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Impact of AI-enabled personalized E-learning on employee skill development and career advancement

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Abstract
Purpose: Artificial intelligence (AI) is rapidly transforming organizational learning and skill development. However, empirical evidence examining how AI-enabled personalized e-learning impact employee skill development and career advancement remains limited. This study examines the impact of AI-enabled personalized e-learning on employee skill development and career advancement outcomes. It also investigates the mediating role of learning engagement and the moderating roles of digital literacy and organizational learning culture.
Methodology: A quantitative research approach was adopted for this. Primary Data were collected from 100 employees who had prior exposure to AI-enabled learning platforms across different organizational functions. In the study, partial least squares structural equation modeling (PLS-SEM) was applied to validate the hypothesized model developed for this study.
Findings: The findings reveal that AI-enabled personalized e-learning significantly enhances employee skill development, which in turn positively influences career advancement outcomes. Learning engagement was found to partially mediate the relationship between AI-enabled learning and skill development, highlighting the importance of active cognitive, emotional, and behavioral participation in digital learning environments. Furthermore, digital literacy strengthens the relationship between AI-enabled learning and skill development, while organizational learning culture amplifies the effect of skill development on career advancement outcomes.
Implications: These findings provide empirical evidence that AI-enabled learning systems can support workforce capability development when supported by employee digital competencies and a strong learning culture.

Keywords: Artificial intelligence, personalized e-learning, skill development, career outcomes, learning engagement, digital literacy

Introduction

Artificial intelligence (AI) is rapidly transforming the human resource management and development practices globally, especially in organizational learning and talent development (Nawaz *et al.*, 2024) [32]. Worldwide, organizations are investing in AI technologies and it is projected to rise 3000 USD billion in 2027 (LoDolce & Moran, 2026) [28]. India has allocated over ₹10,300 crore under the India AI Mission and it is expected that AI will contribute $1.7 trillion more to the economy by 2035 (PIB, 2025) [29]. The reason companies need AI to help with employee learning is that the skills people need to do their jobs are changing very quickly. The World Economic Forum estimates that by 2025[34], 4 0% of core skills required for employees expected to change. In addition, 50% of the total workforce will require reskilling (Withing, 2021) [56]. These figures show a drastic transformation in how organizations build and sustain human capital.

AI-enabled personalized e-learning techniques help to provide adaptive, data-driven and personalized learning experiences which is tailored to individual employee needs and paces. At the same time, it significantly boosts employee engagement and learning effectiveness. These AI-enabled e-learning platforms also adjust content difficulty based on user requirement, recommend targeted learning resources, and generate predictive insights based on employee performance and competency gaps (Rahayu & Bablu, 2023) [41]. These systems learn from the learners. Therefore, it not only works efficiently, but become precise over the course. Employee skill development is considered to be a key mechanism for sustaining competitive advantage. Employee promotions, role expansion, employability and career satisfaction, are often viewed as tangible returns. Still, while AI-enabled learning technologies are expanding rapidly, their strategic contribution to employee skill development and career advancement remains underexplored in empirical human resource management research (Basnet, 2024) [8].

Although organizations are rapidly adopting AI-enabled learning systems, empirical evidence explaining their impact on employee skill development and career advancement remains limited (Babashahi *et al.*, 2024) [6]. According to Mayer *et al.* (2025) [29] nearly 46 % of leaders report that employee skill gaps constitute a major barrier in AI adoption within their organizations. HR platforms have enabled AI recruitment systems (75%) and payroll automation (85%) in organization operations (Mahmood *et al.*, 2025) [29] also in learning. Recent reviews and studies highlight that AI-driven personalization research predominantly focuses on technology acceptance, usability, and algorithmic efficiency, with limited emphasis on skill acquisition and career returns (Fortuna *et al.*, 2025[29];). Moreover, training technologies alone do not ensure effective learning transfer, as employee engagement that plays a critical role in determining whether training content is meaningfully absorbed and applied. Further, digital literacy influences employee' ability to utilize AI-based platforms, while organizational learning culture determines whether newly acquired skills are supported and translated into career mobility (Basher *et al*., 2025) [29]. However, integrated empirical models incorporating engagement as a mediator and digital literacy and organizational learning culture as moderators within AI-enabled personalized e-learning contexts remain scarce. This study addresses these gaps by proposing and empirically testing an integrated model linking AI-enabled personalized e-learning to employee skill development and career advancement outcomes, incorporating learning engagement as a mediator and digital literacy and organizational learning culture as moderators.

The primary objective of this study is to examine the impact of AI-enabled personalized e-learning on employee skill development. Furthermore, the study aims to analyze how skill development influence career advancement outcomes of employee. Additionally, it investigates the mediating role of learning engagement in the relationship between AI-enabled personalized e-learning and employee skill development. The study further examines the moderating role of digital literacy in the relationship between AI-enabled personalized e-learning and employee skill development. Finally, it explores the moderating role of organizational learning culture on the effect of employee skill development on career advancement outcomes.

