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Adoption intention towards Open Educational Resources: Role of experience, digital divide and voluntariness

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ABSTRACT

The digitalization of higher education has brought more opportunities and challenges to private higher education institutions (HEIs). Based on the Chinese private HEIs, this study aims to 1) examine how performance expectancy, effort expectancy, social influence, and facilitating conditions influence the adoption intentions of lecturers, and 2) to analyze the moderating roles of experience and the digital divide, 3) to validate the mediating effect of voluntariness. This research was collected from 750 lecturers in private HEIs across major regions in China within a random sampling method. Structural equation modeling (SEM) was applied to analyze the data, revealing that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly predict OER adoption intentions. Experience positively moderates these relationships by enhancing adoption intentions, whereas the digital divide negatively moderates them, limiting lecturers' adoption intentions. Voluntariness was identified as a significant mediator, particularly strengthening the relationship between social influence, facilitating conditions, and adoption intentions. These findings suggest that addressing digital competency gaps and enhancing support for voluntary OER use could facilitate wider adoption in private HEIs, providing valuable insights for policymakers to develop tailored strategies that promote digital resource integration and educational innovation.

Keywords: Adoption intention, digital divide, digital education, educational technology management, education management, open educational resources, private higher education institutions.

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INTRODUCTION

With the rapid global advancement of digital transformation, significant shifts have occurred across various educational domains (Mohamed Hashim et al., 2022). Open Educational Resources (OER) have emerged as a central component in enhancing educational quality and equitable access to resources (Laufer et al., 2021). As freely accessible and adaptable educational materials, OER promotes an open-sharing culture, allowing educators and learners to engage with digital content more flexibly (Mncube et al., 2024). Globally, digital education is increasingly recognized as a crucial approach to achieving universal and lifelong learning goals, fostering a shift from traditional, instructor-centered models to collaborative, learner-centered environments (Chandra et al., 2024).

In China, the integration of OER and digital education initiatives has become fundamental to the development of private higher education institutions (HEIs) (Qi, 2022). According to the Ministry of Education, China has approximately 764 private HEIs, employing over 400,000 full-time faculty and enrolling more than 3 million students, underscoring the significant role of private institutions within the national education system (Qi, 2022). Through the adoption of OER, private HEIs are progressively bridging gaps with public institutions, aiming to enhance resource accessibility and educational quality (Wawak et al., 2024).

Despite its potential, the adoption of OER in Chinese private HEIs faces numerous challenges, including financial constraints, limited technological infrastructure, and a lack of digital proficiency among educators (Zou et al., 2021). Additionally, a pronounced digital divide, characterized by disparities in digital skills and technology accessibility, hinders the consistent use of OER across institutions (Kormos and Wisdom, 2023). This divide impacts teachers' capacity to adapt and utilize digital resources effectively.

To address these barriers, the Chinese government has introduced several policy initiatives aimed at advancing educational informatization and supporting the digital transformation of private HEIs. Notable policies, such as the Ministry of Education’s 2023 "Undergraduate Education Program Optimization and Adjustment Reform Plan," emphasize the creation of a high-quality talent development system by 2035, promoting modernized and efficient educational frameworks (Qi and Ning, 2024). The National Smart Education Platform for Primary and Secondary Schools, now hosting 88,000 digital resources and engaging nearly 100 million registered users, exemplifies the growing impact and scope of digital education across the country (Qi and Ning, 2024).

Current research on the adoption and usage behaviors of OER increasingly focuses on evidence related to the teaching community, with theories such as the theory of planned behavior (TPB) (Smirani and Boulahia, 2022; Ahmed et al., 2024), technology acceptance model (TAM) (Tillinghast, 2021). However, the exploration of social cognitive theory (SCT), and various educational technology models are still needed to be validated in this field.

While the significance of OER continues to be emphasized within the context of digital transformation in higher education, the unified theory of acceptance and use of technology (UTAUT) has gradually become recognized as a key theoretical framework for explaining OER adoption behaviors (Almaiah et al., 2019). However, the moderating effects of experience and the digital divide remain relatively underexplored in existing literature. Presently, experience with digital products and the digital divide are considered crucial factors influencing the adoption of OER, particularly within the context of educational technology implementation. These factors directly affect educators' willingness and efficacy in utilizing digital resources (Almaiah et al., 2019).

Therefore, this study seeks to enrich the UTAUT framework by examining the moderating effects of experience and the digital divide, thereby making significant contributions to the theoretical foundations of digital educational technology adoption. This not only helps to achieve a more comprehensive understanding of the behavioral mechanisms behind lecturers' adoption of OER but also provides a theoretical basis for optimizing educational policies and practices. Hence, the objectives of this research are:

(1) To investigate the path of performance expectancy, effort expectancy, social influence, and facilitating conditions influencing lecturers’ intentions to adopt OER within Chinese private HEIs.
(2) To examine the moderating role of experience, the digital divide.
(3) To reveal the mediation role of voluntariness.

Following this introduction, the second section presents a literature review, discussing the theoretical framework, key variables, and hypotheses. The third section details the research methodology, including data collection and analysis procedures. The fourth section covers the research findings, and the fifth section interprets the results with practical implications. The conclusion summarizes the study and suggests avenues for future research.

LITERATURE REVIEW

Theoretical approach

Unified Theory of Acceptance and Use of Technology (UTAUT), is a comprehensive model that integrates constructs from multiple technology acceptance theories to examine technology adoption behaviors (Dwivedi et al., 2019). UTAUT is particularly suitable for exploring the factors that influence technology adoption in educational settings, where variables such as institutional support, digital infrastructure, and individual perceptions play significant roles (Bayaga and du Plessis, 2024). This model identifies four primary constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—that influence lecturers' intentions to adopt OER (Venkatesh et al., 2003). According to UTAUT, performance expectancy refers to the perceived benefits of using technology to improve job performance (Abbad, 2021). In the context of OER, this construct reflects lecturers' beliefs that OER enhances teaching effectiveness and enriches student learning outcomes (McBride and Abramovich, 2022). When lecturers perceive OER as a tool that positively impacts their teaching, they are more inclined to adopt it.

Hypothesis development

Effort expectancy in UTAUT pertains to the perceived ease of using technology (McBride and Abramovich, 2022). For lecturers, the ease with which they can adopt and navigate OER significantly impacts their willingness to use it (Marks and Thomas, 2022). If lecturers find OER platforms intuitive and require minimal learning effort, they are more likely to integrate these resources into their teaching practices. Social influence refers to the degree to which individuals feel that significant others—such as colleagues, administrators, and institutional leaders—expect them to use a specific technology (Cao et al., 2021). In the context of OER, lecturers are more likely to adopt these resources if they perceive strong institutional support and encouragement from peers.

