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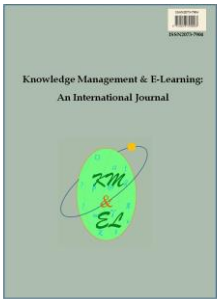

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Exploring the factors influencing e-learning readiness of academic staff in higher education

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Abstract: The study explores the factors influencing academic staff readiness for e-learning in higher education institutions (HEIs) in Jammu and Kashmir of India. By synthesizing elements from existing e-learning readiness (ELR) models, the researchers identified the most relevant factors and proposed an indigenous reflective measurement model for assessing ELR of academic staff. The model was empirically tested using Confirmatory Factor Analysis (CFA) and Covariance-Based Structural Equation Modeling (CB-SEM). A sample of 281 academic staff members from HEIs in Jammu and Kashmir of India was used for analysis. The CFA results revealed that the model accounted for 52% of the variance in the key factors affecting ELR. Additionally, SEM demonstrated that approximately 39.3% of the variance in ELR could be explained by the factors integrated into the model. The findings indicate that Facilitating Conditions (FC), Self-Efficacy (SE), and Pedagogical Attitude (PA) significantly influence ELR, although their impacts vary in magnitude. These results offer practical insights that are transferable to other regions grappling with similar constraints for raising awareness among academic staff regarding the critical factors that contribute to enhancing their readiness for e-learning. By improving their pedagogical attitude and self-efficacy, they can better harness the potential of e-learning technologies for effective teaching and learning.

Keywords: e-Learning readiness; Facilitating conditions; Self-efficacy; Pedagogical attitude; Academic staff; Confirmatory factor analysis; Structural equation modeling

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1. Introduction

The alignment of e-learning with various theoretical frameworks, including the constructivist approach, technological determinism, social constructivism, connectivism, and activity theory, validates its integration into higher education (Ukpe, 2023). Across the globe, higher education institutions are increasingly embracing e-learning as a means to offer educational opportunities in an effective and innovative manner (Shard et al., 2024). Since the emergence of the COVID-19 pandemic, e-learning has become an essential component of higher education, with its widespread adoption in many universities (Santally et al., 2020). However, ensuring the quality of e-learning is a complex task (Chou et al., 2019) and is influenced by various factors that affect its adoption by both teachers and students in HEIs (Lal et al., 2024). In the era of e-learning, educators are expected to function as facilitators, equipped with techno-pedagogical knowledge to enhance learners' independence and abilities (Malec, 2024). They must integrate a variety of digital tools, such as email, message boards, live chat, videoconferencing, and other online communication platforms, into blended learning environments (University Grants Commission, 2021). Readiness of e-learning also enhances the academic performance of academic staff (Khasawneh, 2025). Despite its potential advantages, the adoption of e-learning in HEIs remains limited (Shard et al., 2024). Therefore, ELR models serve as tools for educational organizations to assess their capabilities and identify gaps, ultimately guiding the development of strategies for the implementation and adoption of e-learning systems (Al-Rikabi & Montazer, 2024; Safarifard et al., 2024).

2. Literature review and theoretical framework

ELR denotes the psychological and practical preparedness, along with the requisite user competencies, necessary for the effective utilization of e-learning platforms (Borotis et al., 2008; Farazkish & Montazer, 2019). Al-Rikabi and Montazer (2024) define ELR as the capacity of organizations and stakeholders to utilize electronic media effectively and efficiently. Globally, particularly after the COVID-19 pandemic, e-learning integration in higher education has often proceeded without adequately assessing stakeholders' readiness (Khasawneh, 2025). Within this context, academic staff represent a critical stakeholder group, often requiring substantial training and retraining to adapt to the new educational paradigm. Many also encounter resistance, experiencing pressure and difficulties in perceiving the advantages of e-learning over conventional teaching methods (Egielewa et al., 2022).

One of the main reasons for the failure of e-learning system development in universities is the lack of readiness among instructors (Farazkish & Montazer, 2019). While teachers generally exhibit a positive attitude toward e-learning due to the benefits it offers, they often feel overwhelmed by the technical requirements, their existing academic responsibilities, and the stress associated with adopting this new mode of teaching (Alammary et al., 2022; Egielewa et al., 2022; Hoq, 2020; Saekow, 2011). Challenges such as heavy workloads, inadequate internet connectivity, limited ICT skills, shortages of computers or laptops, and insufficient time for online interaction are significant barriers that affect the readiness of teachers in HEIs to embrace e-learning (Mutisya & Makokha, 2016).

Recognizing the importance of ELR, previous studies have explored the readiness of academic staff (Al-Araibi et al., 2019; Alshammari & Adaileh, 2018; Bhardwaj et al., 2021; Shard et al., 2024; Tom et al., 2019; Zine et al., 2023). These studies collectively illustrate the multifaceted nature of ELR and the diverse factors that influence it, including self-efficacy, facilitating conditions, technology, pedagogy, attitude, environmental factors, content, institutional characteristics, and other contextual elements specific to the study location (Safarifard et al., 2024). The findings underscore the necessity of acknowledging that various factors impact the acceptance of different technologies. Similarly, the industry, national and cultural contexts in which e-learning is adopted significantly shape the factors that must be considered for assessing ELR (Alammary et al., 2022; Al-Rikabi & Montazer, 2024; Demir & Yurdugül, 2015; Majid & Lakshmi, 2024; Nwagwu, 2020).