Review of Literature

1. Theoretical framework

As the study fundamentally investigates the role of investment in human resource through AI-enabled learning, it is primarily based on Human Capital Theory (Becker, 1964), Self-Determination Theory and Resource-Based View. Human Capital Theory posits that investment in training or teaching human capital increases employees' knowledge and skills which leads to better career outcomes (Awu *et al*., 2025) [29]. AI-enabled personalized training is an investment for employees and by applying the skills employees learnt in the training organizations prosper which is the return on investment. This study is aligned with self-determination theory by examining learning engagement of employees. Self-determination theory suggests that autonomy-supportive environments enhance motivation, engagement and competence development (Ye, 2025) [29]. The resource-based view is a theory on strategic management which adopts an inside-out approach emphasizing on the fact that distinctive organizational capabilities enhance performance. Together, these theories based on human resource and organizational culture provide an extensive foundation for examining the relationships proposed in this study.

2. Hypothesis development

2.1 AI-enabled personalized e-learning and employee skill development

AI-based personalized e-learning is a technology-driven approach that used AI to deliver adaptive and individualized education and professional training content (Ahmed & Meraj, 2024) [3]. It enables learners, to develop skills according to their unique needs, abilities, and pace, often with minimal or no direct human intervention (Nagarajan, 2024) [31]. A empirical studies reveal that learning programs exert a significant influence on continuous skill development, highlighting the effectiveness of personalized learning initiatives in strengthening employees' skill acquisition and continuous competency growth (Atmaja *et al*., 2024) [4]. Further, adaptive learning environments significantly improve knowledge acquisition and competency development in employees by replacing "one-size-fits-all" training with personalized, data-driven pathways. Personalized learning focus to fill specific skill deficiencies rather than repeating previously learnt content (Zhong & Zhong, 2022) [61]. Moreover, data-driven learning systems help employees to close competency gaps in a systematic manner. It helps to strengthens skills over time (Lai *et al*., 2025) [29]. Thus, it is more likely that AI-enabled personalized e-learning positively influences employee skill development.

H1: AI-enabled personalized e-learning has a positive and significant effect on employee skill development.

2.2 Employee skill development and career advancement outcomes

Employee skill development encompasses the enhancement of technical skills, soft skills, skill application, and learning agility resulting from structured training interventions (Erfan & Bakri, 2025) [12]. Technical skills are job-specific abilities, knowledge, and analytical capabilities required to perform specialized tasks, such as programming, data analysis, or operating machinery, while soft skills include communication, leadership, and collaboration competencies (Prathyusha, 2025) [29]. Skill application reflects the transition point where an individual's acquired skills are converted into workplace performance, and learning agility denotes the ability to adapt and acquire new competencies in evolving workplace. Human capital theory posits that skill acquisition enhances employee productivity and labor market value, which in turn increases career mobility and advancement opportunities, Empirical research consistently demonstrates that employees who develop higher competencies experience promotion and salary growth (Rashmi & Samartha, 2024) [42]. Additionally, skill development enhances subjective career outcomes such as improved mental health, sense of coherence, confidence and career satisfaction. Employees who continuously upgrade their competencies are better positioned to adapt to organizational changes.

H2: Employee skill development has a positive and significant effect on career advancement outcomes.

Mediating role of learning engagement

Learning engagement refers to the extent to which an individuals' are behaviorally involved, emotionally invested, and cognitively absorbed in learning activities (Zhang *et al*., 2025) [29]. Employee engagement consists of cognitive, emotional, and behavioral components, where cognitive engagement refers to employees' mental focus and absorption in their work, emotional engagement reflects their positive feelings toward their job and organization, and behavioral engagement indicates their willingness to go beyond formal job requirements (Kossyva *et al*., 2023) [24]. Engaged learners are more likely to experience improved learning outcomes, including stronger skill acquisition, greater employee satisfaction, and higher productivity (Roopalatha, 2025) [29]. Employee training effectiveness study emphasizes that engagement is a key mechanism linking e-leaning to skill acquisition. When employees are behaviorally active, emotionally motivated, and cognitively immersed, they are more likely to internalize knowledge and apply skills effectively. AI-enabled tools lead to improvements in individuals achievement through personalized learning paths and increased engagement (Sahito *et al*., 2024) [48]. Consequently, learning engagement may function as a mediating mechanism between AI-enabled personalized e-learning and employee skill development.

H3: Learning engagement mediates the relationship between AI-enabled personalized e-learning and employee skill development.