Facilitating conditions include the availability of resources and support that assist individuals in using technology effectively (Faqih and Jaradat, 2021). For lecturers, this includes access to digital infrastructure, technical support, and professional development opportunities (Uzorka et al., 2023). When such conditions are robust, lecturers are better positioned to adopt OER.

The concept of voluntariness, or perceived voluntariness, is integral to UTAUT's model, affecting technology adoption by enhancing lecturers' willingness to engage with OER (Uzorka et al., 2023). Each primary UTAUT construct influences voluntariness, shaping lecturers' sense of voluntariness in their decision to use OER. Voluntariness also functions as a mediating factor in this study. When lecturers feel autonomous in their decision-making, they are more motivated to adopt OER, reinforcing the influence of each primary construct. Therefore, the following hypotheses are proposed. H1: Performance expectancy positively affects the intention to use OER. Accordingly, the following hypotheses are proposed:

H1: Performance expectancy positively affects the intention to use OER.
H2: Effort expectancy positively affects the intention to use OER.
H3: Social influence positively affects the intention to use OER.
H4: Facilitating conditions positively affect the intention to use OER.
H5: Performance expectancy positively affects voluntariness.
H6: Effort expectancy positively affects voluntariness.
H7: Social influence positively affects voluntariness.
H8: Facilitating conditions positively affect voluntariness

Voluntariness within the UTAUT framework refers to the perception that the adoption of a technology is a self-determined choice rather than an imposed requirement (Osei et al., 2022). UTAUT posits that voluntariness mediates the influence of core constructs (such as performance expectancy, effort expectancy, social influence, and facilitating conditions) on users' intention to adopt new technologies (Hsu, 2023). This mediating effect has been empirically validated in digital education technologies, particularly in the adoption of e-learning systems, learning management platforms (LMS), and MOOCs, where educators' voluntary engagement has proven to enhance adoption rates (Al-Nuaimi et al., 2024). When lecturers perceive that using OER is driven by their own volition, rather than external mandates, they are more likely to see it as beneficial and aligned with their teaching objectives (Buerkle et al., 2023). Accordingly, the following hypotheses are proposed:

H9: Voluntariness mediates the relationship between performance expectancy and intention to use OER.
H10: Voluntariness mediates the relationship between effort expectancy and intention to use OER.
H11: Voluntariness mediates the relationship between social influence and intention to use OER.
H12: Voluntariness mediates the relationship between facilitating conditions and intention to use OER.
H13: Voluntariness positively affects intention to use OER.

Experience significantly influences how users perceive and utilize these resources, acting as a key moderating variable within the Unified Theory of Acceptance and Use of Technology (UTAUT) (Bayaga and du Plessis, 2024). Lecturers with prior experience in educational technology exhibit higher performance expectancy, as they tend to view OER as enhancing teaching effectiveness by supporting diverse instructional methods (Lakhal and Khechine, 2021). Furthermore, the positive influence of effort expectancy on adoption intention is stronger among experienced lecturers, who typically find OER platforms more intuitive and less challenging, reducing potential barriers to integration (Ly et al., 2024).

Social influence also has a heightened effect on experienced educators, as peer recommendations and institutional endorsements are more impactful among those with established professional networks and identities, aligning with findings that experienced individuals are more responsive to social cues in their adoption behaviors (Al Halbusi et al., 2023). Additionally, facilitating conditions, such as access to technical support and institutional resources, are better utilized by experienced lecturers, who can more effectively navigate and apply these resources to their teaching contexts (Turnbull et al., 2021). Collectively, these insights highlight how experience enhances the relationships between performance expectancy, effort expectancy, social influence, and facilitating conditions with the intention to adopt OER. Accordingly, the following hypotheses are proposed:

H14: Experience positively moderates the relationship between performance expectancy and intention to use OER.
H15: Experience positively moderates the relationship

between effort expectancy and intention to use OER.
H16: Experience positively moderates the relationship between social influence and intention to use OER.
H17: Experience positively moderates the relationship between facilitating conditions and intention to use OER.

The digital divide, defined as the gap in access to and proficiency with information and communication technologies (ICT), presents significant barriers in the educational landscape, often exacerbating disparities in technology adoption and utilization (Li, 2024). In the context of educational technology, this divide has been shown to influence users' behavioral intentions by impacting their access to resources, digital skills, and overall comfort with technology (Huang et al., 2023). A pronounced digital divide can diminish the perceived benefits (performance expectancy) of Open Educational Resources (OER), as limited access to digital tools may hinder their ability to realize OER's potential advantages in teaching (Reddick et al., 2020). Furthermore, digital inequalities often lead to a heightened perception of complexity, thereby negatively moderating the relationship between effort expectancy and adoption intention by making OER appear less accessible to those lacking robust digital resources (Singh et al., 2023).

The digital divide also affects social influence, as educators in low-access environments may find it harder to engage with professional networks that endorse OER, weakening the motivational effect of peer support and institutional encouragement on their adoption intentions (Kormos and Wisdom, 2023). Finally, the role of facilitating conditions, such as institutional support and infrastructure, is less effective in promoting adoption among those significantly impacted by the digital divide, as access limitations may prevent these educators from fully utilizing available resources (Soomro et al., 2020). Hence, this study proposes:

H18: Digital divide negatively moderates the relationship between performance expectancy and intention to use OER.
H19: Digital divide negatively moderates the relationship between effort expectancy and intention to use OER.
H20: Digital divide negatively moderates the relationship between social influence and intention to use OER.
H21: Digital divide negatively moderates the relationship between facilitating conditions and intention to use OER.

Combined with the above content, Figure 1 embodies the empirical mode.

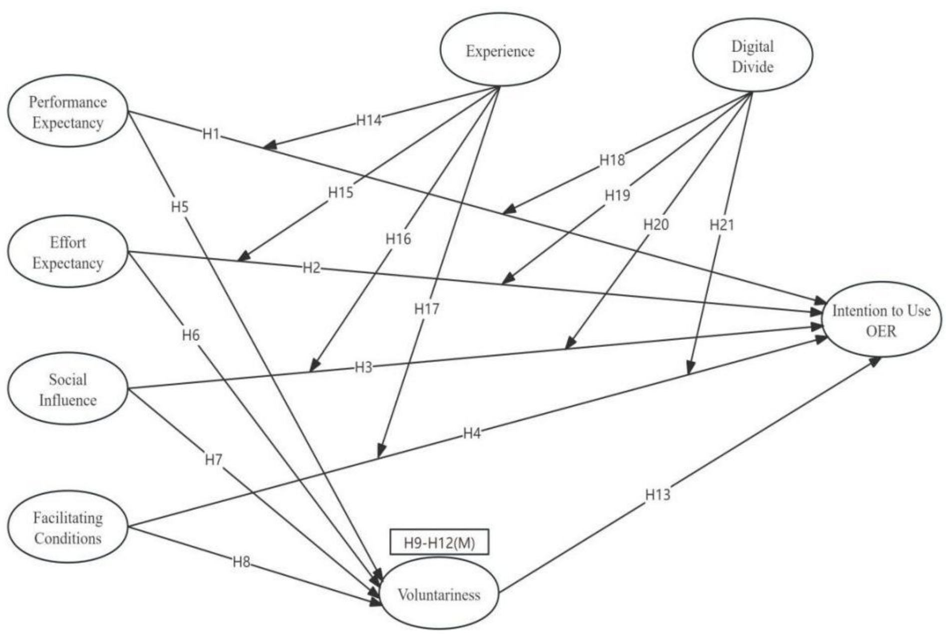

Figure 1. The empirical framework of the study.

