International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol. 12, No. 4, 2025, pp. 287-298.

ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

Effect of Gamified Learning and Emotional Intelligence on Adaptive Performance in Digital Workplace Environments

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Abstract

This study focuses on the application of gamified learning to adaptive performance in the digital workplace and specifically examines the mediating and moderating roles of emotional intelligence. A cross-sectional survey design was used to conduct quantitative research with an explanatory empirical design. Data were collected from 250–400 employees across digitally enabled organizations using structured questionnaires. The constructs were measured using validated Likert-scale instruments. Structural equation modeling (SEM) was applied to test direct, mediating, and moderating relationships. The reliability and validity were checked by use of Cronbach's alpha (0.87-0.90), Composite Reliability (0.90-0.92), and AVE (0.61-0.66). The result indicated that gamified learning (3.87), emotional intelligence (3.92), and adaptive performance (4.01) had high mean values. Correlation analysis showed significant positive relationships among variables ($r = 0.56–0.65$, $p < 0.01$). Structural results indicated that gamified learning significantly influences adaptive performance ($\beta = 0.34$) and emotional intelligence ($\beta = 0.56$), while emotional intelligence also affects adaptive performance ($\beta = 0.41$). The effect was found to be significant as mediated ($\beta = 0.23$) and moderated ($\beta = 0.19$). The explanation of adaptive performance had a model variance of 58% ($R^2 = 0.58$). Control variables were deemed not to be significant ($p > 0.05$). The study concludes that gamified learning is a major strategy to facilitate adaptive performance both directly and indirectly through the emotional intelligence aspect. This relationship is reinforced and elaborated through emotional intelligence, which is dual-potent. The results highlight the necessity of combining gamification with emotional skill formation to enhance adaptability on the Internet.

Keywords: Adaptive Performance, Emotional Intelligence, Gamified Learning, Mediation, Moderation, Digital Workplace, Structural Equation Modeling.

DOI: 10.71086/IAJSE/V12I4/IAJSE1296
Received: 08 October 2025/Revised: 15 November 2025/Accepted: 10 December 2025/Published: 30 December 2025

Introduction

The fact that modern workplaces are rapidly changing to be digital has remarkably changed the way employees socialize, learn, and carry out their work. The shift towards digital workplaces has also emphasized the importance of self-reflective learning and critical evaluation of one's own performance, which supports adaptive behavior in rapidly changing environments (Al Hatmi et al., 2024). Organizations are turning more to online platforms, artificial intelligence, and remote working technologies, which require more flexibility on the part of employees (Yasmeen et al., 2024). Moreover, the adaptability of employees is essential because it is the skill to handle the intricate systems and evaluate the uncertainties, as is done in financial and risk modeling in dynamic situations (Velanganni, 2024). Adaptive performance, the ability to effectively adapt to changing work requirements, technologies, and environments, has become a very important competency in this regard. One of the most effective methods of employee engagement, motivation, and skill development is called gamified learning (GL) and entails the elements of gamification such as points, badges, leaderboards, and challenges in non-gaming environments (KS, 2023). The innovations in nanoscale and real-time communication technologies also demonstrate how the next-generation immersive and response learning spaces can be utilized to support the acquisition of skills in the digitally empowered workplaces (Uvarajan, 2024). Gamification can enhance the retention of knowledge and promote lifelong learning in online platforms by making it more interactive and immersive.

Meanwhile, emotional intelligence (EI) also plays a crucial role in assisting employees to work under stress, collaborate, and cope with the problems of the dynamic work environment. Higher EI people at the workplace are better placed to control their emotions, understand others, and still be able to deliver in unclear and rapidly shifting scenarios. Additionally, in multi-agent systems, autonomous intelligent systems and reinforcement learning methods can give us a clue of how adaptive strategies may be optimized to be resilient and make decisions under uncertainty, similar to human adaptive performance (Aravindhan, 2024). The intersection of gamified learning and emotional intelligence is an attractive construct for the improvement of adaptive performance in a digital work environment, in the sense that it remains less represented in the empirical literature. Emerging research in molecular communication and information coding at the nanoscale highlights the importance of precise information processing and responsiveness, which can be analogously applied to designing digital learning systems that enhance employee adaptability (Vimal Kumar, 2024).

The primary objective was to examine the effects of gamified learning on adaptive performance within the digital workplace context. The study aimed to establish the relevance of emotional intelligence in enhancing the ability of employees to respond favorably to transforming technological environments. Besides, the study examined the synergistic impact of gamified learning and emotional intelligence on adaptive performance. One of the major concerns was to establish the dual aspect of emotional intelligence as an intervening variable as well as an adjusting variable in the relationship between GL and adaptive performance (AP), which offers a deeper explanation of employee flexibility.

