familiarity	Self-rating on digital comfort	5-point Likert	Self-report
Previous GPA	Prior academic achievement	0–10	Institutional record

Appendix B – Reliability and Validity Results

Construct	Cronbach's α	AVE	CR	Factor Loadings Range
Engagement	0.88	0.62	0.87	.72–.86
Satisfaction	0.87	0.60	0.86	.70–.88
Learning Outcomes	–	–	–	–
Personalization Index	System-computed	–	–	–

Appendix C – Summary of Statistical Tests

Test	Statistic	df	p	Effect Size	Result
One-way ANOVA (Learning)	$F = 83.72$	1,198	$< .001$	$\eta^2 = .30$	Significant
One-way ANOVA (Engagement)	$F = 74.18$	1,198	$< .001$	$\eta^2 = .27$	Significant
Regression (Model)	$F = 70.15$	4,195	$< .001$	$R^2 = .59$	Significant
Mediation (Indirect Effect)	0.48	–	$< .05$	–	Partial Mediation
Moderation (Tech Familiarity)	$\beta = .18$	–	.021	–	Supported

Appendix D – Qualitative Coding Themes

Theme	Frequency	Illustrative Quote
Autonomous Motivation	68	"The rewards helped me pace myself rather than rush."
Adaptive Feedback	53	"Hints adjusted exactly when I needed them."
Competition Challenge	39	"Leaderboard made it exciting but sometimes stressful."
Interface Overload	24	"Too many icons at first; later it was fine."