India is considered home to one of the worlds' largest higher education systems, which is characterized by a highly fragmented educational ecosystem. Despite its unique characteristics and challenges, the Indian higher education sector is committed to enhancing access, equity, quality, and inclusion, which necessitates the integration of e-learning platforms. Previous studies conducted in India have highlighted the importance of considering both individual and technological factors in understanding the adoption of e-learning in HEIs (Tyagi & Krishankumar, 2024; Lakshmi et al., 2020). Key factors such as perceived ease of use, perceived usefulness, learners' attitudes, self-efficacy, facilitating conditions, interaction, availability of support, and infrastructure have been identified as influencing e-learning readiness and were included in ELR studies across India (Kumar et al., 2023; Lal et al., 2024; Patra et al., 2021; Shard et al., 2024; Tyagi & Krishankumar, 2024). Furthermore, studies suggest that teachers' satisfaction plays a more significant role in the adoption of e-learning than perceived usefulness (PU) and perceived ease of use (PEOU) (Kumar et al., 2023). Factors such as user-friendliness, convenience, and performance are key motivators for teachers to adopt e-learning systems (Patra et al., 2021). However, research in India has also identified challenges, including technical issues, adaptability, lack of motivation, the absence of personal interaction, substantial financial investment, internet accessibility, ICT literacy, and technological support (Patra et al., 2021; Taso & Chakrabarty, 2020) which are also often considered globally as challenges in adopting e-learning (Eslaminejad et al., 2010; Mutisya & Makokha, 2016; Sadik, 2007).

Higher education in Jammu and Kashmir (J&K), which includes institutions of national importance, state universities, and a network of colleges, has experienced significant development. Digital transformation initiatives, such as converting traditional classrooms into digital learning environments and utilizing e-content through cloud platforms, are currently underway. Additionally, platforms like MOOCs, SWAYAM, and EduSat have been employed to expand learning opportunities, while faculty training programs focus on enhancing IT skills and e-content delivery (Jammu and Kashmir Higher Education Department, n.d.). The COVID-19 pandemic highlighted the potential of e-learning to bridge educational gaps in J&K, including reducing gender disparities (Nazeer, 2023). With the increasing penetration of the internet, J&K is well-positioned to harness e-learning as a transformative force in higher education. These developments create a compelling context for this study at this pivotal moment.

Although prior studies in J&K have examined e-learning applications, effectiveness, and challenges (Namita & Devanand, 2012; Suri, 2013; Ahad & Dar, 2017), they remain descriptive and outcome-focused, offering little assessment of academic staff preparedness, institutional conditions, or pedagogical adaptability. Thus, despite documenting e-learning initiatives, these works do not provide a structured evaluation of ELR. This study examines the under-explored dimensions of ELR in J&K by integrating key constructs into a unified reflective measurement model, offering insights for the development of e-learning platforms and the academic community.

3. Proposed research framework and development of hypotheses

To account for the unique contextual factors influencing e-learning adoption in the J&K region (Ahad & Dar, 2017; Government of Jammu and Kashmir, 2023; Namita & Devanand, 2012; Nazeer, 2023), this study refrains from relying on any single existing technology acceptance frameworks. Instead, it synthesized relevant factors from existing ELR models and identified the most pertinent elements, leading to the proposal of an indigenous reflective measurement model, as illustrated in Fig.1. This approach of synthesizing factors from various models and incorporating context-specific determinants is a commonly employed strategy in studies of technology readiness (Alammary et al., 2022).

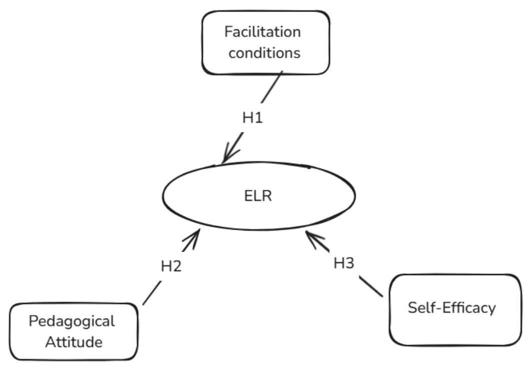

Fig. 1. Proposed research framework

The proposed research framework in current study is based on key dimensions drawn from various established frameworks, such as the "Technology-Organization-Environment (TOE), Innovation-Organization-Environment (IOH), Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT)", and ELR. Our framework focuses on three primary factors: facilitating conditions (FC), pedagogical attitude (PA), and self-efficacy (SE) in the use of technology which are considered to reflect the ELR of academic staff (Shard et al., 2024). Thus, the nature of these factors, direction of causality between the indicators and the factors, characteristics of the indicators and the inter-correlation between the indicators guided us to propose a reflective measurement model rather than a formative model of measurement (Coltman et al., 2008).