Although the gamified learning and emotional intelligence have been explored in the literature as separate constructs, the literature gap in the interaction between these two variables in promoting adaptive performances in online workplaces is quite large (Castellano-Tejedor & Cencerrado, 2024). The majority of the previous research is oriented towards the application of gamification in the educational environment, not in the workplace, which restricts the scope of the research in the field of organizational performance. Moreover, the role of emotional intelligence as a mediating or moderating variable in digitally enabled learning systems has not been adequately analyzed. Empirical studies that combine these constructs into one of the analytical frameworks to explain adaptive behaviour in the rapidly changing working environments are also lacking. This study overcomes these limitations by filling the gaps in the theoretical and empirical fronts and providing a holistic view.

According to the conceptual reasoning, the study had an assumption that adaptive performance would be improved with the help of gamified learning based on collaborative engagement and long-term learning (Schoebel et al., 2022). The research also hypothesized that emotional intelligence contributes considerably to adaptive performance, where the ability of emotionally intelligent people to cope with uncertainty is more pronounced. The framework also theorized that learning through gamification leads to the emerging of emotional intelligence. In particular, the model was used to test two different paths, the first one, namely, that emotional intelligence mediates the relationship between gamified learning and adaptive performance (H4), is the underlying process with the help of which GL promotes its influence. Second, emotional intelligence mediates this relationship (H5), whereby the beneficial effect of gamified learning on adaptive performance is enhanced among individuals who have high levels of emotional intelligence.

This study makes several important contributions:

- **Theoretical Contribution:** It integrates gamified learning and emotional intelligence into a unified framework to explain adaptive performance in digital workplaces.
- **Empirical Contribution:** Provides quantitative evidence on how gamification and EI jointly influence employee adaptability.
- **Practical Contribution:** Offers practical insights to organizations in need of developing gamified training systems that are also conducive to the development of emotional intelligence.
- **Methodological Contribution:** Presents a multi-variable model of analysis using the effects of mediation and moderation to understand the dynamics of learning at the workplace in a better way.

The article is divided into five major parts. The Introduction presents the research problem, the objective, the hypotheses, and the contributions. The Literature Review summarises the previous works in gamified learning, emotional intelligence, and adaptive performance, and identifies the main gaps in research. The Methodology describes the research design, conceptual model, sampling, data collection, and scales of measurement, and the analytical methods, such as SEM. The Results section gives the descriptive statistics, reliability and validity test, hypothesis test, mediation and moderation analysis, and control variable assessment. Lastly, the Discussion and Conclusion present results, point out theoretical and applied implications, reflect on weaknesses, and propose future research recommendations.

Literature Review

The concept of gamified learning has received a lot of publicity as an advanced method to facilitate engagement, motivation, and performance in either a learning or a working setting. It incorporates the features of games like rewards/challenges/feedback in the non-game settings and manipulates user behavior and learning results. It has been studied that gamification not only enhances cognitive performance but also has an impact on emotional and behavioral growth, which is vital in adaptive digital workplace performance.

The need to develop emotional intelligence is indicated in several works that refer to the value of gamification. In particular, gamified and cooperative learning environments have high levels of emotional intelligence, patterns of learning, and inspiration among learners (Redondo-Rodríguez et al., 2022). It has also been found that gamification tools also affect emotional skills such as emotional self-awareness and emotional regulation, which are important in addressing complex work environments (Fedorova et al., 2024). Gamification, as an online training, also positively influences emotional engagement and problem-solving, which implies that it can be effective in developing cognitive and emotional skills (Schöbel et al., 2023). Furthermore, it has been learned that the gamified tests and serious games do find use in the measurement and training of soft skills, such as adaptability and emotional intelligence (Marengo et al., 2024; Altomari et al., 2023).

In the digital workplace, emotional intelligence plays a significant role in enhancing performance and flexibility. It is mentioned that in organizational environments, emotional intelligence has been linked to successful teamwork, virtual work, and responsive leadership in dynamic environments (Yasmeen et al., 2024). Moreover, gamification at work promotes self-directed actions and improves flexibility by establishing immersive experiences at work (Seo et al., 2020). Empirical data also indicate that gamification has a positive impact on employee engagement and performance outcomes, and it could be a useful instrument in the organization (Putranti et al., 2024; Ikhide et al., 2023). Moreover, systems based on gamification have been linked to the agility of employees, which is one of the major elements of adaptive performance (KS, 2023).

