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From hesitation to integration: A UTAUT model analysis of ChatGPT adoption in Moroccan universities

Bennagem Touati Ali[1], Hadj-Ali Abdellah[2], Ouzif Hicham[3], Benlamrabet Ouidad[4], Es-Sanoun Mohamed[5]*
[1,2,3,4,5]Faculty of Legal, Economic and Social Sciences, Sidi Mohammed Ben Abdellah University, Fez, Morocco.
mohamed.essanoun20@gmail.com (E.S.M.)

Abstract: This study explores the determinants of ChatGPT adoption by Moroccan university teachers, applying the UTAUT model. The results show that facilitating conditions have a significant and positive effect on the intention to use, underlining the importance of resources and institutional support in fostering the adoption of this technology. Social influence also exerts a significant positive impact, indicating that the opinions of colleagues and superiors play an important role in teachers' decisions. Effort expectancy, on the other hand, shows a negative effect, suggesting that teachers perceive some difficulty in using ChatGPT. Finally, perceived usefulness shows no significant effect, suggesting that teachers do not yet fully perceive the benefits of the tool for their teaching practices. These results have important implications for institutions, which should strengthen the technical infrastructure and provide better pedagogical support to encourage the adoption of educational technologies such as ChatGPT in Moroccan universities.

Keywords: *Adoption of educational technologies, ChatGPT, UTAUT Model, Enabling conditions, University teachers.*

1. Introduction

Artificial intelligence (AI) is establishing itself today as a disruptive technology, overturning traditional paradigms in fields as varied as healthcare, finance, security and, more recently, education [1, 2]. Its growing importance in higher education lies in its capacity to transform pedagogical practices, reshape teacher-student interactions, and redefine digital competencies. The meteoric rise of generative models, such as ChatGPT developed by OpenAI, illustrates this technological mutation. Launched in 2022, ChatGPT quickly won over the general public and the academic world thanks to its ability to understand and generate natural language fluidly and consistently [3]. In the higher education sector, the arrival of this generative artificial intelligence (AI) raises major issues linked to pedagogical innovation, the transformation of teaching practices and the redefinition of digital skills [4-6]. It represents what some scholars describe as “a silent revolution in academic practices” [7]. It arouses both enthusiasm and concern: while some see it as an opportunity to enrich learning, others warn of the risks of unsupervised use, particularly in terms of academic integrity, reliability of the content generated and technological dependence [8, 9]. In this context, a central research question arises: what are the factors that influence the intention of Moroccan university teachers to adopt ChatGPT in their teaching practices? In this context, it becomes crucial to understand the factors influencing the adoption of these technologies by university teachers, particularly in southern countries where infrastructural and pedagogical challenges persist. The Sidi Mohamed Ben Abdellah University of Fez (USMBA), one of Morocco's largest public institutions, with its multiple faculties spread between Fez, Sefrou and Taounate, is a particularly relevant field of study. For several years now, it has been engaged in a process of digitizing its services and gradually integrating educational technologies, without however having a formal framework for the use of generative AI tools. As recent studies have shown in other

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* Correspondence: mohamed.essanoun20@gmail.com

sectors such as industry, Morocco's economic performance and competitiveness are closely linked to structural variables such as investment, human capital, and technological openness [10]. To analyze the adoption of ChatGPT by university teachers at the USMBA, this article mobilizes the UTAUT (Unified Theory of Acceptance and Use of Technology) model by Venkatesh, et al. [11] a widely recognized approach used to study technology adoption. This model is based on four main variables: expected performance, defined as the degree to which an individual believes that a technology will improve his or her performance; expected effort, which measures the perceived ease of using the technology; social influence, which refers to perceived peer pressure to adopt the technology; and facilitating conditions, which refer to the resources and perceived support necessary for the effective use of the technology [11]. Numerous studies have validated the predictive relevance of these variables in various technological contexts, including higher education [12-14]. With this in mind, this research aims to explore how these variables influence the intention to adopt ChatGPT by teachers at Sidi Mohamed Ben Abdellah University (USMBA), while taking into account the specificities of the Moroccan institutional, cultural and techno-pedagogical context. The aim of this study is to contribute to the literature on the intention to adopt emerging technologies in higher education, and to provide concrete recommendations to university decision-makers for the responsible and effective integration of artificial intelligence into pedagogical practices. The remainder of the article is structured as follows: the next section presents the literature review, followed by the methodology. The results of the study are then reported and interpreted in the discussion section. Finally, the conclusion highlights theoretical and practical contributions, along with suggestions for future research.