3.1. Facilitating conditions

ELR is closely linked to the FC available within an institution. FC refers to the perception among academic staff that the organizational and technological resources necessary to use a particular technology are readily accessible (Venkatesh et al., 2003). Inadequate infrastructure can hinder teachers' and students' readiness in adopting e-learning systems. Naidu (2006) and Khasawneh (2025) emphasize the importance of preparedness and the integration of infrastructure components, noting that the readiness of infrastructure and equipment is critical for supporting e-learning initiatives. Venkatesh et al. (2003) identified FC as a key factor influencing technology adoption and usage. Collectively, these studies highlight the essential role of infrastructure to ensure effective implementation of e-learning. As a fundamental component of ELR, FC is incorporated into most e-learning frameworks (Alammary et al., 2022; Asamoah et al., 2024; Chatterjee & Bhattacharjee, 2020; Shard et al., 2024). Its inclusion as a core variable in e-learning research is crucial to gain comprehensive understanding of ELR. In context of present study, the FC is defined as perception of academic staff regarding availability of both physical & digital resources required to support e-learning and digital teaching processes, including technical support and access to essential tools and platforms. Based on this understanding, the researchers put forth the following hypothesis:

H1: FC significantly influence the e-learning readiness of academic staff

3.2. Pedagogical attitude

Attitude refers to an individual's positive or negative perception of performing a specific behavior (Venkatesh et al., 2003). Insufficient technical and pedagogical preparedness, combined with a reluctance to experiment with new methods, can hinder the successful implementation of e-learning (Koehler & Mishra, 2016; Sadik, 2007). The knowledge of technology, availability of infrastructure, and the readiness of educators to integrate e-learning into their teaching practices are critical to the success of e-learning initiatives (Koehler & Mishra, 2016). A positive pedagogical attitude enables teachers to employ appropriate instructional methods and pedagogical approaches throughout development and delivery of e-learning content. As such, it is a key component in several e-learning readiness models (Alammary et al., 2022; Asamoah et al., 2024; Eslaminejad et al., 2010; Nwagwu, 2020; Shard et al., 2024). For instructors in e-learning environments, their attitude toward the changing paradigm of teaching is a significant factor. A teacher's willingness to act as a facilitator influences their level of online interaction with students (Eslaminejad et al., 2010). Pedagogical attitude encompasses various aspects, including content, audience, medium, design, instruction, organization, and the use of blended learning strategies (Khasawneh, 2025). Educators with positive perception of e-learning's usefulness and who actively incorporate these aspects into their teaching practices are generally better prepared for e-learning as compared to those who neglect these factors. Therefore, the pedagogical attitude of academic staff in adopting e-learning principles is a critical determinant of their overall ELR. In the present study, PA evaluates the willingness and ability of academic staff to adopt innovative, learner-centered teaching methods, integrate multimedia tools, and adapt teaching strategies to enhance the learning experience in digital environments. Based on this understanding, the researchers put forth the following hypothesis:

H2: PA significantly influences the e-learning readiness of academic staff

3.3. Self-efficacy

Self-efficacy in using e-learning tools refers to an individual's judgment of their ability and belief in their capacity to use e-learning solutions effectively (Venkatesh et al., 2003). Technology competency is considered a core factor in various technology acceptance models, including the TOE, IOH, TAM, and UTAUT. Self-efficacy is often examined in terms of technology capabilities, skills, perceived ease of use, efficiency, and the ability to use technology effectively (Al-Fraihat et al., 2020; Al-Rikabi & Montazer, 2024; Demir & Yurdugül, 2015; Farazkish & Montazer, 2019). It plays a significant role in the context of technology acceptance and is considered a key predictor of ELR (Alammary et al., 2022). E-learning users are more likely to adopt new technology if they consider they have the ability to use it and that it will enhance their educational performance and efficacy. In current study, self-efficacy is defined as the ability of academic staff to adopt and effectively use digital tools and platforms for teaching and administrative tasks. It includes familiarity, confidence, and proficiency in utilizing both online and offline technological resources for academic purposes. Moreover, self-efficacy in using computers can reduce the likelihood of technostress (Siddiqui et al., 2023). Meriem & Youssef (2020), through Principal Component Analysis (PCA), identified enjoyment and self-efficacy in using e-learning as two critical factors for the continued use of e-learning platforms by higher education teachers. Based on this understanding, the researchers put forth the following hypothesis:

H3: SE significantly influences the e-learning readiness of academic staff

4. Methods

This study aims to test the proposed research model by investigating the impact of various factors on ELR through a quantitative approach. A cross-sectional survey design, widely utilized in technology readiness research (Shard et al., 2024), was selected to explore the individual factors of ELR and their interrelationships. Additionally, nomothetic approach was employed to identify universal patterns and general principles, thereby enhancing reliability and generalizability of study's findings.

4.1. Instrument development and pilot test

The current study is grounded in conceptualization of ELR discussed earlier, which offers a comprehensive framework incorporating the core factors of ELR. The development of the ELR tool followed a deductive approach, informed by extensive review of existing literature and established scales. The factors and indicators used in the tool were selected based on several criteria. First, care was taken to consider only those indicators which are influenced by the latent variable i.e., ELR (Coltman et al., 2008). Second, factors and indicators that were most frequently identified in prior ELR studies conducted in India (Bhardwaj et al., 2021; Chatterjee & Bhattacharjee, 2020; Mohan et al., 2020; Shard et al., 2024; Vanitha & Alathur, 2020; Vanitha & Alathur, 2021) were incorporated. Third, factors that had a significant explanatory role in earlier studies on ELR (Alammary et al., 2022; Asamoah et al., 2024; Shard et al., 2024; Tayyib et al., 2020) were also considered. Additionally, the work of Nisperos (2014), Farazkish & Montazer (2019) and Nwagwu (2020) further helped in defining of the latent construct of ELR in observable terms. Based on these sources, a few items that were deduced from these studies are: "I am ready for e-learning, technical support for e-learning, conducts e-learning related training, LMS/CMS, online library, internet connectivity, network speed, knowledge and ability to create e-learning content, use of online tools/asynchronous tools, ability to develop electronic assessments, support student-centered learning, view as a facilitator, and willingness to experiment with new pedagogical approaches". From these items, the "ELR of Academic Staff" scale was developed, comprising 45 items designed to define the factors of ELR. The items within each factor were assessed using bipolar adjectives measured on a five-point Likert scale. SE was measured from 1 (very proficient) to 5 (not at all proficient), FC from 1 (excellent) to 5 (poor), and PA and ELR from 1 (strongly agree) to 5 (strongly disagree). To address acquiescence bias, four negatively worded items were reverse-coded (Garg, 2023).