Digital technologies and gamified systems find their application especially in the changing Industry 4.0 and 5.0. Game-based learning can be used to train the new competencies required in the digital labor market, especially adaptability, emotional awareness, and problem-solving skills (Reuter et al., 2021). Research also focuses on the fact that the new learning environment should embrace emotional intelligence and digital technology to equip individuals with complex and highly dynamic work environments (Drigas et al., 2023; Zenjari et al., 2024). In addition, adaptive e-learning systems, emotional intelligence, and artificial intelligence that support the engagement and flexibility of learners can also be implemented (Sargazi Moghadam et al., 2024).

Although much has been done in the study of gamification and emotional intelligence, the connection between the two when it comes to adaptive performance in the digital workplace setting has not been thoroughly understood. Although these constructs have been studied separately in the previous literature, very little research has incorporated them into a single framework. Thus, the paper filled this gap by revealing the contribution of gamified learning with

emotional intelligence to adaptive performance to get a more detailed understanding of the performance improvement in the digital environment.

Methodology

Research Design

The research design used is a quantitative, explanatory research design because the study aims to determine the relationships between gamified learning, emotional intelligence, and adaptive performance in digital workplaces. The study is a hypothesis-based investigation that is based on both behavioral and organizational theory and seeks to establish direct and indirect associations. The cross-sectional survey design is used, which provides the opportunity to efficiently collect data on a large population and make structural modeling of latent constructs.

Conceptual Model and Variable Specification

The study proposes a structural model in which gamified learning functions as the independent variable, adaptive performance as the dependent variable, and emotional intelligence as both a mediating and moderating variable. Control variables such as age, gender, work experience, and industry type are included to reduce potential confounding effects.

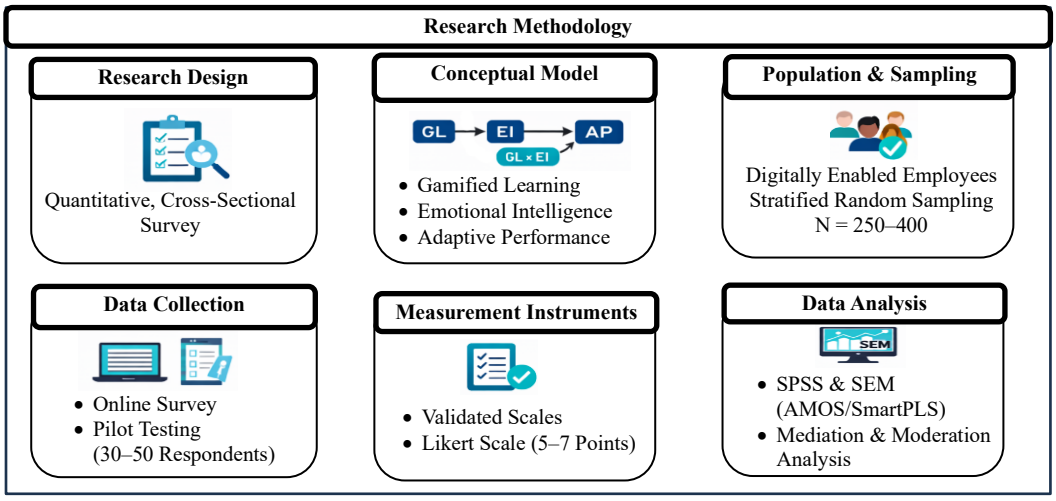

Fig. 1: Research Methodology Framework for Gamified Learning and Adaptive Performance

Fig. 1 shows the general research methodology that was used in the study. It introduces the quantitative cross-sectional design, theoretical framework connecting gamified learning, emotional intelligence, and adaptive performance, sampling plan, data-gathering processes, measuring tools, and statistical analysis tools (SEM). Validity, reliability, and checks of robustness that guarantee methodological rigor are also brought out in the framework.

The Functional Relationship Can be Expressed as

$$AP = \beta_0 + \beta_1(GL) + \beta_2(EI) + \beta_3(GL \times EI) + \epsilon \qquad (1)$$

In equation (1), adaptive performance (AP) is dependent on gamified learning (GL), emotional intelligence (EI), and the interaction effect. The structural model examines the indirect path of assessment of the mediation effect.

Population and Sampling Technique

The population to be targeted is the employees who are employed in digitally empowered organizations that are connected with e-learning systems, enterprise, or training applications that are gamified. The sampling frame comprises professionals in information technology, education, and finance sectors as well as service industries.

They use a stratified random sampling method in order to get representation in sectors and experience levels. The assessed power analysis is used to determine the minimum sample size in structural equation modeling, which suggests a minimum of 10 respondents for each indicator variable. Based on this, a population of around 250-400 respondents was targeted, which would guarantee strength and generalizability.