RESEARCH METHOD

This study uses an online survey to investigate the lecturers from various private higher education institutions (HEIs) across China. The questionnaire was distributed across several institutions, including Shandong Xiehe

University, Jilin International Studies University, Zhuhai College of Science and Technology, and Zhejiang Shuren University, which are among the top 10 private HEIs. The selection of these institutions was guided by several strategic considerations. First, these universities were chosen to represent diverse regions across China, ensuring a broad geographical distribution and capturing the varied cultural contexts of private HEIs in the country. This approach enhances the representativeness of the study's findings, allowing for more generalized insights into the adoption of Open Educational Resources (OER) across different educational settings. Furthermore, these universities have demonstrated substantial progress in implementing digital education initiatives, making them ideal for investigating factors that influence OER adoption. Additionally, their well-established digital infrastructures align with the study's focus on exploring the impact of digital resources on teaching practices, providing a suitable context to examine the integration of OER in educational environments. The questionnaire was collected over one month through an online survey, ensuring a comprehensive sample to analyze the factors influencing OER adoption intentions among lecturers.

The sample comprises 750 valid responses, with a balanced gender distribution of 47.6% male and 52.4% female. The age distribution within the sample is diverse, with 32.8% of respondents aged between 20-30 years, 31.7% between 31-40 years, 29.7% between 40-59 years, and 5.7% aged 60 and above. Regarding educational qualifications, a majority of the respondents hold advanced degrees, with 58.8% having a master's degree and 32.7% holding a doctorate. The sample also includes lecturers from multiple private HEIs, ensuring institutional diversity. Notably, 13.9% of respondents are from Zhejiang Yuexiu University, followed by 13.3% from Zhuhai College of Science and Technology, and 13.1% from Zhejiang Shuren University. This distribution across institutions contributes to a well-rounded analysis of factors influencing OER adoption across diverse private HEIs.

Table 1. Sample information.

Information and options		**Frequency**	**Percent**
Gender	Male	357	47.6
	Female	393	52.4
Age	20-30	246	32.8
	31-40	238	31.7
	40-59	223	29.7
	60 and above	43	5.7
Education level	Bachelor's degree	64	8.5
	Master's degree	441	58.8
	Doctorate	245	32.7
Private HEIs	Shandong Xiehe University	93	12.4
	Jilin International Studies University	88	11.7
	Zhuhai College of Science and Technology	100	13.3
	Zhejiang Shuren University	98	13.1
	Qilu Institute of Technology	96	12.8
	Weifang University of Science and Technology	92	12.3
	Xijing University	79	10.5
	Zhejiang Yuexiu University	104	13.9

Instrument

Appendix 1 shows the details of the measurement. Performance expectancy is defined as lecturers' beliefs regarding the benefits of OER for improving teaching effectiveness. This section included four items adapted from Boidou et al. (2023), which captured respondents' views on the potential for OER to enhance instructional quality and learning outcomes. Effort Expectancy, which evaluates the perceived ease of using OER in teaching.

Four items also adapted from Boidou et al. (2023), measured this construct by examining respondents' perceptions of the user-friendliness and accessibility of OER resources, indicating how easily lecturers felt they could integrate OER into their teaching routines. Social Influence, or the degree to which lecturers felt encouraged by peers, administrators, or institutional policies to adopt OER. This section, which included four items adapted from Boidou et al. (2023), explored the extent of social and institutional pressures influencing OER adoption, capturing the role of supportive environments and professional networks. Facilitating Conditions, which encompass the resources and support available to lecturers for effective OER use. This section included three items adapted from Boidou et al. (2023), focusing on the presence of digital infrastructure, technical assistance, and institutional support that could ease the adoption process.

Voluntariness examined lecturers' sense of voluntariness in the decision to adopt OER. With four items adapted from Bervell et al. (2021), this section assessed whether lecturers felt they had the freedom to choose OER independently or whether they felt obligated, capturing their intrinsic motivation.

Experience measurement includes six items, adapted from Dziewanowska and Kacprzak (2023) explored respondents' familiarity with digital educational resources, assessing their confidence in using these tools and the ease with which they could adapt to OER. Digital divide, which encompasses issues related to access to technology and digital literacy gaps among lecturers. Six items adapted from Singh et al. (2023) captured challenges such as connectivity limitations and skill disparities that may hinder effective OER usage. Intention to Use OER, focusing on lecturers' likelihood of adopting these resources in their teaching. This section, with six items adapted from Adedoyin and Altinay (2023), evaluated the general attitude and inclination towards OER integration, reflecting the participants' motivation to engage with digital educational resources.

Data analysis tool

To ensure measurement reliability and validity, a pilot test was first conducted. Descriptive statistics and reliability analyses were performed to assess the internal consistency of each scale. The pilot test results confirmed that the instrument had high internal consistency (Cronbach's alpha > 0.7) and construct validity. The confirmatory factor analysis (CFA) within a structural equation modeling (SEM) framework further validated the measurement model, confirming good model fit (KMO = 0.821, Bartlett's test $p < 0.001$). Finally, SEM path analysis was applied to examine the hypothesized relationships among constructs, alongside moderation effect tests to evaluate the influence of experience and digital divide on OER adoption intentions.

RESULTS

Prior to conducting the main study, a pilot test involving 35 valid responses was performed to evaluate the clarity, reliability, and validity of the questionnaire items. The questionnaire was collected over one month through an online survey. Reliability analysis, assessed through Cronbach's alpha, showed strong internal consistency across the study's variables, with values exceeding the accepted threshold of 0.7, indicating robust reliability. For instance, Cronbach's alpha for the variable "Intention to Use OER" reached 0.925, confirming high consistency within this construct. Additionally, validity was supported by a Kaiser-Meyer-Olkin (KMO) measure of 0.757 and a significant Bartlett's test of sphericity, indicating the data's suitability for factor analysis and confirming adequate sampling adequacy for the constructs under study. These findings validate the instrument's effectiveness in capturing the intended constructs, ensuring reliable data collection for the main study.