The reliability of the scale was measured through a pilot study involving 32 academic staff members from HEIs. After removing one item from the PA factor to improve reliability, the final scale consisted of 44 items, with an overall reliability coefficient of 0.80. The Cronbach's alpha scores for the factors were 0.87 for SE, 0.79 for PA, 0.93 for FC, and 0.68 for ELR, suggesting satisfactory reliability (Heale & Twycross, 2015).

4.2. Data collection

The finalized 44-item tool was utilized for the final data collection. The tool was organized into two sections. The initial section provided preliminary information about the study's primary purpose, instructions for participants, and ethical considerations related to data collection. The first section of the tool contained a set of items designed to measure the constructs of the study, while the second section collected demographic information from participants. To administer the survey, the researchers obtained the email addresses of the Principals/Heads of HEIs in J&K from the Department of Higher Education's website. A link to the Google Form was sent to these institutional leaders, with a request to distribute the form to their academic staff. In instances where direct email addresses for academic staff were available, the form was sent directly to them. Additionally, the survey link was shared across several major social media platforms including Facebook, LinkedIn, Instagram, and WhatsApp. A follow-up was conducted across all platforms to encourage greater participation. In total, 302 academic staff members participated in the survey, forming the study's sample.

4.3. Data analysis

Mahalanobis distances were employed to detect multivariate outliers, as recommended by Tabachnick and Fidell (2019). The developed reflective measurement model was tested empirically through "Confirmatory Factor Analysis (CFA)" to assess the extent to which the indicators in the tool accurately measure the latent constructs (Coltman et al., 2008). Additionally, "Covariance-Based Structural Equation Modeling (CB-SEM)" was utilized to test the proposed hypotheses. CB-SEM allows for the simultaneous analysis of latent structures and observed variables, as well as the exploration of their interrelationships and effects on the associated constructs (Thakkar, 2020). The evaluation of the structural model was conducted using fit indices and path coefficients. All statistical analyses were carried out using JASP 0.18.3.0 (JASP Team, 2023).

5. Results

5.1. Participants and their profile

The sample comprised academic staff across academic streams, with representation of both genders, and drawn from both state and central institutions located in urban and rural areas. Data collection was conducted online, with prior informed consent obtained from all participants. After identifying and removing 21 outlier responses using Mahalanobis distances, the remaining data from 281 academic staff members were used for further statistical analysis. As detailed in Table 1, the sample included a higher proportion of male participants compared to female participants. However, the sample maintained a relatively balanced geographic representation, with an almost equal distribution between urban and rural HEIs. Furthermore, the sample encompassed a broad spectrum of academic streams, with a comparable representation of staff from science and non-science academic fields.

Table 1
Sample metrics ($N = 281$)

Variable	Category	Frequency	Percentage
Gender	Male	171	60.9
	Female	110	39.1
Location of institution	Urban	141	50.2
	Rural	140	49.8
Academic stream	Sciences	136	48.4
	Other than Sciences	145	51.6
Type of institution	State	190	67.6
	Central	91	32.4

5.2. Measurement model and fitness

The Kaiser-Meyer-Olkin (KMO) measure for the dataset was found to be 0.929, indicating excellent sampling adequacy and confirming its suitability for factor analysis. Additionally, the majority of individual variables exhibited high Measures of Sampling Adequacy (MSA) values (above 0.90), further supporting the appropriateness of the dataset for exploratory factor analysis (EFA). Bartlett's test of sphericity produced a significant chi-square statistic ($\chi^2 = 8526.108$, $df = 946$, $p < .001$), validating that the correlation matrix is not an identity matrix and that significant relationships exist among the variables (Reinard, 2006).

CFA using CB-SEM was performed in two phases: the Measurement Model and the Structural Model. The Maximum Likelihood Estimation (MLE) method of extraction was applied during the analysis. JASP 0.18.3.0 was employed to perform CFA and assess model fit by evaluating the goodness-of-fit indices (GoF), as presented in Table 2 and Fig. 2.

The fit indices for the proposed model, as presented in Table 2, are as follows: $\chi^2 = 1915.50$ with $df = 850$, $p < 0.001$, indicating a significant chi-square value. The CFI = 0.865 and TLI = 0.856 are below the conventional threshold of 0.90, suggesting a marginal fit and pointing towards appropriateness of a close-fit assessment model than the exact model fit (Bentler, 2007; Browne & Cudeck, 1992; MacCallum, 2003). It is important to note that such close-fit model can still provide valuable insights and are common in studies where comparisons are made at group level and the emphasis is less on individual measurements (Moshagen & Erdfelder, 2016). Furthermore, the RMSEA = 0.067, with a 90% Confidence Interval (CI) [0.063, 0.071], RMSEA p-value (< .001) and SRMR = 0.067 all meet the recommended thresholds for an acceptable fit (< 0.08) thereby supporting the adequacy of the model even when CFI and TLI fall slightly below the critical criteria (Byrne, 2016). The standardized factor loadings were all significant (p

< .001) and ranged from moderate to strong values, indicating the validity of the measurement model. Furthermore, the total variance explained by the model is 52.2%, which reflects a good variance explanation rate and suggests an adequate model fit.