Data Collection Procedure

In this case, a structured self-administered questionnaire was used to collect primary data, which was delivered using online survey tools. To enhance the levels of clarity, reliability, and construct validity, in a pilot study, the instrument is pre-tested on 30-50 respondents. The period of data collection is spelled out to achieve consistency, and costly mechanisms like assuring anonymity and different endpoints of scales are used to eliminate common method bias.

Measurement Instruments and Scale Development

Validated multi-item scales, which are developed with regard to previous studies, are used in the operationalization of all constructs. The dimensions used in measuring gamified learning include engagement, reward systems, feedback mechanisms, and user interaction. Emotional intelligence is measured on some major dimensions such as self-awareness, self-regulation, social awareness, and relationship management. The adaptive performance is measured based on indicators of problem-solving flexibility, learning flexibility, stress management, and change responsiveness.

A five-point or seven-point Likert scale is used to rate each item. Construct validity is ascertained through the use of confirmatory factor analysis, and convergent and discriminant validity are ascertained through the use of average variance extracted (AVE) and composite reliability (CR). Maintenance of AVE > 0.50 and CR > 0.70 is maintained as a threshold value.

Data Analysis Techniques

The analysis of data is performed with the help of the high-level statistical programs SPSS and Structural Equation Modeling (SEM) software, AMOS, or SmartPLS. The analysis can take a two-step approach where the measurement model is evaluated, and structural model testing is conducted.

The model used to measure is subject to the assessment of reliability tests, Cronbach's alpha, factor loading (≥ 0.70), and model fit aspects such as CFI, TLI, RMSEA, and SRMR. The structural model is then tested to test the path coefficient, t-statistic, and significance level of the hypothesized relationship.

The mediation of the effect is performed by bootstrapping methods to estimate the significance of the indirect effect, and moderation analysis is performed by including the interaction terms or multi-group analysis. The Coefficient of determination (R^2), the magnitude of the effect (f^2), and the relevance of prediction (Q^2) also define the performance of the model.

Robustness and Validity Checks

To ensure high methodological rigor, the research conducts numerous powerful tests of soundness, including checking the multicollinearity test by computing the variance inflation factor (VIF), testing the normality, and heteroscedasticity. Harman's single-factor test and marker variable methods are used in identifying common method variance.

Data Analysis Software

Analysis performed in IBM SPSS Statistics (Version 26) and AMOS (Version 24). Preliminarily, the data were screened using IBM SPSS and descriptive statistics, correlation analysis, and reliability test. SEM was conducted on AMOS to test both the measurement model and the structural model. Also, bootstrapping procedures of 5, 000 resamples were introduced in AMOS to evaluate mediation effects, and moderation analysis was done through establishing interaction terms within the SEM framework. Model fit indices, path coefficients, and indirect effects were estimated using maximum likelihood estimation techniques.

Ethical Considerations

The study adheres to established ethical standards for academic research. All subjects are informed about the study, and their willingness to participate is voluntary. Respondent anonymity and data confidentiality are maintained throughout the research process. The data is provided to be used solely for academic purposes, and no personal identifiers are provided.

Results

Descriptive Statistics and Correlation Analysis

The descriptive statistics as well as Pearson correlation coefficients were calculated to check the distribution and initial relationship between the variables of study. The average scores demonstrate that the respondents have rated quite highly the scales of GL, EI, and AP, which is a positive perception of the digital learning environment.

Correlation analysis demonstrates that all constructs are positively and significantly related ($p < 0.01$). Gamified learning is correlated with adaptive performance, whereas emotional intelligence has an even higher correlation with adaptive performance. Also, emotional intelligence is strongly associated with gamified learning ($r = 0.56$), which is an initial positive indication of the proposed relationships.

Table 1: Descriptive Statistics and Correlation Matrix of Study Variables

Variable	Mean	SD	1	2	3
Gamified Learning (GL)	3.87	0.68	1.000		
Emotional Intelligence (EI)	3.92	0.64	0.56**	1.000	
Adaptive Performance (AP)	4.01	0.59	0.61**	0.65**	1.000

Note: $p < 0.01$

The descriptive statistics and correlation analysis of the variables: Gamified Learning (GL), Emotional Intelligence (EI), and Adaptive Performance (AP) are in table 1. The average scores indicate that all the variables are quite high, and this means that respondents are strong. The values of standard deviation are moderate. The outcomes of correlation analysis confirm that GL is positively and statistically related to EI and AP, and EI is positively related to AP ($r = 0.65$), which suggests that there are strong interrelations between the constructs.

