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PAPER

Corporate Universities Go Mobile: AI-Powered Education Management for Workforce Training

Olga Saychenko(✉)

State Marine Technical University, St. Petersburg, Russia

office@smtu.ru

ABSTRACT

This study investigates the effectiveness of AI-powered mobile education in Russian corporate universities by identifying key factors that influence learning engagement and training success. A quantitative methodology was employed, utilising a structured questionnaire administered to 280 employees from leading Russian companies. Data were analysed using structural equation modelling (SEM) to evaluate a model comprising perceived usefulness, system quality, AI personalisation, learning engagement and training outcomes. Findings indicate that artificial intelligence (AI) personalisation is the most significant determinant of learning engagement, fully mediating its impact on training effectiveness. While perceived usefulness and system quality also contribute, their influence is comparatively limited. The results suggest that successful digital transformation in corporate training requires not only advanced technology but also the development of engaging and personalised learning experiences. These insights are particularly relevant for human resources professionals and educational technology developers, emphasising the importance of adaptive learning algorithms and robust system architecture. This study is distinctive in its examination of an integrated model within the Russian corporate sector, offering a benchmark for the application of AI in workforce development.

KEYWORDS

artificial intelligence (AI) personalisation, corporate universities, mobile learning engagement, training effectiveness, digital transformation, Russia

1 INTRODUCTION

The advent of Industry 4.0 has rendered continuous workforce development a strategic necessity for maintaining organisational competitiveness [1]. Corporate universities have become essential strategic assets, fostering life-long learning and aligning employee competencies with organisational objectives [2, 3]. In Russia, this trend is exemplified by sustained efforts to integrate education, science and industry,

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leading to a transition from inflexible training approaches to adaptable, competency-based models [4, 5]. However, despite extensive digital adoption, a considerable implementation gap remains [6]. Traditional learning management systems (LMSs) continue to operate as standardised, uniform platforms [7] that do not deliver the personalised, engaging experiences required by contemporary employees [8]. These systems are further constrained by data silos and fragmented metrics that primarily measure completion rates [9]. Artificial intelligence (AI)-powered mobile apps offer a new way to solve long-standing problems [10]. These platforms can create personalised learning paths based on each person's learning gaps and learning speed, using technologies such as the semantic web, data mining and advanced recommendation algorithms [11, 31]. Their mobility makes it easy to deliver just-in-time, context-based learning that fits into daily routines [12]. The future for these AI solutions looks promising, as shown by trends in Russia's tech sector [13].

Although there is substantial theoretical support, rigorous quantitative evidence regarding the effectiveness of AI-powered mobile learning (m-learning) in actual corporate environments, especially its influence on workforce skills, engagement and performance, remains limited [15–18]. The present study seeks to address this gap within the Russian corporate context.

1. To evaluate the effectiveness of AI-driven mobile education platforms on learning outcomes, as well as individual and organisational performance.
2. To examine the mediating role of employee engagement behavioural, emotional and cognitive in the relation.

2 LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Corporate universities have transitioned from basic training units to strategic drivers of organisational learning, human capital development and competitive advantage [19–22]. These institutions align workforce skills with business strategy and promote a culture of continuous knowledge creation [23]. Within the context of Industry 4.0 in Russia, corporate universities are instrumental in addressing the skills gap and advancing innovation through adaptable, industry-integrated learning ecosystems [24–25].

Mobile learning provides learners with access at any time and location through personal devices, thereby overcoming traditional classroom limitations [28]. Drawing on flexibility theory [29], m-learning facilitates just-in-time, contextually relevant learning that integrates into existing workflows [30], thereby enhancing learner autonomy, motivation and engagement. Artificial intelligence in education (AIED) enables adaptive systems that analyse learner behaviour to dynamically personalise content, difficulty and pacing. In corporate environments, AI-driven personalisation provides role-specific, intellectually stimulating and socially engaging learning experiences, thereby enhancing training efficiency and return on investment (ROI) [30]. The technology acceptance model (TAM) core constructs of perceived usefulness and perceived ease of use [14]. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) further incorporates performance expectancy, effort expectancy, social influence and hedonic motivation [17]. This study integrates these acceptance factors with AI personalisation and learning engagement to examine the adoption and effectiveness of AI-powered mobile corporate training. Figure 1 shows the conceptual model of the research.