Table 2
Model fit summary related to the research model

Fit index	Acceptable fit criteria	Value in the model
X^2/df	$2 \leq X^2/df \leq 3$ (Hair et al. 2019)	2.2
CFI	≥ 0.9 (Hair et al. 2019)	.87
GFI	≥ 0.9 (Byrne, 2016)	.96
RMSEA	< 0.08 (Hair et al. 2019)	.06
SRMR	< 0.08 (Hair et al. 2019)	.06
TLI	≥ 0.9 (Hair et al. 2019)	.85

Note. CFI: Comparative Fit Index; GFI: Goodness-of-Fit Index; RMSEA: Root Mean Standard Error of Approximation; SRMR: Standardized Root Mean Square Residual; TLI: Tucker-Lewis Index

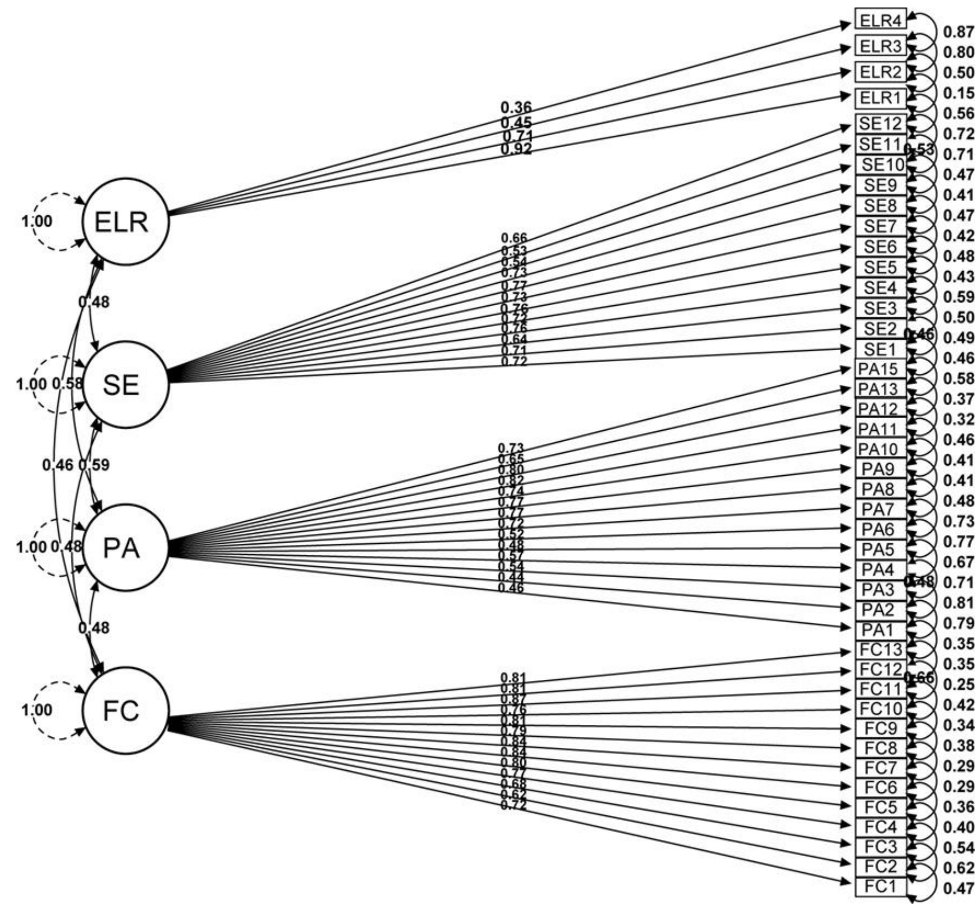

Fig. 2. CFA for instrument used in this research design

After ensuring that the overall model fit indices indicated an adequate fit of the hypothesized measurement model to the data, the essential requirements for evaluating reliability, convergent validity, and discriminant validity were calculated (Cheung et al., 2024). Construct reliability (CR) was established based on the standardized factor loadings and Cronbach's alpha (CA). Following the removal of one item in the PA factor, which cross-loaded on FC, the factor loading values for the remaining items, along with the CA values, met the threshold criteria of 0.40 and 0.7 respectively (Cheung et al., 2024), indicating satisfactory construct reliability as presented in Table 3. Additionally, the CR and average variance extracted (AVE) values met the threshold criteria of 0.7 (Hair et al., 2019) and 0.5 (Fornell & Larcker, 1981), ensuring convergent validity of the constructs (Table 3).

Discriminant validity (DV) was confirmed using the AVE shared variance (SV) approach (Fornell & Larcker, 1981), as the AVEs associated with the constructs exceeded the shared variance (Table 4). Moreover, the absence of cross-loadings (Table 3) and the HTMT values being below the threshold of 0.85 (Cheung et al., 2024) (Table 5) further supported the DV of the constructs.