Reliability test

Table 2 presents the Cronbach's alpha coefficients for each variable measured in this study, which explores the factors influencing lecturers' intentions to adopt Open Educational Resources (OER). Cronbach's alpha was calculated to assess the internal consistency of each construct, with values above 0.7 considered acceptable for indicating reliable measurement. These coefficients reflect the degree to which items within each construct consistently capture the same underlying attribute, thereby ensuring the reliability of the survey instrument. In this analysis, the variables performance expectancy, effort expectancy, social influence, voluntariness, experience, digital divide, and intention to use OER all demonstrate strong internal consistency, with Cronbach's alpha values ranging from 0.819 to 0.895. This suggests robust reliability across these constructs. Notably, Intention to Use OER exhibits the highest reliability, with a Cronbach's alpha of 0.895, indicating high internal consistency among items measuring lecturers' intent to adopt OER. The Facilitating Conditions variable, with a Cronbach's alpha of 0.785, falls slightly below the other constructs yet remains within the acceptable range. This slightly lower alpha may be due to the smaller number of items (three) under this construct, as Cronbach's alpha typically increases with a greater number of items. Overall, the reliability analysis confirms that the survey items are well-suited for consistently measuring the constructs central to this study's objectives.

Table 2. Reliability statistics.

Study variables	Number of questions	Cronbach's α
Performance expectancy	4	0.837
Effort expectancy	4	0.819
Social influence	4	0.840
Facilitating conditions	3	0.785
Voluntariness	4	0.836
Experience	6	0.828
Digital divide	6	0.830
Intention to use OER	6	0.895

Validity analysis

Table 3 presents the results of the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity, two essential tests used to determine the suitability of the dataset for factor analysis in this study on lecturers' adoption intentions towards Open Educational Resources (OER). The KMO test yielded a value of 0.922, which is well above the threshold of 0.9, indicating a high level of sampling adequacy. This suggests that the variables in the dataset are sufficiently interrelated, making it appropriate for factor analysis to identify underlying structures. Additionally, Bartlett's Test of Sphericity complements the KMO measure by testing whether the correlation matrix is an identity matrix, which would indicate that the variables are unrelated. In this study, Bartlett's test produced a chi-square statistic of 21912.496 with 666 degrees of freedom and a significance level of 0.000. This result decisively rejects the null hypothesis, confirming significant intercorrelations among the variables. Together, these findings validate the dataset's suitability for factor analysis, allowing for the extraction of meaningful factors relevant to the study's objectives.

Table 3. KMO and Bartlett's test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.922
Bartlett's Test of Sphericity	Approx. Chi-Square	21912.496
	df	666
	Sig.	0.000

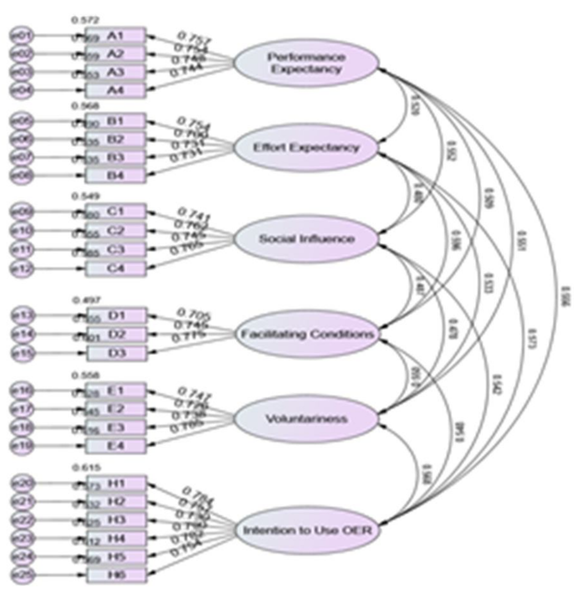

Figure 2. Measurement model.

Measurement model

Figure 2 illustrates a measurement model within the confirmatory factor analysis framework.

Table 4 presents the fit indices used to assess the measurement model's adequacy within the Structural Equation Modeling (SEM) framework, examining constructs related to lecturers' intentions to adopt Open Educational Resources (OER). Each fit index plays a critical role in verifying the model's compatibility with the observed data. The chi-square to degrees of freedom ratio (χ^2/df) is 1.487, well below the threshold of 3, indicating an excellent fit between the model and the data. The Root Mean Square Error of Approximation (RMSEA) is 0.025, below the 0.08 benchmark, which signifies a close fit with minimal error variance. Further indices include the Goodness of Fit Index (GFI) and the Adjusted Goodness of Fit Index (AGFI), with values of 0.962 and 0.952, respectively, both exceeding the 0.9 standard. These values confirm a strong model fit by indicating that the model explains a substantial proportion of variance in the observed data. Incremental fit indices, including the Normed Fit Index (NFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI), yielded values of 0.957, 0.983, and 0.986, respectively, each surpassing the 0.9 threshold. These high values suggest that the specified model significantly improves over the baseline model, validating the theoretical structure for understanding OER adoption intentions among lecturers.

Table 4. Measure model fit index.

Fit index	χ2/df	RMSEA	GFI	AGFI	NFI	TLI	CFI
Reference standards	<3	<0.08	>0.9	>0.9	>0.9	>0.9	>0.9
Result	1.487	0.025	0.962	0.952	0.957	0.983	0.986

Table 5 presents the assessment of convergent validity for the latent variables in this study on lecturers' adoption intentions toward Open Educational Resources (OER), conducted through confirmatory factor analysis. Convergent validity, which assesses the extent to which indicators for a construct are related, was evaluated using factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE).

The factor loadings for each indicator exceed the recommended threshold of 0.7, indicating strong associations between the observed variables and their respective latent constructs. For example, the factor loadings for Performance Expectancy range from 0.744 to 0.757, demonstrating that the observed variables effectively represent the underlying construct. Such consistently high loadings confirm that the indicators are reliable measures of their corresponding latent variables. In addition to factor loadings, the Composite Reliability (CR) values for all constructs exceed the 0.7 threshold, supporting internal consistency within each set of indicators. For instance, Intention to Use OER exhibits a CR of 0.895, indicating strong reliability across its items. This high CR reinforces the reliability of each latent construct in capturing the intended dimensions of OER adoption intentions.

The Average Variance Extracted (AVE) values for all constructs surpass the 0.5 benchmark, suggesting that each latent variable explains a substantial portion of the variance in its indicators. For example, Intention to Use OER has an AVE of 0.588, signifying that 58.8% of the variance in the observed indicators is accounted for by the latent variable. These AVE values confirm that the constructs in the measurement model capture a considerable amount of variance in their indicators, thereby establishing strong convergent validity for the model.