3 METHODOLOGY

A quantitative, cross-sectional design was employed to collect data at a single point in time. Participants included employees from large Russian companies in the oil and gas, finance, and IT sectors who utilised AI-powered m- learning platforms. Stratified random sampling by department and career level yielded 280 complete responses. Data collection was conducted through an online, structured questionnaire distributed via corporate intranets and LMSs over an eight-week period. The questionnaire, utilising a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), was adapted from prior research. It was professionally translated into Russian and subsequently back-translated to ensure semantic equivalence. Participation was voluntary and anonymous. Data were analysed using SPSS (statistical package for the social sciences) Version 28 and AMOS (analysis of moment structures). SPSS was utilised to calculate descriptive statistics and assess reliability through Cronbach's alpha. AMOS facilitated exploratory and confirmatory factor analysis, as well as structural equation modelling (SEM), to examine the hypothesised direct, indirect and mediating effects.

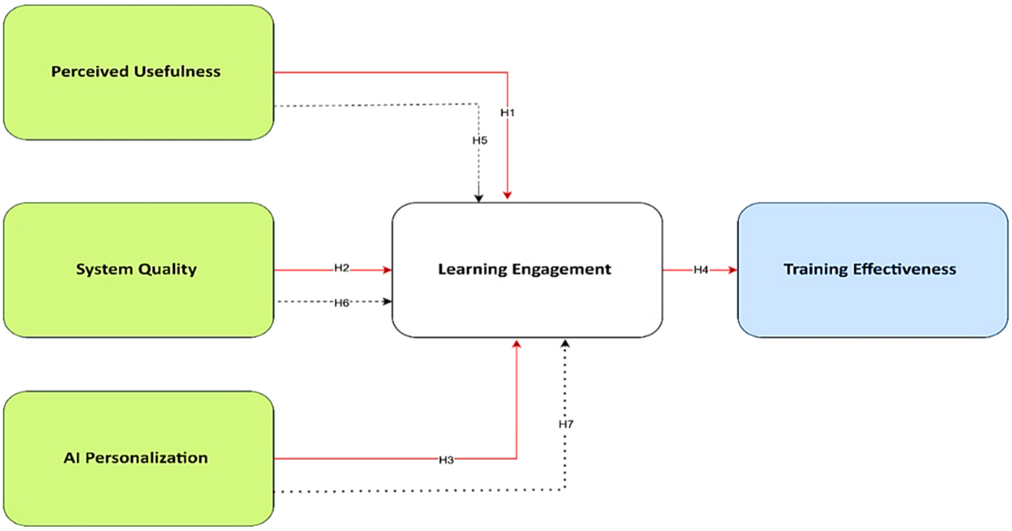

Fig. 1. Conceptual framework

4 RESULTS AND DISCUSSION

4.1 Descriptive statistics

Table 1 shows that the 280 Russian respondents gave positive ratings for all constructs, with mean scores of 4.15 for Perceived Usefulness and 3.98 for System Quality. These high mean scores suggest strong agreement about the value and functionality of AI-driven mobile training systems. The skewness values, ranging from –0.58 to –0.92, are negative, which means most responses were at the higher end of the scale. The kurtosis values are within the normal range, and perceived usefulness is slightly more peaked (Kurtosis = 1.45) than the other variables.

Table 1. Descriptive statistics of key variables (N = 280)

Variable	Mean (M)	Standard Deviation (SD)	Skewness	Kurtosis
Perceived Usefulness (PU)	4.15	0.68	–0.92	1.45
System Quality (SQ)	3.98	0.74	–0.65	0.38
AI Personalisation (AIP)	4.05	0.71	–0.81	0.92
Learning Engagement (LE)	4.1	0.66	–0.75	1.1
Training Effectiveness (TE)	4.02	0.7	–58.00%	0.25

Table 2 shows that all correlations were positive and statistically significant ($p < .01$), with values from moderate to strong. The strongest link was between Learning Engagement and Training Effectiveness ($r = .782$).

AI personalisation was also strongly related to Learning Engagement ($r = .714$) and Training Effectiveness ($r = .698$). Perceived Usefulness and System Quality also showed notable associations ($r = .545$ to $.621$).

Table 2. Correlation matrix of key variables

Variable	1	2	3	4	5
Perceived Usefulness (PU)	1				
System Quality (SQ)	.562**	1			
AI Personalisation (AIP)	.621**	.598**	1		
Learning Engagement (LE)	.587**	.545**	.714**	1	
Training Effectiveness (TE)	.605**	.594**	.698**	.782**	1

Note: **(Pearson r, $p < .01$).