5.3. Structural model and hypotheses testing

The measurement model developed through CFA was subsequently incorporated into the SEM to test the research hypotheses (Fig. 3). The summary of the path diagram, presented in Table 6, reveals that all three hypotheses (H1, H2, H3) were supported. Specifically, the analysis shows that FC has a positive and significant effect on ELR, with a path coefficient of $\beta = 0.269$ ($p = 0.002$, $p < 0.05$), thereby supporting Hypothesis 1. PA demonstrated the strongest relationship with ELR ($\beta = 1.458$, $p < 0.001$), indicating its substantial influence and supporting Hypothesis 2. Additionally, SE was found to have a positive and significant relationship with ELR ($\beta = 0.268$, $p = 0.039$, $p < 0.05$), thus confirming Hypothesis 3.

The analysis also revealed significant positive covariances among the latent factors (e.g., FC ↔ SE = 0.314), suggesting interrelationships among the constructs. Furthermore, several indicators, such as PA8 (residual = 0.174) and PA12 (residual = 0.254), exhibited low residuals, indicating strong alignment with the model. However, the presence of higher residual variances in a few items suggests potential areas for model refinement. The R^2 value of 0.392 indicates that 39.3% of the variation in ELR can be explained by the proposed research model (Fig. 4), suggesting that additional factors influencing ELR among academic staff may exist but were not explored in the present study.

Thus, the overall model fit for the full SEM was nearly identical to that of the CFA model ($\chi^2 = 1915.50$ with $df = 850$, p < 0.001, CFI = 0.865 and TLI = 0.86, RMSEA = 0.07 [0.06, 0.07], RMSEA *p*-value (< .001), SRMR = 0.07), indicating that the hypothesized structural paths among the latent variables did not significantly reduce model fit. This suggests that the structural relationships are well supported by the data and the established model captures the interdependencies among the latent factors. For instance, FC may have an indirect effect on PA by providing the essential tools and resources required for academic staff to effectively engage with e-learning. Additionally, SE could potentially mediate the relationship between FC and PA, highlighting the synergistic interactions among these constructs. Collectively, the results suggest that the model is robust and demonstrates a good fit, confirming its significance and acceptability in explaining the key factors influencing ELR among academic staff.

Table 3
Confirmatory factor analysis and reliability test

Factor	Item code	Loading	CA	McDonald's ω	CR	AVE
FC	FC 5	0.82	0.95	0.95	0.934	0.62
	FC 4	0.80				
	FC 12	0.80				
	FC 8	0.77				
	FC 9	0.77				
	FC 10	0.76				
	FC 1	0.76				
	FC 3	0.74				
	FC 13	0.70				
	FC 2	0.70				
PA	PA14	0.41				
	PA12	0.79	0.89	0.90	0.91	0.43
	PA8	0.77				
	PA11	0.74				
	PA7	0.73				
	PA9	0.72				
	PA13	0.71				
	PA3	0.68				
	PA6	0.68				
	PA10	0.67				
	PA4	0.63				
	PA15	0.62				
	PA2	0.44				
	PA1	0.44				
	PA5	0.44				
SE	SE7	0.82	0.92	0.91	0.91	0.50
	SE9	0.73				
	SE5	0.73				
	SE6	0.71				
	SE8	0.70				
	SE4	0.70				
	SE10	0.68				
	SE3	0.68				
	SE11	0.64				
	SE12	0.61				
	SE2	0.57				
	SE1	0.49				
ELR	ELR2	0.65	0.68	0.74	0.70	0.5
	ELR3	0.63				
	ELR1	0.59				
	ELR4	0.54				
Overall			0.98	0.94		

Table 4
Discriminant validity

Construct	AVE	SE	PA	ELR	FC
SE	0.50				
PA	0.44	.566 (0.32)			
ELR	0.50	.353 (0.12)	.398 (0.15)		
FC	0.62	.442 (0.19)	.515(0.26)	.277(0.07)	

Note. The shared variances are shown in brackets

Table 5
Heterotrait-monotrait ratio (HTMT)

FC	PA	SE	ELR
1.000			
0.461	1.000		
0.428	0.570	1.000	
0.164	0.368	0.346	1.000

Table 6
Structural paths and hypotheses testing results

Hypothesis	Path	Sign	*β*- value	SE	*p*-value	Results
H1	FC -> ELR	+	0.269	0.087	< 0.05	Supported
H2	PA -> ELR	+	1.46	0.325	< 0.001	Supported
H3	SE -> ELR	+	0.27	0.130	< 0.05	Supported