Moderating role of digital literacy

Digital literacy represents an individual's ability to effectively use digital tools, navigate online platforms using digital technologies in a secured way to support academic, personal, and professional development (Agaoglu *et al*., 2025) [2]. In human resource development context, digital literacy influences the extent to which employees can effectively utilize AI-based personalization features for skill development. Employees with higher digital literacy are better equipped to navigate AI-enabled platforms by interpreting algorithmic feedback, adaptive learning pathways and translating AI-generated outputs into actionable decisions that enhance task effectiveness and continuous skill development (Niam *et al*., 2025) [29]. Low digital literacy may hinder effective interaction with AI systems, thereby weakening developmental outcomes. Research on AI usage suggests that digital literacy's ability to critically access, evaluate, and apply digital technologies, mediates the relationship between AI usage and employee development (Bohra, 2025) [29]. Therefore, digital literacy is expected to strengthen the relationship between AI-enabled personalized e-learning and employee skill development.

H4: Digital literacy moderates the relationship between AI-enabled personalized e-learning and employee skill development.

Moderating role of organizational learning culture

Organizational learning culture refers to organizational environment that provides employees with the time and space to continuously develop knowledge and skills, encourages them to create, acquire, and transmit information (Tripathi, 2024) [32]. It prioritizes ongoing learning, growth, and knowledge sharing to enhance competencies and sustain competitive advantage. A strong learning culture reinforces employee engagement and supports career advancement through recognition and organization support (Sankar Singh, 2025) [49]. Organizational learning culture influences creativity, encourages innovation and supports the development of new knowledge (Otoo, 2024) [36]. It influences whether acquired skills are applied and rewarded within the workplace. When organizations is able to understand learning achievements and further encourage for skill application, skill development translates into career advancement smoothly (Hosen *et al*., 2024) [20]. On the other hand, weak learning cultures limit organization competencies.

H5: Organizational learning culture moderates the relationship between employee skill development and career advancement outcomes.

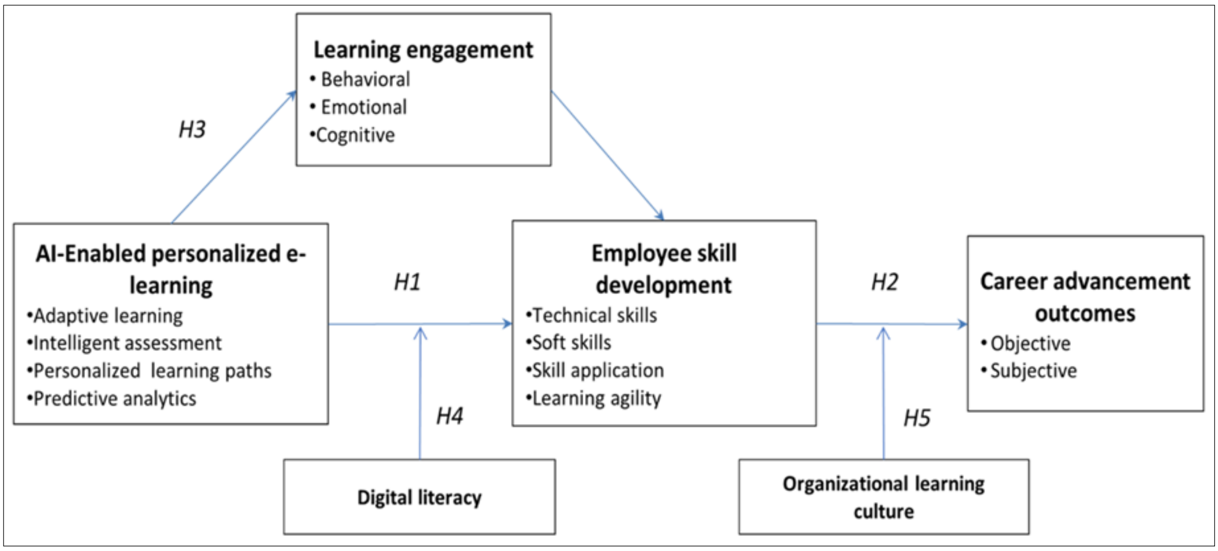

Fig 1: Conceptual model

Methodology

1. Procedure and participants

The study focuses on working professionals who use AI-enabled personalized e-learning platforms within their organizations. The respondents were employed across various sectors, including information technology, operations, marketing, finance and human resources. The target population were the employees who have prior exposure to AI-driven learning systems, such as adaptive content platforms, intelligent assessment tools and personalized learning pathways. The structured questionnaires were distributed through online and offline modes. In total 100 employees were selected by using purposive sampling. Purposive sampling is a non-probability sampling technique and it is suitable for studies requiring respondents with specific technological exposure (Kim, 2022) [23]. The survey instrument was developed using Google forms. Participants were invited to voluntarily provide responses. In the study, a cross-sectional research design was adopted, as data were collected at a single point in time.