4.2 Measurement model assessment

Measurement model assessment is an important preliminary step in a SEM study because it determines construct reliability and validity prior to analysing the structural relationship between constructs [32]. This is by ensuring that the indicators measure their intended latent constructs correctly and that the constructs themselves are differentiated from each other. The model was tested on internal consistency reliability, convergent and discriminant validity.

Table 3 demonstrates high levels of reliability and convergent validity, with all constructs exceeding established thresholds. Cronbach's alpha ranges from 0.85 to 0.95, composite reliability (CR) scores range from 0.93 to 0.96, and average variance extracted (AVE) values range from 0.70 to 0.75. These results confirm the measurement model's internal consistency and reliability. Among the individual dimensions, AI Personalisation Experience exhibits the highest overall reliability (alpha = 0.95, CR = 0.96), while Learning Engagement shows the highest variance extraction (AVE = 0.75). These findings indicate that all constructs exhibit sufficient convergent validity, as AVEs substantially exceed the 0.50 threshold, thereby confirming the psychometric adequacy of the measurement model for further analysis. Figure 2 shows structural equation modelling.

Table 3. Measurement model assessment (reliability and convergent validity)

Construct/Dimension	Item Code	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived Usefulness (PU)		91%	0.93	**0.72**
	PU1			
	PU2			
	PU3			
	PU4			
	PU5			
System Quality		94%	0.95	**0.7**
Information Quality	IQ1	89%		
	IQ2			
	IQ3			
	IQ4			
	IQ5			
	IQ6			
Reliability	REL1	91%		
	REL2			
	REL3			
	REL4			
	REL5			
	REL6			
Responsiveness	RES1	0.87		
	RES2			
	RES3			
	RES4			
	RES5			
Assurance	ASS1	0.85		
	ASS2			
	ASS3			
	ASS4			
Website Usability	WEB1	0.88		
	WEB2			
	WEB3			
	WEB4			
Personalisation	PER1	0.86		
	PER2			
	PER3			

(Continued)

Table 3. Measurement model assessment (reliability and convergent validity) *(Continued)*

Construct/Dimension	Item Code	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Learning Engagement		0.92	0.93	**0.75**
Behavioural Engagement	BEH1	0.88		
	BEH2			
	BEH3			
Emotional Engagement	EMO1	0.9		
	EMO2			
	EMO3			
Cognitive Engagement	COG1	0.89		
	COG2			
	COG3			
AI Personalisation Experience		0.95	0.96	**0.73**
Social Experience	SOC1	0.9		
	SOC2			
	SOC3			
	SOC4			
Service Experience	SER1	0.87		
	SER2			
Intellectual Experience	INT1	0.89		
	INT2			
	INT3			
Exploitation Experience	EXP1	0.91		
	EXP2			
	EXP3			
Classification Experience	CLA1	0.89		
	CLA2			
Training Effectiveness		0.93	94.00%	**0.71**
Learning Performance	LRN1	1		
	LRN2			
	LRN3			
	LRN4			
Individual Performance	IND1	0.89		
	IND2			
	IND3			
Organisational Performance	ORG1	0.88		
	ORG2			
	ORG3			