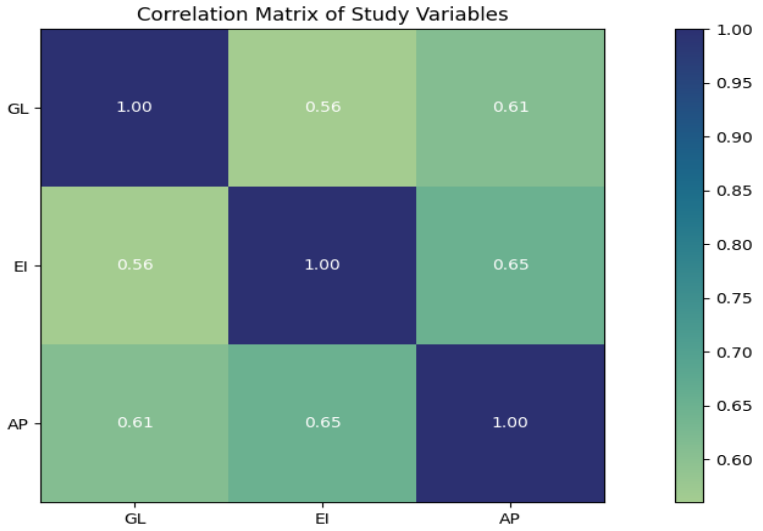

Fig. 2: Correlation Matrix Heatmap of Study Variables

Fig. 2 is a heatmap, which shows the correlation between GL, EI, and AP. The correlations are also strong, as illustrated by the strength of the colors, with dark colors showing the stronger correlations. The variables have moderate to high positive correlations, with the greatest correlation between EI and AP ($r = 0.65$), GL and AP ($r = 0.61$), and GL and EI ($r = 0.56$). This visual representation confirms that improvements in one variable are associated with increases in the others.

Reliability and Validity Analysis

The measurement model was assessed using confirmatory factor analysis to establish reliability and validity. The constructs were all showing a high internal consistency, and the Cronbach alpha value was higher than the recommended level of 0.70. The values of CR were between 0.90 and 0.92, which proved high reliability. Convergent validity was determined because all the values of AVE were more than 0.50.

Table 2: Reliability and Convergent Validity of Constructs

Construct	Cronbach's Alpha (α)	CR	AVE
Gamified Learning	0.88	0.91	0.63
Emotional Intelligence	0.90	0.92	0.66
Adaptive Performance	0.87	0.90	0.61

The reliability and validity level of three study constructs, gamified learning, emotional intelligence, and adaptive performance, are displayed in table 2. The values of Cronbach's Alpha (Alpha) in all constructions exceed the recommended value of 0.70, which is the measure of strong internal consistency. Also, there is high construct

dependability with a minimum value of above 0.70 on Composite dependability (CR). The convergent validity is sufficiently high when the average variance extracted (AVE) values are above 0.50. In general, the findings demonstrate that the measuring model is valid and can be used in further studies.

The statistical test formulations of reliability and validity are the following:

Cronbach's Alpha:

$$\alpha = \frac{k}{k-1}\left(1-\frac{\sum\sigma_i^2}{\sigma_t^2}\right) \quad (2)$$

Composite Reliability:

$$CR = \frac{(\sum\lambda_i)^2}{(\sum\lambda_i)^2 + \sum(1-\lambda_i^2)} \quad (3)$$

Average Variance Extracted:

$$AVE = \frac{\sum\lambda_i^2}{n} \quad (4)$$

In equations (2), (3), and (4), λ_i represents standardized factor loadings,k is the number of items, σ_i^2 is the variance of the item, σ_t^2 is the total variance, and n is the number of indicators.

Discriminant validity was further confirmed using the Fornell–Larcker criterion, ensuring that each construct is empirically distinct.

Measurement Model Fit

The confirmatory factor analysis shows that the measurement model can fit the data.

Table 3: Model Fit Indices of the Measurement Model

Fit Index	Value	Threshold
CFI	0.94	> 0.90
TLI	0.93	> 0.90
RMSEA	0.045	< 0.08
SRMR	0.041	< 0.08

Table 3 gives the model fit indices that are adopted to determine how well the structural equation model fits. The values show a good fit of the model since all the indices are within the recommended limits. Particularly, CFI (0.94) and TLI (0.93) are above the acceptable figure of 0.90, which indicates a high comparative fit. Also, the value of RMSEA (0. 045) and SRMR (0. 041) are under the value of 0.08, which means that there is a low approximation error and a good fit to residual value. In general, the findings prove that the suggested model is adequate to explain the data.

These values confirm the adequacy of the measurement model.