2. Assessment tools

Primary data were collected using a structured, self-administered questionnaire rated on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

The questionnaire comprised two sections. In the first section, question items related to demographic information including age, gender, educational qualification, functional area / department, total work experience, and experience of using AI-Enabled Learning Platform were provided. In the next sections, multi-item scales measuring the study constructs were given. AI-enabled personalized e-learning was measured by sub-variables, namely adaptive learning (6 items), intelligent assessment (6 items), personalized learning paths (6 items) and predictive analytics (6 items). All the question items were adapted from prior research on AI-driven learning systems and technology-enhanced training (Atmaja *et al*., 2024; Sadeeq Akintola *et al*., 2025) [4, 47]. Learning engagement was measured across behavioral (6 items), emotional (6 items) and cognitive (6 items) dimensions (Huang *et al*., 2022; Roopalatha, 2025; Shang *et al*., 2025) [22, 29]. Employee skill development was measured through technical skills development (6 items), soft skill development (6 items), learning agility (6 items), and skill application (6 items), adapted from human capital development literature (Hosen *et al*., 2024; Wolor *et al*., 2025) [20, 29]. Career advancement outcomes incorporated both objective and subjective perspectives of career growth (Aburumman, 2020; Piteira & Cervai, 2023) [1, 38] with 6 items for each sub variables. Digital literacy was measured based on individuals' ability to effectively use digital technologies through 6 items (Agaoglu *et al*., 2025) [2]. Organizational learning culture was assessed using 6 items reflecting knowledge sharing, continuous learning orientation and managerial support (Nayak *et al*., 2025[29];).

3. Statistical analysis

Data were analyzed using SPSS v24 and AMOS 23.0. Given the complex nature of the model, inclusion of mediation and moderation effects along with hierarchical constructs, Partial Least Squares Structural Equation Modelling (PLS-SEM) was considered to be appropriate for this study (Hair *et al*., 2021; Sarstedt *et al*., 2022) [17, 50]. PLS-SEM is particularly suitable for complex predictive models. Also, it does not require strict normality assumptions. The analysis followed a two-step procedure. First, the measurement model was assessed for reliability and validity. Internal consistency reliability was evaluated using composite reliability (CR) where values need to exceed the recommended threshold of 0.70 to be suitable (Hair *et al*., 2021) [17]. Convergent validity was assessed using average variance extracted (AVE) with values above 0.50 indicating adequate validity (Fornell & Larcker, 1981) [13]. Discriminant validity was established using the Heterotrait-Monotrait (HTMT) ratio (Chin & Dibbern, 2010) [10] and Fornell-Larcker Criterion. Next, the structural model was evaluated by examining path coefficients, indirect effects, and moderation effects using bootstrapping 5000 resamples to determine statistical significance. Model fit was evaluated using the standardized root mean square residual (SRMR) (Hu & Bentler, 1999) [21]. The significance of mediation effects was determined through bootstrapped confidence intervals, while moderation effects were assessed using interaction terms.

Results

1. Respondent profile

The demographic characteristics of the studied employees are presented in Table 1. The majority of the participants were aged between 25–34 years (38%) followed by 35–44 years (26%), which indicate the study population represent early- to mid-career professionals. The gender distribution was almost balanced (56% male; 44% female). Most respondents have Bachelor's degree (46%), followed by Master's degree (30%). In terms of functional area, a significant part of the respondents belonged to the Technical/IT department (28%), Operations (20%) and Marketing/Sales (18%) department. Regarding work experience, 30% had 2–5 years of experience, and 26% had 6–10 years of experience. Additionally, a significant number of respondents (32%) reported 1–2 years of experience using AI-enabled learning platforms.

Table 1: Employees' demographic profile

Demographic Parameters	Frequency	Percent
Age		
Below 25 years	12	12.0
25–34 years	38	38.0
35–44 years	26	26.0
45–54 years	16	16.0
55 years and above	8	8.0
Gender		
Male	56	56.0
Female	44	44.0
Educational Qualification		
Diploma / Certificate	14	14.0
Bachelor's Degree	46	46.0
Master's Degree	30	30.0
Doctorate	4	4.0
Others	6	6.0
Functional Area / Department		
Technical / IT	28	28.0
Operations	20	20.0
HR	12	12.0
Finance / Accounts	14	14.0
Marketing / Sales	18	18.0
Administration	8	8.0
Total Work Experience		
Less than 2 years	15	15.0
2–5 years	30	30.0
6–10 years	26	26.0
11–15 years	17	17.0
More than 15 years	12	12.0
Experience Using AI-Enabled Learning Platform		
Less than 6 months	28	28.0
6 months – 1 year	20	20.0
1–2 years	32	32.0
More than 2 years	20	20.0

Measurement model assessment

The reliability and validity of the measurement model were assessed by measuring internal consistency, construct reliability, convergent and discriminant validity. Construct reliability was checked by measuring the outer loadings of the measurement model items. Cronbach's alpha and composite reliability (rho_a) were used to check internal consistency of the model. As shown in Table A1, all constructs showed strong internal consistency where Cronbach's alpha values ranging from 0.808 to 0.945 and composite reliability values between 0.813 and 0.965. All values crossed the recommended minimum threshold of 0.70, indicating satisfactory internal consistency reliability. The average variance extracted (AVE) values for all factors exceed the recommended threshold of 0.50. Therefore, it confirmed adequate convergent validity (Table A1). Discriminant validity was evaluated using the HTMT criterion (Table A2). All HTMT values were within acceptable limits which suggests that the constructs are empirically distinct from one another. The Fornell–Larcker criterion was also used to assess discriminant validity. As shown in Table 4, the square root of AVE for each construct (diagonal values) is greater than the inter-construct correlations, confirming adequate discriminant validity (Table A3).