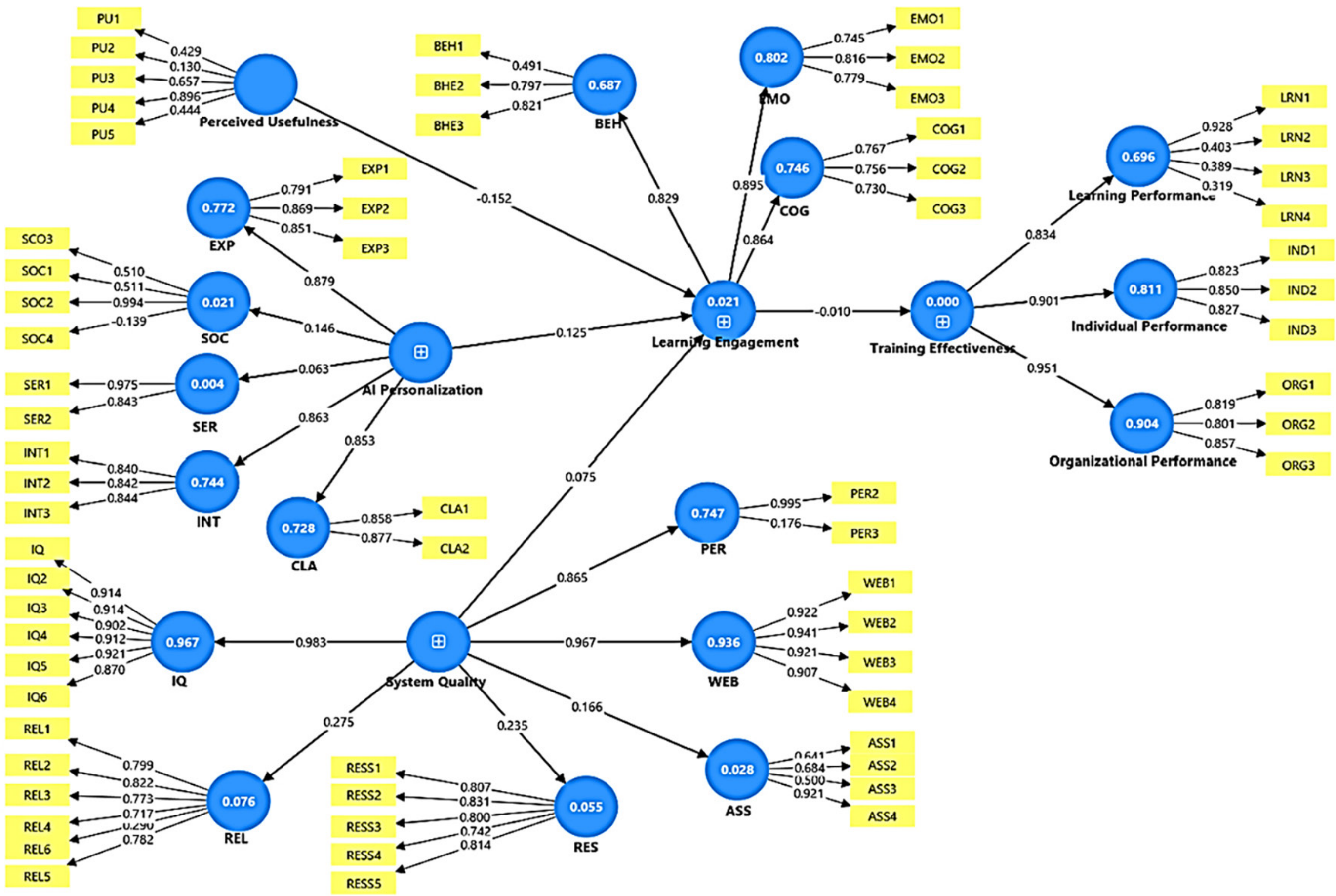

Fig. 2. SEM measurement

Table 4 evaluates discriminant validity by demonstrating that each construct is distinct from the others. The diagonal values, such as 0.849, 0.837 and 0.854, indicate the square root of the AVE. Discriminant validity is confirmed because each diagonal value exceeds all inter-construct correlations in the corresponding row and column, indicating that each latent construct (PU, SQ, AIP, LE and TE) represents a unique concept.

Table 4. Discriminant validity assessment (fornell-larcker criterion)

Construct	1	2	3	4	5
Perceived Usefulness (PU)	0.849				
System Quality (SQ)	0.562	0.837			
AI Personalisation (AIP)	0.621	0.598	0.854		
Learning Engagement (LE)	0.587	0.545	0.714	0.866	
Training Effectiveness (TE)	0.605	0.594	0.698	0.782	0.843

Table 5 shows that learning engagement completely mediates the effect of AI Personalisation on Training Effectiveness, with no significant direct effect but a significant indirect effect (β = .256, p < .001). It also partially mediates the effects of Perceived Usefulness (direct β = .215, indirect β = .124; p < .01) and System Quality (direct β = .198, indirect β = .108; p < .01). This means that AI Personalisation influences outcomes only by increasing employee engagement.