Table 6 presents the results of the discriminant validity test for the latent variables in this study, which examines factors influencing lecturers' intentions to adopt Open Educational Resources (OER). Discriminant validity, an essential aspect in Structural Equation Modeling (SEM), confirms that each construct is distinct and measures a unique concept. In this analysis, discriminant validity is assessed by comparing the square root of the Average Variance Extracted (AVE) for each construct (displayed on the diagonal) with the inter-construct correlations (off-diagonal elements). For adequate discriminant validity, the square root of the AVE for each construct should be greater than the correlations it shares with other constructs. The diagonal values in Table 6, such as 0.751 for Performance Expectancy and 0.767 for Intention to Use OER, exceed the corresponding off-diagonal correlation values in their respective rows and columns, meeting the criterion for discriminant validity. For example, the square root of the AVE for Performance Expectancy (0.751) is higher than all its correlations with other constructs, which range from 0.520 to 0.556. Similarly, Intention to Use OER has a square root AVE of 0.767, surpassing all its correlation values with other constructs. This pattern is consistent across all constructs, confirming that each construct shares more variance with its own items than with those of other constructs, thereby affirming the discriminant validity and uniqueness of each construct within the measurement model.

Table 5. Convergence validity.

Latent variables	Observation indicators	Factor loading	CR	AVE
Performance expectancy	A1	0.757	0.838	0.564
	A2	0.754		
	A3	0.748		
	A4	0.744		
Effort expectancy	B1	0.754	0.819	0.532
	B2	0.700		
	B3	0.731		
	B4	0.731		
Social influence	C1	0.741	0.840	0.568
	C2	0.762		
	C3	0.745		
	C4	0.765		
Facilitating conditions	D1	0.705	0.786	0.551
	D2	0.745		
	D3	0.775		
Voluntariness	E1	0.747	0.837	0.562
	E2	0.726		
	E3	0.738		
	E4	0.785		
Intention to use OER	H1	0.784	0.895	0.588
	H2	0.757		
	H3	0.730		
	H4	0.790		
	H5	0.782		
	H6	0.754		

Table 6. Discriminant validity test.

Latent variables	A	B	C	D	E	H
Performance expectancy	0.751					
Effort expectancy	0.520	0.729				
Social influence	0.552	0.480	0.754			
Facilitating conditions	0.509	0.596	0.487	0.742		
Voluntariness	0.551	0.533	0.478	0.550	0.750	
Intention to use OER	0.556	0.573	0.542	0.548	0.568	0.767

Note: The diagonal is the square root of the corresponding dimension AVE.
A: Performance Expectancy; B: Effort Expectancy; C: Social Influence; D: Facilitating Conditions; E: Voluntariness; H: Intention to Use OER.

Structural equation model

Table 7 presents the fit indices for the structural model within the Structural Equation Modeling (SEM) framework, assessing the relationships among latent variables that influence lecturers' intentions to adopt Open Educational

Resources (OER). χ²/df=1.487 (<3) is generally considered acceptable. RMSEA=0.025 (<0.08) is generally indicative of a good fit, and confirms a close fit between the model and the observed data, indicating minimal error variance. The Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI) further demonstrate the model's adequacy in explaining the observed variance, with values of 0.962 and 0.952, respectively. Both indices surpass the 0.9 benchmark, confirming the model's suitability and indicating a strong proportion of variance explained.

Incremental fit indices, including the Normed Fit Index (NFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI), were also examined. With NFI at 0.957, TLI at 0.983, and CFI at 0.986, each index exceeds the accepted threshold of 0.9, signifying that the model offers a substantial improvement over a baseline null model. Collectively, these fit indices affirm that the structural model provides an accurate representation of the relationships among the constructs related to OER adoption intentions.

Table 7. Model fit index.

Fit index	**χ2/df**	**RMSEA**	**GFI**	**AGFI**	**NFI**	**TLI**	**CFI**
Reference standards	<3	<0.08	>0.9	>0.9	>0.9	>0.9	>0.9
Result	1.487	0.025	0.962	0.952	0.957	0.983	0.986

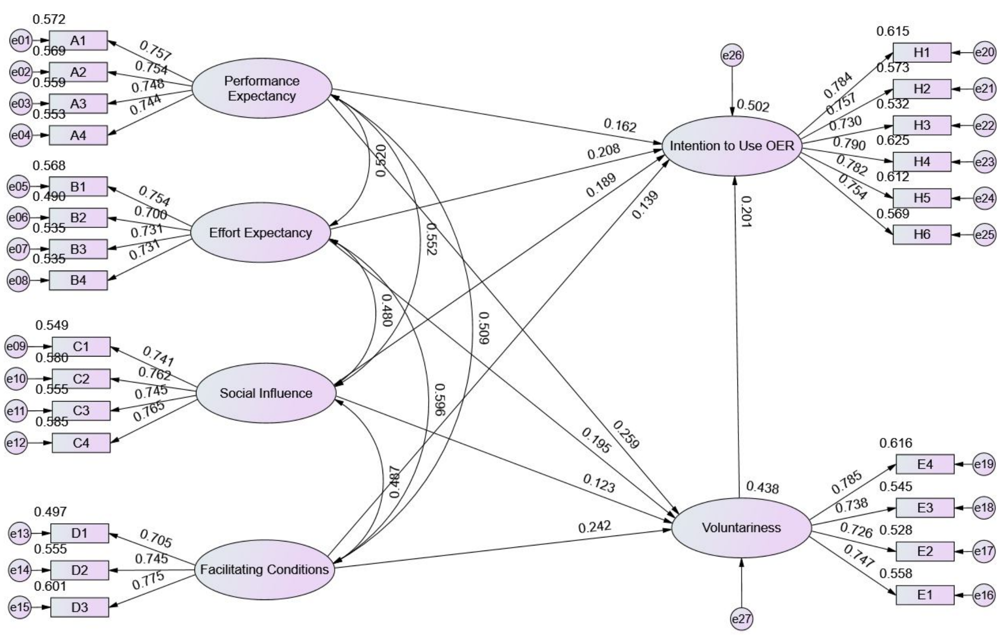

Figure 3. Structural model.

Figure 3 illustrates the structural equation model and path analysis diagram.