Table A1: Construct reliability and validity

	Cronbach's alpha	**Composite reliability (rho_a)**	**Average variance extracted (AVE)**
AI-enabled personalized e-learning	0.945	0.946	0.505
Adaptive content	0.879	0.885	0.734
Behavioral engagement	0.859	0.868	0.781
Career advancement outcomes	0.936	0.937	0.588
Cognitive engagement	0.808	0.813	0.723
Digital literacy	0.904	0.965	0.838
Emotional engagement	0.925	0.926	0.769
Employee skill development	0.944	0.946	0.531
Intelligent assessment	0.895	0.898	0.76
Learning agility	0.897	0.9	0.764
Learning engagement	0.909	0.911	0.527
Objective outcomes	0.917	0.918	0.707
Organizational learning culture	0.922	0.943	0.76
Personalized paths	0.918	0.922	0.712
Predictive analytics	0.919	0.92	0.756
Skill application	0.896	0.905	0.706
Soft skills	0.896	0.897	0.707
Subjective outcomes	0.902	0.906	0.674
Technical skills	0.853	0.86	0.772

Table A2: Discriminant validity – HTMT

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
AI-Enabled personalized e-learning (1)																			
Adaptive Content (2)	0.89																		
Behavioral Engagement (3)	0.58	0.33																	
Career Advancement Outcomes (4)	0.31	0.19	0.24																
Cognitive Engagement (5)	0.68	0.52	0.80	0.18															
Digital Literacy (6)	0.09	0.04	0.21	0.19	0.10														
Emotional Engagement (7)	0.53	0.49	0.56	0.24	0.52	0.21													
Employee skill development (8)	0.52	0.40	0.48	0.59	0.40	0.25	0.51												
Intelligent Assessment (9)	0.87	0.61	0.44	0.38	0.55	0.08	0.40	0.47											
Learning agility (10)	0.46	0.38	0.42	0.46	0.33	0.26	0.43	0.92	0.39										
Learning engagement (11)	0.68	0.54	0.93	0.27	0.92	0.22	0.94	0.56	0.53	0.47									
Objective Outcomes (12)	0.25	0.12	0.23	1.00	0.17	0.20	0.21	0.56	0.32	0.48	0.25								
Organizational Learning Culture (13)	0.10	0.10	0.12	0.34	0.15	0.11	0.11	0.14	0.07	0.09	0.14	0.34							
Personalized Paths (14)	0.93	0.67	0.57	0.30	0.59	0.08	0.45	0.50	0.72	0.47	0.61	0.26	0.10						
Predictive Analytics (15)	0.87	0.66	0.55	0.19	0.62	0.09	0.43	0.38	0.56	0.29	0.60	0.14	0.08	0.58					
Skill application (16)	0.55	0.41	0.49	0.49	0.41	0.24	0.48	0.96	0.44	0.75	0.55	0.45	0.15	0.53	0.44				
Soft skills (17)	0.42	0.31	0.41	0.57	0.39	0.13	0.46	0.94	0.41	0.69	0.51	0.54	0.10	0.40	0.29	0.72			
Subjective Outcomes (18)	0.34	0.23	0.22	1.00	0.17	0.16	0.23	0.54	0.40	0.39	0.25	0.77	0.30	0.30	0.22	0.47	0.52		
Technical skills (19)	0.39	0.30	0.32	0.55	0.22	0.28	0.39	0.88	0.40	0.65	0.39	0.51	0.14	0.34	0.28	0.69	0.70	0.52	

Table A3: Discriminant validity – Fornell Larcker criterion

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
AI-enabled personalized e-learning (1)	0.71																		
Adaptive content (2)	0.81	0.86																	
Behavioral engagement (3)	0.53	0.30	0.88																
Career advancement outcomes (4)	0.29	0.15	0.22	0.77															
Cognitive engagement (5)	0.60	0.44	0.67	0.15	0.85														