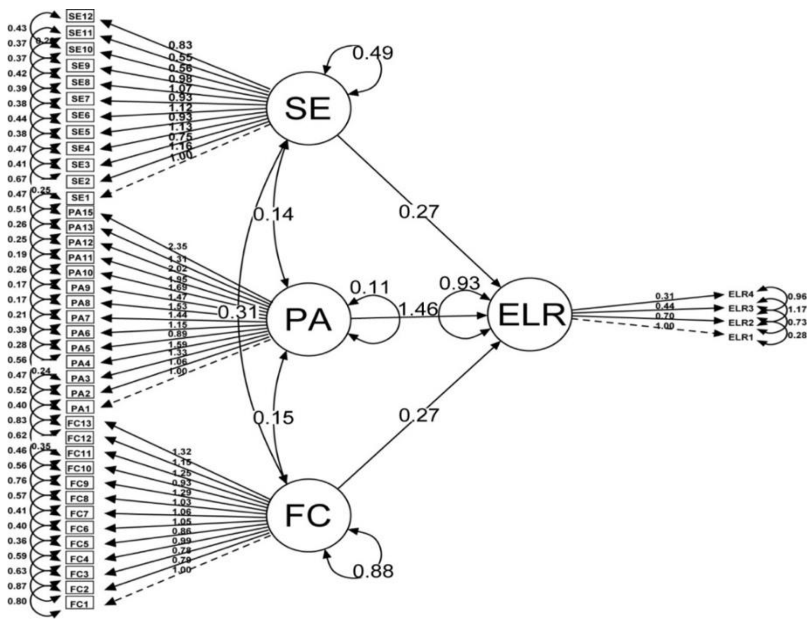

Fig. 3. Path diagram of SEM and unstandardized estimates

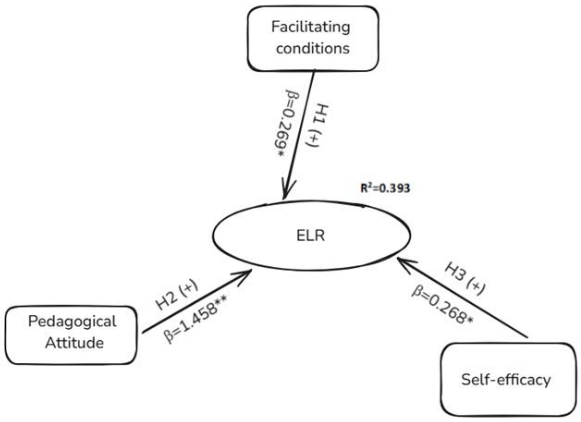

Fig. 4. Proposed research model, reflecting the hypotheses tested in the study

6. Discussion and implications

The study aimed at examining the impact of SE, PA, and FC on ELR of academic staff. The proposed model, while integrating elements from various technology adoption frameworks, did not fully adhere to any single pre-existing model, allowing for a more context-specific and targeted inclusion of variables. The findings from the CFA indicated that the model explains 52% of the variance in the key factors influencing ELR suggesting the scope for inclusion of other variables. Moreover, SEM demonstrated that approximately 39.3% of the variance in ELR could be accounted for by the factors incorporated into the model. These findings suggest that FC, SE, and PA collectively provide a meaningful explanation of ELR, although their effects on ELR vary in magnitude.

The FC factor in this study reflects academic staff's perceptions of the essential physical and digital resources required for effective implementation of e-learning. The path coefficients derived from the analysis indicate a significant positive relationship between FC and overall ELR, suggesting that improvements in infrastructure—such as internet connectivity, hardware availability, and institutional support systems—are strongly associated with enhanced ELR. Supporting this, Asamoah et al. (2024) found that FC positively and significantly influences the actual use of Learning Management Systems (LMS) by faculty members. Similarly, previous research has highlighted the significance of dependable infrastructure and support mechanisms in facilitating ELR, with Selim (2007) noting that internet accessibility and support systems significantly impact the adoption of e-learning. Furthermore, Chatterjee and Bhattacharjee (2020) concluded that FC positively influences the attitudes of both teachers and students, leading to favorable intentions toward adopting technologies such as Artificial Intelligence (AI) and Moodle in higher education. In contrast, Alammary et al. (2022) found no statistically significant influence of FC on academics' intentions to adopt e-learning solutions, though they noted that FC had a more pronounced positive impact on the behavioral intentions of female academic staff compared to male staff. Additionally, Mohan et al. (2020) reported that FC did not significantly influence students' behavioral intentions to use Massive Open Online Courses (MOOCs).

PA reflects academic staff's positive or negative perceptions regarding the design, delivery, and assessment of e-learning. The path coefficients associated with PA highlight its influence on the readiness of the system to transition to e-learning. A strong, positive coefficient underscores the critical role that pedagogical preparedness plays in determining e-learning success. The results of this study demonstrate that PA has the most significant contribution to ELR, indicating that instructors' pedagogical aspects are more influential in defining their ELR compared to SE and FC. These findings align with prior research, which suggests that instructor attributes have a greater influence on user satisfaction in e-learning contexts (Daultani et al., 2021; Pham et al., 2019). Alammary et al. (2022) also concluded that attitudes toward e-learning and self-efficacy positively affect the behavioral intention to adopt e-learning. Similarly, Siddiqui et al. (2023) argued that improving teachers' attitudes and readiness for the integration of technology not only helps alleviate technostress but also enhances the use of technology in educational settings. Tayyib et al. (2020) and Khasawneh (2025) recommended that enhancing faculty members' familiarity with information and technology systems would foster a more positive attitude toward e-learning, suggesting that institutional efforts to increase exposure to e-learning practices are crucial. Aspects such as having a positive attitude toward using computers and the internet, improving teaching quality through educational technology, and adopting new teaching methods are critical components in shaping instructors' pedagogical attitudes (Eslaminejad et al., 2010; Safarifard et al., 2024). However, Sadik (2007) noted that faculty members with modest technical and pedagogical competencies and limited e-learning experience, despite having a positive attitude toward e-learning, showed limited interest in developing and delivering e-learning courses, primarily due to the lack of institutional support and encouragement.