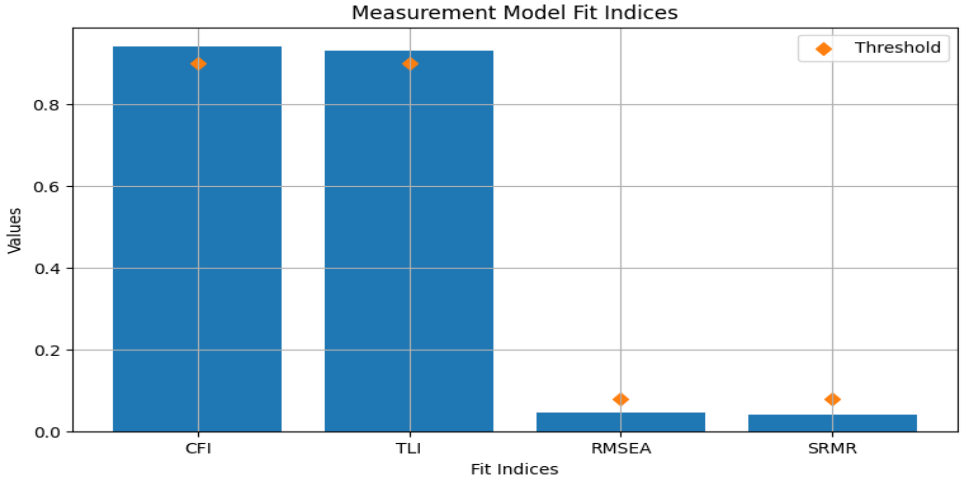

Fig. 3: Measurement Model Fit Indices Visualization

Fig. 3 shows the measurement model fit indices (CFI, TLI, RMSEA, SRMR) and their respective thresholds. The bar chart indicates that the model fits very well, as CFI (0.94) and TLI (0.93) are greater than 0.90, which is the recommended minimum for the model. In the meantime, the values of RMSEA (0.045) and SRMR (0.041) are much lower than the maximum acceptable value (0.08), which indicates low levels of error. On the whole, the visual comparison of the results indicates that all the fit indices are within the necessary levels and, therefore, the model is acceptable.

Structural Model and Hypothesis Testing

The hypothesis on the relationships within the structural model was tested using path analysis. The results support H1 by indicating that gamified learning has a considerable favorable impact on adaptive performance ($\beta = 0.34$, $p < 0.001$). Adaptive performance is significantly improved by emotional intelligence ($\beta = 0.41$, $p < 0.001$), supporting H2. Additionally, the H3 is supported by the fact that gamified learning significantly predicts emotional intelligence ($\beta = 0.56$, $p < 0.001$).

Table 4: Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	t-value	p-value
H1	GL → AP	0.34	5.21	<0.001
H2	EI → AP	0.41	6.18	<0.001
H3	GL → EI	0.56	8.02	<0.001

Table 4 indicates the testing of the hypothesis of the structural model. The results of the study suggest that all the suggested correlations are favorable and statistically significant. Precisely, Adaptive Performance (AP) can be greatly influenced by Gamified Learning (GL) ($\beta = 0.34$, $p < 0.001$), and Adaptive Performance (AP) can also be greatly influenced by Emotional Intelligence (EI) ($\beta = 0.41$, $p < 0.001$). Also, GL has a significant positive effect on EI ($\beta = 0.56$, $p < 0.001$). All three hypotheses (H1, H2, and H3) are validated, as the t-values and significant p-values prove.

Mediation Analysis

The mediating role of emotional intelligence was tested using bootstrapping with 5,000 resamples. The indirect effect of gamified learning on adaptive performance via emotional intelligence was significant ($\beta = 0.23$, $p < 0.001$). Emotional intelligence is found to be a partial mediator because direct and indirect effects are still relevant, which is the reason why H4 is accepted.

Table 5: Mediation Analysis Results (Indirect Effects)

Path	Indirect Effect	t-value	p-value
GL → EI → AP	0.23	4.87	<0.001

Table 5 displays the examination of the structural model's mediation (indirect effect). The results show that Gamified Learning (GL) has a substantial indirect effect on Adaptive Performance (AP) through Emotional Intelligence (EI) ($\beta = 0.23$, $p < 0.001$). A significant degree of statistical significance is indicated by the extremely high t-value (4.87). Because gamified learning enhances emotional intelligence, it has a favorable direct and indirect impact on adaptive performance, which is indicative of the function of EI in mediating the link between GL and AP.

Moderation Analysis

Moderation analysis was developed, in which an interaction term (GL EI) was added. The effect of interaction was seen to have been significant, and this demonstrates that emotional intelligence reinforces the relationship between adaptive performance and gamified learning.

Table 6: Moderation Analysis Results (Interaction Effects)

Path	β	t-value	p-value
GL × EI → AP	0.19	3.45	<0.01

Table 6 gives the outcome of the moderation analysis of the interaction effect between Gamified Learning (GL) and Emotional Intelligence (EI) on Adaptive Performance (AP). The interaction term (GL × EI) exhibits a positive statistically significant $\beta = 0.19$, $p < 0.01$, with a t-value of 3.45.