Digital literacy (6)	0.00	-0.02	0.19	0.18	0.06	0.92													
Emotional engagement (7)	0.49	0.44	0.51	0.22	0.45	0.19	0.88												
Employee skill development (8)	0.50	0.37	0.44	0.55	0.35	0.24	0.47	0.73											
Intelligent assessment (9)	0.81	0.55	0.39	0.35	0.48	-0.03	0.37	0.43	0.87										
Learning agility (10)	0.42	0.34	0.38	0.42	0.29	0.23	0.39	0.85	0.35	0.87									
Learning engagement (11)	0.64	0.48	0.84	0.24	0.79	0.19	0.86	0.52	0.48	0.43	0.73								
Objective outcomes (12)	0.22	0.07	0.21	0.93	0.14	0.18	0.20	0.52	0.29	0.43	0.22	0.84							
Organizational learning culture (13)	-0.01	-0.07	0.05	0.33	-0.13	0.10	0.10	0.10	0.05	0.02	0.03	0.32	0.87						
Personalized paths (14)	0.88	0.61	0.51	0.27	0.51	-0.02	0.41	0.47	0.65	0.42	0.56	0.23	-0.05	0.84					
Predictive analytics (15)	0.80	0.59	0.49	0.17	0.53	0.07	0.40	0.36	0.51	0.27	0.55	0.12	0.05	0.54	0.87				
Skill application (16)	0.51	0.37	0.43	0.45	0.36	0.23	0.44	0.89	0.40	0.68	0.50	0.41	0.12	0.48	0.40	0.84			
Soft skills (17)	0.39	0.28	0.37	0.52	0.33	0.13	0.42	0.87	0.36	0.62	0.46	0.49	0.08	0.36	0.26	0.65	0.84		
Subjective outcomes (18)	0.31	0.21	0.19	0.92	0.14	0.15	0.22	0.50	0.35	0.34	0.23	0.71	0.28	0.27	0.20	0.43	0.47	0.82	
Technical skills (19)	0.35	0.26	0.28	0.49	0.18	0.25	0.34	0.79	0.35	0.57	0.34	0.45	0.13	0.30	0.25	0.61	0.62	0.46	0.88

Table A4: Collinearity statistics – VIF

AI-Enabled Personalized E-Learning							
Personalised Paths		**Predictive Analytics**		**Adaptive Content**		**Intelligent Assessment**	
Personalised Paths 1	3.82	Predictive Analytics 1	3.29	Adaptive Content 2	2.97	Intelligent Assessment 1	2.88
Personalised Paths 2	3.31	Predictive Analytics 2	3.12	Adaptive Content 3	1.87	Intelligent Assessment 2	2.7
Personalised Paths 3	2.55	Predictive Analytics 3	2.41	Adaptive Content 4	2.67	Intelligent Assessment 3	2.28
Personalised Paths 4	2.38	Predictive Analytics 4	2.77	Adaptive Content 5	2.24	Intelligent Assessment 4	2.89
Personalised Paths 5	1.92	Predictive Analytics 6	3.13				
Personalised Paths 6	3.04						
Employee Skill Development							
Soft skill development		Skill Application		Learning Agility		Technical skill development	
Soft 1	2.45	Application 1	2.03	Agility 1	2.26	Technical 1	2.01
Soft 2	2.35	Application 3	1.98	Agility 2	2.33	Technical 3	2.28
Soft 3	2.55	Application 4	2.72	Agility 4	2.66	Technical 5	2.06
Soft 4	2.18	Application 5	2.68	Agility 6	3.06		
Soft 6	2.74	Application 6	2.98				
Career Advancement Outcomes				Organizational Learning Culture		Digital Literacy	
Objective outcomes		Subjective outcomes					
Objective 1	3.24	Subjective 1	1.82	Learning 1	3.6	Digital 2	2.31
Objective 2	3.08	Subjective 2	2.71	Learning 2	3.16	Digital 3	3.9
Objective 3	3.13	Subjective 3	1.92	Learning 3	2.23	Digital 5	3.53
Objective 4	1.97	Subjective 4	3.17	Learning 4	2.33		
Objective 5	2.44	Subjective 5	2.15	Learning 5	3.39		
Objective 6	2.25	Subjective 6	2.63				
Learning Engagement							
Emotional Engagement		Cognitive Engagement		Behavioral Engagement			
Emotional 1	2.5	Cognitive 3	2.04	Behavioral 2	2.24		
Emotional 2	2.76	Cognitive 4	1.68	Behavioral 3	1.98		
Emotional 3	2.75	Cognitive 5	1.72	Behavioral 6	2.94		
Emotional 4	2.92						
Emotional 5	4.16						

Table A5: Model fit

	Saturated model	**Estimated model**
SRMR	0.061	0.061
d_ULS	66.674	66.673

Structural model and hypothesis testing

The structural model results are presented in Figure 2, Table 2 and Table3. The assessment of structural model included evaluating model fit indices, coefficient of determination (R^2), effect size (f^2), collinearity measurement and path coefficients. The model fit indices such as standardized root mean square residual (SRMR)=0.061 and squared Euclidean distance (d_ULS) = 66.673 were within the specified values showing that the model had a good fit. Finally, to understand collinearity among the variables, variance inflation factor (VIF) was used. A VIF value exceeding 5 indicates the presence of collinearity among the variables. From the result, it can be observed that all variables had VIF values lesser than 5 which indicate that the collinearity among the indicators were absent (Tables in appendix).