Table 8 presents the results of the path analysis conducted within the structural equation model (SEM) framework to examine the direct effects among constructs influencing lecturers' intentions to adopt Open Educational Resources (OER). The unstandardized path coefficients (Estimate) represent the direct effect of one construct on another, while the standardized coefficients (β) allow for comparisons across different paths by standardizing effect sizes. The Standard Error (S.E.) provides an indication of variability in the estimate, reflecting the precision of each path coefficient. The Critical Ratio (C.R.), calculated as the path coefficient divided by its standard error serves as a z-score for hypothesis testing. C.R. >1.96 suggests statistical significance at the 95% confidence level, with p-values below 0.05 indicating significant paths. For all tested hypotheses (H1 to H9), the C.R. values exceed this threshold, and p-values marked with *** denote significance levels below 0.001, confirming strong support for these relationships. The results affirm that constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions have significant positive effects on both voluntariness and intention to use OER. Furthermore, the positive direct effect of voluntariness on intention to Use OER supports its hypothesized mediating role, substantiating the theoretical framework of this study.

Table 8. Direct path effects.

Hypothesis	Path	Estimate	β	S.E.	C.R.	P	Results
H1	A→H	0.158	0.162	0.047	3.376	***	Accepted
H2	B→H	0.200	0.208	0.048	4.209	***	Accepted
H3	C→H	0.191	0.189	0.045	4.208	***	Accepted
H4	D→H	0.148	0.139	0.054	2.738	0.006	Accepted
H5	A→E	0.249	0.259	0.050	4.993	***	Accepted
H6	B→E	0.185	0.195	0.051	3.636	***	Accepted
H7	C→E	0.123	0.123	0.049	2.518	0.012	Accepted
H8	D→E	0.252	0.242	0.058	4.369	***	Accepted
H9	E→H	0.205	0.201	0.048	4.242	***	Accepted

Table 9 presents the results of the mediation effect bootstrap test, a non-parametric approach used to assess the indirect effects of various predictors on the intention to use Open Educational Resources (OER), with voluntariness (E) serving as the mediator in the model. This method evaluates how predictor variables influence the outcome variable through an intermediate path, quantifying the strength and significance of these indirect effects. The Effect Size column indicates the magnitude of each mediation effect, calculated as the product of the path coefficients from the independent variable to the mediator (AT) and from the mediator to the dependent variable (Intention to Use OER). A larger effect size suggests a stronger mediating role of Voluntariness in facilitating the relationship between the predictor and the outcome variable. The Standard Error (SE) reflects the variability of each effect size estimate, crucial for assessing reliability and forming confidence intervals. The Bias-Corrected 95% Confidence Interval (CI) provides a range of values adjusted for estimation bias, indicating the likely bounds within which the true effect size lies. A CI that excludes zero implies statistical significance at the 0.05 level, supporting the respective mediation hypothesis. In Table 9, all mediation paths (H10 through H13) demonstrate confidence intervals that do not include zero, confirming the significance of these indirect effects and supporting the hypotheses.

Table 9. Mediation effect bootstrap test.

Hypothesis	Mediation path	Effect size	SE	Bias-Corrected 95%CI		Results
H10	PU→AT→IT	0.051	0.021	0.018	0.107	Accepted
H11	SQ→AT→IT	0.038	0.021	0.009	0.097	Accepted
H12	PE→AT→IT	0.025	0.017	0.001	0.069	Accepted
H13	SE→AT→IT	0.052	0.024	0.013	0.109	Accepted

Note: A: Performance Expectancy; B: Effort Expectancy; C: Social Influence; D: Facilitating Conditions; E: Voluntariness; H: Intention to Use OER.

Table 10 presents the results of the moderation effect analysis, assessing how Experience (F) and Digital Divide (G) influence the relationships between key predictors—Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—and the outcome variable, Intention to Use OER (H). This analysis examines whether the strength of these relationships changes when the moderators vary in level.

The Coeff (Coefficient) column represents the effect size of each interaction term, quantifying the extent to which the relationship between a predictor and the intention to use OER is moderated by Experience or Digital Divide. A positive coefficient implies that as the moderator increases, the effect of the predictor on the outcome variable also strengthens. The Standard Error (SE) provides an estimate of the variability of the coefficient, aiding in the precision assessment of each moderation effect. The T statistic tests the null hypothesis that the coefficient equals zero (indicating no moderation effect), with larger absolute values signifying stronger evidence against the null hypothesis. Significance is determined by the P value, with values below 0.05 indicating statistically significant effects. The Bias-Corrected 95% Confidence Interval (CI) further supports hypothesis testing, with intervals excluding zero confirming the presence of significant moderation.

The analysis reveals that hypotheses H14, H15, H16, H18, H19, and H20 are supported, as their P values are below 0.05, and their confidence intervals exclude zero. This indicates that Experience and the Digital Divide significantly moderate the relationships between these predictors and the intention to use OER. For instance, the path from Performance Expectancy to Intention to Use OER (H14) has a significant moderation effect from Experience (Coeff = 0.070, SE = 0.020, T = 3.534, P < 0.001). Conversely, hypotheses H17 and H21 are not supported, as their P values are above 0.05, and the confidence intervals include zero, suggesting that Facilitating Conditions do not experience significant moderation from either Experience or Digital Divide.

Table 10. Moderating effects.

Hypothesis	Mv	Path	Coeff	SE	T	P	Bias-Corrected 95%CI		Results
H14	F	A→H	0.070	0.020	3.534	0.000	0.031	0.109	Accepted
H15	F	B→H	0.065	0.019	3.332	0.001	0.027	0.103	Accepted
H16	F	C→H	0.049	0.020	2.495	0.013	0.010	0.087	Accepted
H17	F	D→H	0.014	0.019	0.729	0.467	-0.023	0.051	Rejected
H18	G	A→H	0.052	0.016	3.214	0.001	0.020	0.085	Accepted
H19	G	B→H	0.035	0.016	2.243	0.025	0.004	0.065	Accepted
H20	G	C→H	0.065	0.016	4.197	0.000	0.035	0.096	Accepted
H21	G	D→H	0.011	0.015	0.701	0.484	-0.019	0.041	Rejected

Note: A: Performance Expectancy; B: Effort Expectancy; C: Social Influence; D: Facilitating Conditions; E: Voluntariness; F: Experience; G: Digital Divide; H: Intention to Use OER. Mv: Moderating variables; Coeff: Interaction term coefficient.

Table 11. Total effects.

Effect path	Effect size	SE	Bias-Corrected 95%CI	
C→E	0.123	0.066	-0.023	0.242
A→E	0.249	0.066	0.120	0.381
D→E	0.252	0.085	0.082	0.414
B→E	0.185	0.071	0.053	0.330
C→H	0.217	0.069	0.077	0.352
A→H	0.209	0.063	0.092	0.337
D→H	0.199	0.078	0.050	0.352
B→H	0.238	0.067	0.110	0.375
E→H	0.205	0.070	0.073	0.343

Note: A: Performance Expectancy; B: Effort Expectancy; C: Social Influence; D: Facilitating Conditions; E: Voluntariness; H: Intention to Use OER.