The result of the moderation analysis of this interaction effect between Gamified Learning (GL) and Emotional Intelligence (EI) on Adaptive Performance (AP) is provided in table 6. The interaction term (GL x EI) has a statistically significant positive $\beta = 0.19$, $p < 0.01$, with a t-value of 3.45. It means that EI has a strong moderating effect on the

correlation between GL and AP, where the influence of the gamified learning on the adaptive performance is more pronounced with the increase of emotional intelligence.

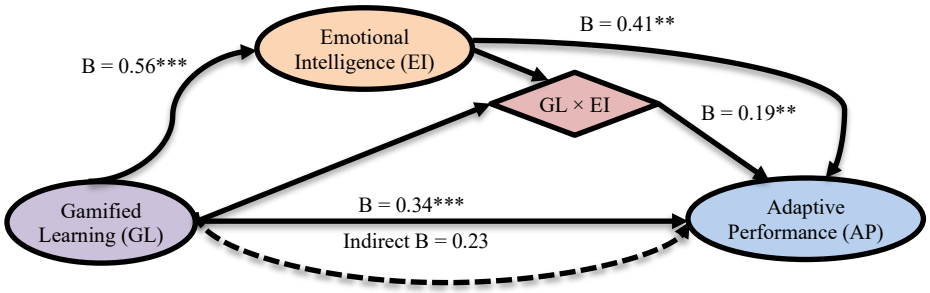

Fig. 4: Structural Model with Mediation and Moderation Effects

The exemplification of fig. 4 demonstrates the structural model that has mediation and moderation effects between Gamified Learning (GL), Emotional Intelligence (EI), and Adaptive Performance (AP). The findings indicate that GL is positively associated with EI (β= 0.56) and directly related to AP (β= 0.34). EI as well affects AP considerably (β=0.41), which demonstrates its mediating effect, but has an indirect impact equal to 0.23. There is also an interaction effect (GL × EI → AP, β = 0.19), which indicates that EI strengthens the correlation between GL and AP. Overall, the model demonstrates both partial mediation and significant moderation effects.

Model Explanatory Power

The Coefficient of determination (R^2) indicates that the model explains a substantial proportion of variance in endogenous variables explained by their respective sets of predictors. The Coefficient of determination (R^2) used in your analysis is calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \dot{y})^2} \qquad (5)$$

In equation (5), y_i is the observed value, $\hat{y}_i$ is the predicted value using the model, and $\dot{y}$ is the average of the observed values. This equation shows the degree of the adaptive performance variance attributed to the independent variables (Gamified Learning and Emotional Intelligence).

Table 7: R^2Values

Dependent Variable	R^2	Predictor Variables
Emotional Intelligence	0.31	Gamified Learning (GL)
Adaptive Performance	0.58	GL, EI, and Interaction Term (GL × EI)

Table 7 gives the R^2 values, which show the percentage of variance that is accounted for by each endogenous variable by its respective predictor variables. These findings indicate that Gamified Learning (GL) can be used alone to explain 31% of the difference in Emotional Intelligence (R^2 = 0.31), which implies that this relationship may be considered as medium strength. In addition, the model describes a significant 58% variance of Adaptive Performance (R^2 = 0.58). The greater predictive accuracy is explained by the joint effect of Gamified Learning (GL), Emotional Intelligence (EI), and the Interaction Term (GL × EI). Once again, these findings indicate that the variables that were included in the structural model have high explanatory power, especially in explaining the dynamics of adaptive performance in a digital workplace context.

Control Variables Analysis

The control variables in the structural model were the age, gender, work experience, and the type of industry, to control any confounding effects. The findings show that no control factors had any statistically significant effect on performance on adaptation ($p > 0.05$). In addition, the addition of these variables did not change the degree or the importance of the primary relationships between gamified learning, emotional intelligence, and adaptive performance. This shows the reliability of the model proposed and that the constructs that make the impacts are inherently based on the basic constructs and not the organizational or demographic differences.

Table 8 indicates the impact of control variables on adaptive performance. Given that the value of all the beta coefficients and t-values exceeds the value of the significance level of 0.05, the results indicate that there exists no statistically significant relationship between adaptive performance and age, gender, job experience, and industry type.

These results validate the viability and consistency of the suggested structural model, as it shows that the organizational and demographic variables do not play a significant role in the dependent variable.