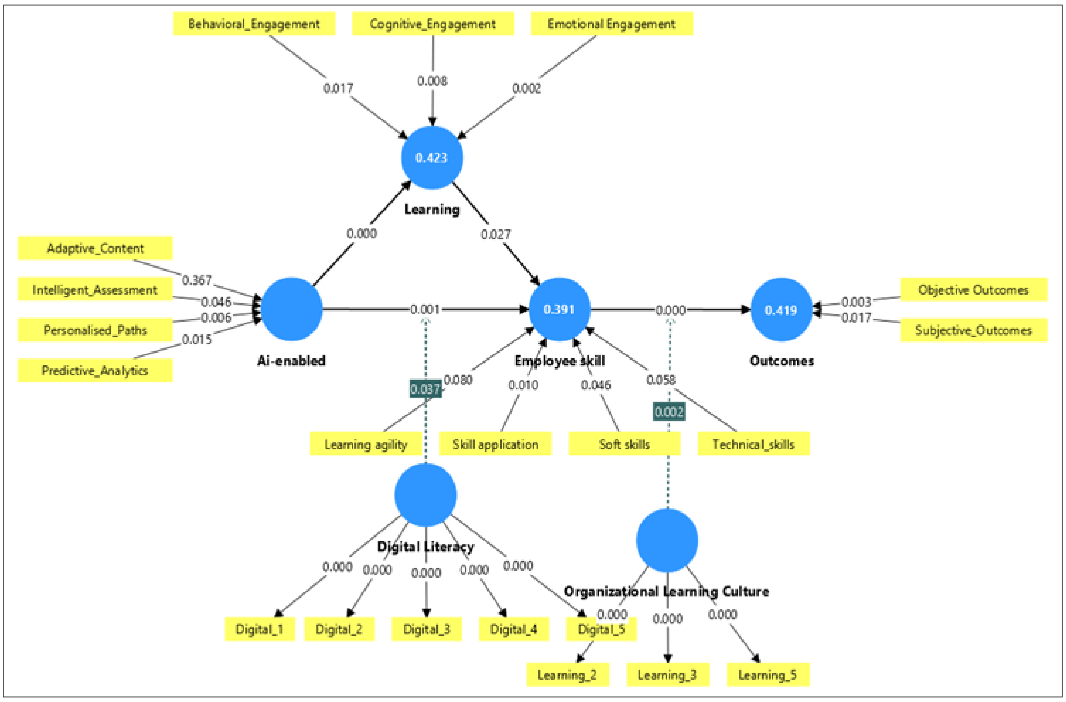

Fig 2: Structural model for mediation and moderation effects

Path coefficients demonstrated that AI-enabled personalized training had a positive and significant effect on employee skill development (β=0.387; t=3.022, p<0.05), supporting H1. Employee skill development significantly influenced career advancement outcomes (β=0.485; t=6.148, p<0.05), supporting H2. The moderating effect of digital literacy on the relationship between AI-enabled personalized e-learning and employee skill development was significant (β=0.189; t=1.781, p<0.05), supporting H4. Similarly, organizational learning culture significantly moderated the relationship between employee skill development and career advancement outcomes (β=0.240; t=2.920, p<0.05), supporting H5.

Furthermore, learning engagement significantly mediated the relationship between AI-enabled personalized e-learning and employee skill development (β = 0.180, t = 1.882, *p* = 0.030), thereby supporting H3. Since the direct effect remained significant, the mediation can be interpreted as partial.

Table 5: Structural model results

Path	Direct effect (β)	t-value	p-value
Direct effects			
AI-enabled -> Employee	0.387	3.022	0.001
Employee skill -> Outcomes	0.485	6.148	0.000
Moderation effect			
Digital Literacy × AI-enabled -> Employee skill	0.189	1.781	0.037
Organizational Learning Culture × Employee skill -> Outcomes	0.24	2.92	0.002
Indirect and mediation effect			
AI-enabled -> Learning -> Employee skill	0.18	1.882	0.03

Discussion

The findings indicate that AI-enabled personalized e-learning significantly enhance employee skill development. This result is consistent with recent research demonstrating that AI-driven training systems improve learning efficiency and skill acquisition by tailoring content for individual performance patterns (Rahayu & Bablu, 2023; Rawat *et al*., 2025) [29, 41]. Personalized learning through AI helps to generate real-time feedback and targeted skill reinforcement which enhances both technical and soft skill acquisition. In line with this, existing studies on technology centric training suggest that tutoring systems conducted by AI systems produce greater learning outcomes and higher organization growth (Zhang *et al*., 2023) [60]. The present findings corroborate this evidence by showing that AI-enabled personalization tools contribute meaningfully to develop workplace skills by workers. Furthermore, the study showed that employee skill development helps the employees to make career advancements, such as receiving promotions, internal job mobility, increasing job responsibilities, increasing work satisfaction and feeling confident after the training. The positive relationship between employee skill development and career advancement outcomes supports prior research connecting continuous learning to career success (Drewery *et al*., 2020) [11]. Skill acquisition, both technical and soft skills enhance employability, internal mobility, employee job satisfaction, and professional confidence.