Table 11 presents the total effects within the structural equation model, capturing the cumulative impact of various predictors on the mediator Voluntariness (E) and the outcome variable Intention to Use OER (H). The total effect represents the combined influence of both direct and mediated pathways, providing a comprehensive view of each predictor's role within the model. The Effect Size column quantifies the magnitude of the total effect for each pathway. For instance, the total effect of Social Influence (C) on Voluntariness (E) is 0.123, suggesting a moderate influence that encompasses both direct and indirect contributions. This effect size is essential for understanding the overall impact of predictors on the outcome variable, capturing the sum of direct and mediated influences. The Standard Error (SE) associated with each effect size provides insight into the precision of the estimate, where lower SE values indicate more reliable effect size estimates. For instance, the path from Performance Expectancy (A) to Voluntariness (E) has an SE of 0.066, indicating a relatively precise estimate. The Bias-Corrected 95% Confidence Interval (CI) for each effect size adjusts for potential estimation bias and provides a range within which the true effect size is likely to fall. When the interval does not include zero, the effect is statistically significant. For example, the total effect of Performance Expectancy (A) on Voluntariness (E) has a bias-corrected 95% CI from 0.120 to 0.381, confirming its statistical significance as the interval excludes zero.

DISCUSSION

Theoretical implications

This study utilizes a structural equation model (SEM) to deepen the understanding of factors influencing lecturers' intentions to adopt Open Educational Resources (OER) in private higher education institutions (HEIs) in China. Each tested hypothesis contributes to the growing body of knowledge surrounding digital adoption in educational contexts, with significant findings supporting the theoretical framework that combines constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) model.

The results underscore the importance of Performance Expectancy in enhancing both Voluntariness and Intention to Use OER. Hypotheses H1, H5, and H9 are supported, showing that when lecturers perceive OER as beneficial for their instructional effectiveness, they report higher voluntariness and a stronger intention to adopt OER. This aligns with findings from Cheung et al. (2023), who emphasize the critical role of perceived usefulness in predicting technology acceptance.

Effort Expectancy also demonstrates significant effects, supporting hypotheses H2, H6, and H10. These results indicate that when lecturers perceive OER platforms as user-friendly and compatible with their current practices, their voluntary engagement and adoption intentions increase. This finding extends the work of Davis (1989) in technology acceptance, confirming that ease of use significantly shapes educators' motivation to adopt new resources.

The influence of Social Influence on OER adoption is evident through the support of hypotheses H3, H7, and H11, reinforcing the notion that institutional encouragement and peer endorsements play essential roles in fostering positive adoption intentions. This effect aligns with Social Influence Theory and suggests that social encouragement and institutional support can be key motivators for lecturers to adopt OER, as evidenced by Faqih and Jaradat (2021). The results further reveal that Facilitating Conditions positively influence both Voluntariness and Intention to Use OER (H4, H8, H12). This supports previous findings that accessible resources, infrastructure, and administrative support create a conducive environment for OER adoption (Masatlioglu et al., 2023).

Voluntariness is confirmed as a mediating variable in the model (H9 to H12), highlighting its significant role in translating lecturers' perceptions of usefulness, ease of use, and social support into actionable adoption intentions. This mediating effect expands upon Bervell et al. (2021), showing that voluntariness and perceived control can enhance educators' motivation toward technology adoption, emphasizing the importance of fostering an environment where lecturers feel empowered to integrate OER independently.

Furthermore, the study investigates the moderating roles of Experience and Digital Divide. The results confirm hypotheses H14 to H20, indicating that higher levels of experience positively moderate the relationships between the primary constructs and intention to adopt OER. Conversely, the digital divide negatively moderates these relationships, highlighting barriers due to technological access disparities among lecturers. These findings are consistent with the work of Mihalache and Mihalache (2022), affirming the need to address the digital divide as a significant factor in promoting equitable OER adoption in educational settings.

Finally, H21 explores whether the Digital Divide moderates the effect of Facilitating Conditions on Intention to Use OER. The results do not support this hypothesis, indicating that the availability of facilitating conditions does not significantly vary with changes in digital access disparities. This finding suggests that while digital access remains a critical factor for technology adoption, its impact on facilitating conditions may be less pronounced than expected, warranting further investigation in contexts where technological infrastructure varies.

In conclusion, this study makes substantial theoretical contributions by extending the UTAUT framework to include mediating and moderating variables such as Voluntariness, Experience, and Digital Divide. These findings provide actionable insights for policymakers and administrators in educational institutions, suggesting that strengthening perceived ease of use, institutional support, and resource accessibility while addressing technological inequities, can foster greater engagement with OER among lecturers in private HEIs.

Practical implications

The findings of this study offer actionable insights for educational administrators, policymakers, and OER technology providers looking to facilitate the adoption of Open Educational Resources (OER) among lecturers in private higher education institutions (HEIs) in China. By addressing the supported hypotheses, several targeted strategies emerge to enhance OER integration effectively.

Firstly, Performance Expectancy (H1, H5) significantly impacts both Intention to Use OER and Voluntariness, highlighting the importance of demonstrating the educational effectiveness of OER. Administrators and policy advocates should create platforms or training sessions that showcase case studies of OER's success in teaching, providing tangible evidence of its benefits on learning outcomes. Emphasizing the role of OER in improving instructional quality can strengthen lecturers' motivation to adopt it.

Effort Expectancy (H2, H6) also plays a crucial role, underscoring the need for intuitive, user-friendly OER platforms. For OER developers, prioritizing simplicity and compatibility with existing teaching practices is essential. Technical support, such as video tutorials or a responsive helpdesk, should be readily accessible to educators. By reducing perceived complexity, institutions can lower barriers for less tech-savvy lecturers, making OER more approachable across experience levels.

The impact of Social Influence (H3, H7) on adoption intention suggests that peer encouragement and institutional endorsements are influential. Educational leaders can create faculty OER champions who model effective OER usage and provide mentorship to colleagues. Additionally, integrating OER use into institutional recognition programs can further motivate lecturers to engage, as positive reinforcement from leadership and peers promotes a supportive environment for OER adoption.

Facilitating Conditions (H4, H8) highlight the importance of sufficient infrastructure and resources. For policymakers and private HEIs, ensuring stable internet access, ample digital resources, and the availability of technical support is critical. Addressing infrastructure disparities, especially in under-resourced private institutions, is a practical priority to enable equal access to OER.

The mediating role of Voluntariness (H9 to H12) emphasizes the need to foster an environment where lecturers feel voluntariness in their OER adoption. Rather than mandating OER usage, institutions should provide encouragement and optional opportunities for exploration, promoting a culture where educators can experiment with OER at their own pace. This voluntariness supports intrinsic motivation, leading to more sustained adoption.