Table 8: Effects of Control Variables on Adaptive Performance

Control Variable	Path	β Coefficient	t-value	p-value
Age	Age → AP	0.05	1.12	> 0.05
Gender	Gender → AP	-0.03	0.89	> 0.05
Work Experience	Experience → AP	0.07	1.34	> 0.05
Industry Type	Industry → AP	0.04	1.01	> 0.05

Discussion

The relationships between Gamified Learning (GL), Emotional Intelligence (EI), and Adaptive Performance (AP) were examined in the study, along with the existence of control factors such as age, gender, work experience, and industry type. The findings showed that while control factors were statistically held to guarantee that the confounding variables were ignored, all of the important variables had moderately high means (GL = 3.87, EI = 3.92, AP = 4.01) and substantially varied. All of the key constructs have substantial positive associations, according to correlation analysis ($r = 0.56$ to 0.65, $p < 0.01$). The measurement model had a high degree of reliability ($\alpha = 0.87$–0.90, CR = 0.90–0.92) and validity (AVE = 0.61-0.66) and good model fit (CFI = 0.94, RMSEA = 0.045). The structural findings supported the view that GL has a significant impact on AP ($\beta = 0.34$) and EI ($\beta = 0.56$), and EI on AP ($\beta = 0.41$). The control variables (age: $\beta = 0.05$, gender: $\beta = -0.03$, work experience: $\beta = 0.07$, industry type: $\beta = 0.04$) were found to be statistically insignificant ($p > 0.05$), indicating that they do not meaningfully influence adaptive performance. Mediation analysis indicated a significant indirect effect ($\beta = 0.23$), and moderation analysis showed a significant interaction effect ($\beta = 0.19$). The model explained 58% of the variance in AP. These results show that gamified learning is a predictive tool of emotional intelligence and adaptive performance that is not affected by demographic and organizational characteristics. The mediation value of large indicates that EI is a psychological process through which gamified learning would enhance performance. The moderation effect also implies that the gamified learning environment can positively impact individuals with a higher degree of emotional intelligence more significantly, which proves the synergistic impact of cognitive and emotional variables on the outcomes of the learning process, regardless of age, gender, and professional experience. The results indicate that the application of gamification strategies in the digital learning system is vital in enhancing flexibility and performance. Educational institutions and organizations can use gamified platforms to help students develop both technical and emotional skills. This two-pronged approach can help students better adapt to the dynamic environment, which is crucial in the realities of modern digital and organizational environments in the context of various workforce segments. Since the research is done utilizing cross-sectional data, it is impossible to make any judgments regarding causality. Self-reported measures can be used, and this can create bias in the response. Also, the model uses two major predictors, which may not be the only important ones, like motivation, engagement, or technological readiness, though control variables were used. The future studies should be conducted in longitudinal or experimental studies to demonstrate causation. Inclusion of more mediators or moderators would be enlightening. It is also advisable that comparative studies in various learning or organizational contexts should be conducted to increase the level of generalizability.

Conclusion

The research problem in this study concerned the increasing interest in learning about the effect of gamified learning environments on adaptive performance, especially through emotional intelligence in a digital and dynamic setting, with the control variables of age, gender, work experience, and industry type. With the growing use of technology-based learning systems in organizations and learning institutions, it is necessary to determine the processes through which adaptability is promoted. The results have shown that gamified learning is very effective in enhancing emotional intelligence and adaptive performance. The respondents found it agreeable due to the fact that the mean scores (GL = 3.87, EI = 3.92, AP = 4.01) were relatively high. The correlation analysis showed that all the variables were significantly positively related to each other ($r = 0.56$-0.65, $p < 0.01$). The structural model results revealed that emotional intelligence was found to have a major influence on the adaptive performance ($\beta = 0.41$), along with gamified learning, which has a positive influence on adaptive performance ($\beta = 0.34$) as well as emotional intelligence ($\beta = 0.56$). It was identified that age ($\beta = 0.05$), gender ($\beta = -0.03$), work experience ($\beta = 0.07$), and industry type ($\beta = 0.04$) were control variables that were statistically non-significant ($p > 0.05$), meaning that adaptive performance was not significantly influenced by organizational and demographic factors. The mediation study that found a significant indirect effect ($\beta = 0.23$) somewhat mediates this relationship with emotional intelligence. Also, the

moderating effect (β = 0.19) implies that the more emotionally intelligent, the greater the impact of gamified learning on performance is. The model contains 58% of the variance of adaptive performance, which is a powerful explanation. In general, the paper highlights the fact that gamified learning is a technological solution as well as a strategic possibility of developing emotional and adaptive skills. The most important lesson is that emotional intelligence development can be effectively incorporated into the gamified systems and can result in a substantial enhancement of performance outcomes. These findings should be further confirmed and expanded by investigating longitudinal designs, other psychological variables, and other contexts in future studies.

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