SE, often considered a key aspect of technology readiness, refers to individual's belief in their ability to effectively use e-learning platforms, software, and applications. It also encompasses users' proficiency and confidence in utilizing technological tools. The significant paths identified between SE and ELR highlight the central role that technological competence plays in determining readiness, emphasizing significance of user friendly and accessible platforms. Çınar et al. (2021) found that even when teachers displayed high self-efficacy regarding their use of technology, they often exhibited a neutral attitude toward e-learning. This ambivalence may stem from limited familiarity with e-learning tools or organizational cultural factors. Similarly, Siddiqui et al. (2023) observed that lower self-efficacy among teachers exacerbates technostress, potentially leading to increased burnout and attrition within the profession. Eslaminejad et al. (2010) further concluded that both technological and pedagogical competencies significantly influence the ELR of instructors. In a related study, Vanitha & Alathur (2021) noted that while learners' internet self-efficacy was relatively high, their computer self-efficacy remained inadequate, which negatively impacted their ELR, particularly within academic contexts. Ogbodoakum et al. (2022) concluded that faculty members who are confident in their ability to use the online learning method and have perception of benefit would accept the online learning method in teaching and learning when compared to others. Agariya and Singh (2012) highlighted that faculty expertise and perceptions of student engagement significantly influence e-learning quality.

Thus, undertaking technology integration readiness assessment studies in HEI's has become quintessential globally (Chou et al., 2019; Khasawneh, 2025; Shard et al., 2024). While the study is grounded in J & K, by including the factors and indicators collated from various globally accepted frameworks rather than adhering to any single one, the study contributes to extending its implications beyond geographical boundaries (Alammary et al., 2022; Al-Araibi et al., 2019; Alshammari & Adaileh, 2018; Bhardwaj et al., 2021; Egielewa et al., 2022; Hoq, 2020; Majid & Lakshmi, 2024; Shard et al., 2024; Zine et al., 2023).

The proposed model strongly establishes that ELR cannot be evaluated solely on basis of any one single factor. Instead, it signifies the importance of FC, PA, SE and their interdependence on ELR of academic staff. Hence, HEI's globally should focus on all on these factors in a holistic way rather than adopting a piece meal approach. Comparable context have been noted elsewhere with reference to these factors. FC was found to be a significant factor of ELR not only in J & K but also in other parts of India (Chatterjee & Bhattacharjee, 2020) and other countries like Ghana (Asamoah et al., 2024), USA (Venkatesh et al., 2003). Among the academic staff of J & K, their PA had the strongest relationship with ELR and it was also found to be significant influencer in case of students in India (Daultani et al., 2021). Similar findings regarding the importance of PA were found in Egypt (Sadik, 2007), Sauid Arabia (Alammary et al., 2022; Tayyib et al., 2020), Ghana (Asamoah et al., 2024), Iran (Eslaminejad et al., 2010), Nigeria (Nwagwu, 2020), Vietnam (Pham et al., 2019) re-emphasizing its importance. SE just like other factors resonate the ELR dimensions considered globally in various studies. The studies carried out globally in United Kingdom (Al-Fraihat et al., 2020), Iraq (Al-Rikabi & Montazer, 2024), Turkey (Demir & Yurdugül, 2015), Iran (Farazkish & Montazer, 2019), Sauid Arabia (Alammary et al., 2022), Morocco (Meriem & Youssef, 2020), Iran (Eslaminejad et al., 2010), Nigeria (Ogbodoakum et al., 2022), India (Agariya & Singh, 2012) have also confirmed that efficiency to use and deal with technological systems is significant and necessary for e-learning adoption. Thus, the findings of the current study not only parallel the importance of identified factors of ELR as documented for higher education across developing countries but also contributes to the global debates on ELR of academic staff and provides practical insights that are transferable to other regions striving for digital transformation in higher education.

7. Conclusion

The findings of this study have important global implications for e-learning readiness in higher education. By emphasizing the role of facilitating conditions, self-efficacy, and pedagogical attitude, this research provides a transferable framework applicable across diverse cultural and institutional contexts. It highlights the universal need for robust infrastructure, capacity-building initiatives, and adaptive teaching practices to ensure effective e-learning integration. Furthermore, the study's focus on context-specific challenges, such as those faced by academic staff in Jammu and Kashmir, underscores the importance of tailoring e-learning strategies to local needs, a lesson that can guide policy development in other regions facing similar socio-educational disparities.

The proposed model examined the factors influencing ELR, raising awareness among academic staff about the critical elements that should be considered to enhance their ELR. By improving their pedagogical attitude and self-efficacy towards e-learning, academic staff can better leverage the benefits of technology integration. Additionally, the study highlights the responsibility of HEIs to enhance facilitating conditions, which have a strong and direct impact on SE and PA.

8. Limitations and recommendations for future research

Inclusion of the academic staff from different academic streams, locations and types of HEIs enhanced the generalizability of findings but still some limitations remain. Our study is exploratory in nature and focused on group measurements and less emphasis on individual aspects remains its limitation. To cover this, future studies can include interviews and focus group discussions to gain in-depth information and explore complex issues of E-learning.

E-learning acceptance is evolving and hence undertaking longitudinal studies can contribute to study its changing aspects. The findings of the present study are generalizable to other developing countries, however, understanding the external aspects like the higher education ecosystem, the level of technological advancements while exploring ELR of academic staff in other regions (Zine et al., 2023) can contribute to additional novel findings. New research can also consider studying the moderating effect of various demographic variables on ELR. Additionally, studies examining the post-adoption behavior of academic staff could provide valuable insights, especially for those with low levels of ELR, thereby contributing to strategies that enhance ELR. With the increasing adoption of blended learning approaches in HEI's, future research could also explore feasibility of implementing mandatory policies for technology adoption by academic staff.

Author Statement

The authors declare that there is no conflict of interest.

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