In digital environments characterized by rapid technological change, upskilling and reskilling has been identified as a critical driver of sustainable career progression (Sundaram, 2025) [29]. The findings of this study further support the argument that competency development enabled via AI-enabled systems leads towards professional growth. The results confirm that learning engagement partially mediates the relationship between AI-enabled personalized e-learning and employee skill development. This finding is in line with prior research which suggest that engagement of learner plays a central role in technology-based learning effectiveness. Digital systems alone do not guarantee skill acquisition. Rather, active behavioral, emotional and cognitive association enhances internalization of knowledge. Recent empirical studies in digital learning areas have shown that engagement significantly increases knowledge retention and performance outcomes (Ghosh *et al*., 2022) [15].

Furthermore, digital literacy was found to strengthen the relationship between AI-enabled learning and employee skill development. This finding is consistent with earlier research which indicated that digital competencies determine individuals' ability to effectively utilize advanced learning technologies (Potemkin & Rasskazova, 2020) [39]. Employees with higher digital proficiency are better equipped to navigate adaptive systems, interpret analytics feedback and leverage personalized features. The present findings suggest that the benefits of AI-driven learning systems are dependent upon technological readiness of individual learners. Organizations investing in AI-enabled training must therefore ensure baseline digital competency among employees to maximize returns.

The study also found that organizational learning culture strengthens the relationship between employee skill development and career advancement outcomes. This finding is supported by prior research demonstrating that supportive learning environments increase the translation of skills into career growth (Rüütmann *et al*., 2021). Organizations, where knowledge sharing, managerial support and continuous improvement practices are nurtured, are more likely to convert employee skills into strategic advantages. The present findings suggest that AI-enabled HRD initiatives achieve optimal impact when embedded within a culture that actively values learning and development.

Limitations

This study has several limitations. First, the cross-sectional research design can limit the causal inference. In future, longitudinal research could better capture the long-term effects of AI-enabled learning on career advancement. Secondly, the use of self-reported data, despite several measures to avoid it, may introduce common method bias. Incorporating multi-source data may enhance methodological rigor. Third, the purposive sampling approach may limit generalizability of the study across industries and organizational contexts. Finally, while digital literacy and organizational learning culture were examined as moderators, other additional factors, such as AI trust or leadership support may further influence outcomes.

Practical implications

From a managerial perspective, the findings offer several actionable insights for organizations investing in AI-enabled learning systems and human resource professionals, development managers and policymakers. Organizations should invest in AI-enabled personalized e-learning platforms which offer adaptative learning procedures, predictive analytics and intelligent assessments. These features in learning platforms ensure that it will identify individual learner's need, recommend personalized content and significantly develop employee skills. Furthermore, learners should be engaged properly by providing motivations in learning experience and developing more interactive platforms. Only increasing technological infrastructure would not help much to increase employee skills, unless employees are engaged to a great extent. Furthermore, the organizations should focus to increase digital competencies of the trainee employees. Learners with a high digital proficiency are observed to translate the training into their skills. Finally, the organizations should pay attention to cultivate a supportive learning culture which foster continuous learning, experimentation, career development and knowledge sharing.

Conclusion

Artificial intelligence is reshaping how organizations develop and nurture talents. Traditional training models are gradually being replaced by intelligent and adaptive learning systems which respond to the unique needs of employees. The present study examined how AI-enabled personalized e-learning influence employee skill development and career advancement outcomes. The findings show that AI-enabled personalized learning, in terms of adaptive learning pathways, intelligent assessments, and predictive analytics significantly improves employee skill development. Improved employee skills, including technical skills, soft skills, learning agility or application of skills lead to better professional growth, in terms of promotion, internal job mobility, increased responsibilities, increased employability, higher compensations and financial benefits. These results strengthen the idea that continuous skill development is a key driver of career advancements in the rapidly changing digital workplaces.

The study also demonstrated the importance of learning engagement in technology-driven training environments. Learning engagement partially mediated the relationship between AI-enabled learning and skill development, suggesting that technology alone is not sufficient. Employees must be cognitively involved, emotionally motivated and behaviorally active in the learning process for meaningful skill development. Furthermore, other contextual factors play an important role. As digitally competent employees can better utilize adaptive systems, digital literacy positively moderated the effectiveness of AI-enabled learning platforms. Furthermore, a supportive organizational learning culture helps translate newly acquired skill into career advancement. Overall, the findings suggest that AI-enabled personalized learning can become a powerful strategic tool for workforce development. However, its success depends not only on technological capabilities but also on employee readiness and supportive organizational environments.

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