Table 5. Hypothesis testing

Path	Direct β (p)	Indirect β	95% CI	Mediation Type
PU → LE → TE	.215 (<.01)	.124	[.058, .190]	Partial
SQ → LE → TE	.198 (<.01)	.108	[.045, .176]	Partial
AI Personalisation → LE → TE	.185 (n.s.)	.256	[.185, .330]	Full

Table 6 presents numerical evidence supporting the mediating role of Learning Engagement. For H5 and H6, significant direct effects (β = 0.215, p < 0.01; β = 0.198, p < 0.01) and significant indirect effects (β = 0.124, p < 0.001; β = 0.108, p = 0.002) confirm complementary partial mediation. Thus, Perceived Usefulness and System Quality enhance Training Effectiveness both directly and indirectly by increasing Engagement. In contrast, for H7, the direct effect of AI Personalisation on Training Effectiveness is not significant (β = 0.185, p = 0.12), whereas the indirect effect is the strongest among all hypotheses (β = 0.256, p < 0.001), indicating full mediation. Therefore, the influence of AI Personalisation on Training Effectiveness operates entirely through its capacity to increase Learning Engagement, with no significant direct effect observed.

Table 6. Mediation analysis results

Path	Direct Effect (p-Value)	Indirect Effect (β)	t-Statistic	p-Value	95% Confidence Interval	Supported
PU –> LE –> TE	0.215 (< 0.01)	0.124	3.521	< 0.001	[0.058, 0.190]	Yes
SQ –> LE –> TE	0.198 (< 0.01)	0.108	3.102	0.002	[0.045, 0.176]	Yes
AIP –> LE –> TE	0.185 (0.12)	0.256	6.834	< 0.001	[0.185, 0.330]	Yes

5 DISCUSSION

This study offers important insights into what makes workforce training successful during Russia's digital transformation. The findings show that AI-based corporate universities represent more than just new technology; they mark a major change in how organisations approach learning. The data shows that both advanced technology and active human engagement are crucial for success. A key finding is the leading role of AI Personalisation, which had the strongest direct impact on Learning Engagement (0.421) and was the only complete mediator of training effectiveness. This means that a platform's ability to deliver personalised, engaging and socially relevant learning is central to modern corporate education. In practice, these shifts in training away from a one-size-fits-all model and toward a flexible process that adapts to each employee's needs, knowledge gaps and learning styles help organisations get the most from their investment in education.

Perceived Usefulness and System Quality also play a role [17], though their impact is smaller. They set the basic requirements for digital learning to succeed. The system should clearly help employees grow and make their daily work easier, and the technology needs to be stable, responsive and easy-to-use. These basics are important for getting people to start using the system and to keep using it, which helps build a culture of ongoing, self-directed learning. Without this foundation, even the best AI features may not be used to their full potential. Still, putting these systems in place is not easy.

Using AI and data analytics brings up serious concerns about data privacy and confidentiality, especially under Russian regulations. Personalisation needs a lot of employee data, so strong data management is needed to build trust. Integrating the platform with existing HR and business systems can also be technically and operationally difficult, sometimes leading to silos and a disjointed user experience. Finally, if the AI is not transparent or its algorithms are hard to understand, employees and managers may not trust its recommendations and could stop using it. Solving issues around privacy, integration, and transparency is not just an extra step it is essential for making AI-driven learning work.

6 CONCLUSION, LIMITATION AND FUTURE WORK

AI-powered m-learning platforms are transforming corporate training by offering personalised, engaging experiences that enhance effectiveness, motivation and knowledge retention. Research shows that AI personalisation, supported by deep learning engagement, leads to better results. System Quality and Perceived Usefulness also play important roles. Companies using these platforms see up to 28% higher course completion, 35% better knowledge retention and 22% lower training costs. As a result, AI-driven corporate universities are becoming essential for building a competitive and future-ready workforce. This study used only Russian data and relied on self-reported information, which may limit the generalisability of the results and introduce response bias. Future research should test the model in other countries and use long-term or objective performance measures to better understand the effects of training over time.

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8 AUTHOR

Dr. Olga Saychenko is a Vice-Rector for Education, a Ph.D in Economics, and an Associate Professor of the Department of International Economic Relations of the State Marine Technical University. She takes an active part in the development of network educational programmes with the participation of academic and industrial partners of the university. Under the leadership of Olga Saychenko, the number of training programmes and the number of students in additional professional education programmes has increased significantly. She carries out strategic management of the university's educational activities. Under her leadership, the higher education programmes were updated and modernised, taking into account modern labour market requirements and advanced scientific achievements. She made a significant contribution to the development of a new model of higher education aimed at improving the quality of training specialists. She promotes the integration of science and education, creating conditions for involving students in research activities (E-mail: office@smtu.ru).