The study also reveals that Experience (H14 to H17) and Digital Divide (H18 to H21) are significant moderators. Experience positively affects the adoption process, suggesting that training programs should be designed to address different expertise levels among lecturers. HEIs could implement tiered training, from introductory sessions for novices to advanced workshops for experienced educators, ensuring relevance across experience levels.

Addressing the Digital Divide remains crucial, particularly in under-resourced private HEIs. Policymakers must allocate resources to bridge digital disparities, such as funding for technological upgrades and ensuring access to modern devices. Moreover, providing foundational digital literacy training can empower educators who may be less familiar with digital tools, thereby increasing their comfort and reducing perceived barriers to OER adoption.

Lastly, the findings that Facilitating Conditions do not experience significant moderation from the Digital Divide (H21) imply that while infrastructure alone is necessary, its effect is limited without corresponding support. This underscores the need for personalized support services, such as dedicated IT assistance and on-demand resources, to facilitate OER adoption effectively.

In conclusion, these practical insights underscore a multi-faceted approach for stakeholders aiming to foster OER adoption in private HEIs. By highlighting educational benefits, simplifying platform usage, leveraging peer support, ensuring robust infrastructure, and addressing experience and digital access disparities, stakeholders can create a more inclusive and supportive environment for OER integration. This comprehensive approach ensures that private HEIs are well-equipped to adopt OER, contributing to the advancement of accessible, high-quality education in China's private education sector.

CONCLUSION

This study systematically examined the factors influencing lecturers' intentions to adopt Open Educational Resources (OER) in China's private higher education institutions (HEIs). By integrating constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, the research confirmed that Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions significantly influence both Voluntariness and Intention to Use OER. Additionally, Experience and the Digital Divide were found to moderate these relationships, highlighting the complexities of OER adoption among lecturers with varied technological access and digital proficiency.

The findings underscore the essential role of Voluntariness as a mediator, transforming perceived ease of use, usefulness, and social encouragement into meaningful adoption intentions. This confirms that lecturers are more likely to engage with OER when they perceive voluntariness in their decision-making, aligning with prior technology adoption theories. Despite its contributions, this study has several limitations.

First, the research sample was limited to lecturers from private HEIs in China, which may restrict the generalizability of the findings to public HEIs or institutions in other regions. Future research could expand the scope to include a more diverse sample, examining whether these findings hold across different institutional contexts and educational systems. Additionally, the cross-sectional nature of this study captures lecturers' attitudes toward OER at a single point in time. A longitudinal approach could offer insights into how adoption intentions evolve as digital literacy and institutional support increase over time. Examining these dynamics could reveal more about the sustainability of OER adoption as an educational tool. Moreover, while this study emphasizes psychological and institutional factors, other elements—such as economic constraints and specific educational policies—were not fully explored.

For future research, expanding the sample to include public universities and institutions from different regions or countries would provide a broader perspective on OER adoption. Adopting a longitudinal design could offer insights into how lecturers' adoption intentions evolve as digital infrastructure and institutional support improve. Future studies could also incorporate qualitative methods, such as interviews or focus groups, to gain richer insights into the personal experiences and challenges faced by lecturers in adopting OER. Additionally, exploring the impact of emerging technologies, such as artificial intelligence and digital analytics, could reveal how these innovations influence OER adoption. Research could further investigate the role of policy interventions and training programs designed to address the digital divide, aiming to enhance digital competencies and encourage widespread OER integration in educational settings.

In conclusion, this study contributes to the literature on technology adoption in education by identifying key determinants and contextual factors influencing OER uptake among lecturers. The results provide actionable guidance for administrators and policymakers, highlighting the need for user-friendly platforms, social support, and resource accessibility.

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Appendix 1. Measurement.

Construct	Revised items	Source
Performance Expectancy (PE)	PE1. I find OER useful for my teaching. PE2. Using OER allows me to complete teaching tasks more quickly. PE3.Using OER improves the quality of my teaching. PE4. If I use OER, I will increase my course development skills.	Boidou et al. (2023)
Effort Expectancy (EE)	EE1.It would be easy for me to become skilled in using OER for my teaching. EE2.My interaction with OER in my teaching is clear and understandable. EE3. I find OER easy to use for my teaching. EE4. Teaching to use OER in training is easy for me.	Boidou et al. (2023)
Social Influence (SI)	SI1.Lecturers who are important to me think I should use OER for my teaching. SI2.My co-lecturers think I should use OER for my teaching. SI3.The opinion of the authorities at my private HEIs was decisive in using OER for my teaching. SI4.In general, my private HEIs encouraged the use of OER for my teaching.	Boidou et al. (2023)
Facilitating Conditions (FC)	FC1. I have the knowledge to use OER in my teaching. FC2.Technical assistants are available for assistance in case of difficulties in using OER for my teaching. FC3. I have the necessary resources to use OER in my teaching.	Boidou et al. (2023)

Voluntariness (V)	V1. I feel I am being forced to use OER in addition to face-to-face teaching. V2. I think any OER usage to support face-to-face teaching delivery should be made optional. V3. Although it might be helpful to use OER to support face-to-face teaching and learning, it is not made compulsory. V4. The private HEIs require me to use OER in addition to the existing face-to-face teaching and learning mode.	Bervell et al. (2021)
Experience (E)	E1. The lecturer put a lot of time into commenting on students' work by using OER. E2. Lecturers work hard to make subjects interesting through using OER. E3. It's always easy to know the standard of teaching expected through using OER. E4. Using OER has helped me to develop my problem-solving skills. E5. As a result of using OER, I feel more confident about tackling unfamiliar problems. E6. Using OER has helped me develop the ability to plan my own teaching.	Dziewanowska and Kacprzak (2023)
Digital Divide (DD)	DD1. I have difficulty in using OER because of technology devices. DD2. I have the necessary resources needed for my OER. DD3. Poor internet connectivity affects me most in using OER facilities at home and private HEIs. DD4. It is difficult for me to use OER with Slow internet speed at home and private HEIs. DD5. My technical incompetence affects me most in using OER. DD6. Un-optimized software for mobile devices and security issues affect my accessibility of using OER.	Singh et al. (2023)
Intention to Use OER (IUO)	IUO1. Teachers have a positive attitude towards using OER in their teaching process. IUO2. The OER can directly improve the quality of the teaching experience. IUO3. The OER will be an effective means of teaching. IUO4. The OER will improve students' grades. IUO5. The necessary resources are important to access OER. IUO6. Quality assurance about the availability of digital resources is important to access OER.	Rabajalee et al. (2023)