2. Literature Review

The emergence of generative artificial intelligence (AI), and ChatGPT in particular, is arousing growing interest in the field of higher education. Several research studies highlight the pedagogical benefits of these technologies, which are asserting themselves as tools for assisting learning, personalizing content or even supporting academic writing [15, 16]. ChatGPT is thus seen as a lever for enriching learning processes, with significant potential for fostering critical thinking, reinforcing engagement and encouraging learner autonomy [17, 18].

Furthermore, studies show that tools like ChatGPT enable students to ask questions at any time, get quick answers, and prepare more effectively for their assessments [17, 18]. However, this craze is accompanied by growing concerns about the risks raised by these technologies. A number of studies have highlighted issues relating to data security, algorithmic bias and the reliability of the answers generated [19, 20].

One of the major warning points concerns potential violations of academic integrity, in particular through the risks of cheating or plagiarism fostered by unsupervised use of generative AI [2, 21]. Against this backdrop, the question of scientific responsibility arises acutely. The automatic generation of text without human supervision is deemed incompatible with the rigorous and ethical requirements of academic production [22].

Thus, critical verification of the content generated is essential, especially as AI systems operate by pattern recognition without any real semantic understanding [20]. In light of these findings, several authors are calling for ChatGPT to be responsibly integrated into educational practices. Farhi, et al. [23] recommend a balanced approach that takes advantage of opportunities while controlling risks.

Similarly, Camilleri [24] stresses the decisive role of the quality of the results produced in assessing the usefulness of these tools, while Sabherwal and Grover [25] emphasize the influence of the context of use in the impact observed. Internationally, interest in ChatGPT in education is evident, as illustrated by studies conducted in various countries (Hong Kong, Vietnam, Spain, United Kingdom, Pakistan, United States, United Arab Emirates), contributing to a global discourse on the pedagogical implications of generative AI [26-28]. Most of this research focuses on students as the target population. For example, Romero-Rodríguez, et al. [28] using the UTAUT2 model, explored the acceptance of ChatGPT in Spanish higher education. Their results show that factors such as experience, performance expectations, hedonic motivation, perceived value and habit influence intention to use, while facilitating conditions and behavioral intention explain actual use. However, as Yilmaz, et al. [29] point out, teachers often remain absent from these analyses, despite their central role in the educational ecosystem. To fill this gap, recent studies have explored their perceptions. Rahman, et al. [30] through interviews in Pakistan, reveal a strong need for training and support for the effective pedagogical use of ChatGPT. Barrett and Pack [31] meanwhile, show that perceptions of generative AI diverge between teachers and students, particularly with regard to its use in academic writing. To better understand the mechanisms of ChatGPT adoption in a pedagogical setting, several authors have mobilized explanatory models. The UTAUT (Unified Theory of Acceptance and Use of Technology) model proposed by Venkatesh, et al. [11] appears to be a robust framework. Superior to other models such as TAM, it incorporates explanatory variables such as performance expectancy, expected effort, social influence and facilitating conditions. This model has already been widely used in the educational sector to study technology adoption [32] including in recent research on the acceptance of ChatGPT. The results of these studies show that factors such as hedonic motivation, habit, or perceived value significantly influence behavioral intention [32]. Other variables, such as technological anxiety or fear of unfair advantage, can also influence the decision to adopt these tools or not [20, 33]. However, UTAUT has been criticized for underestimating hedonic dimensions such as pleasure of use or attractiveness of the tool, which are essential in the case of conversational AI such as ChatGPT [34]. In this sense, the integration of elements from the UTAUT2 model or the diffusion of innovation model [35] is sometimes recommended to adapt the conceptual framework to specific pedagogical contexts. Finally, several researchers [20, 32] insist that knowledge about the use of ChatGPT in education is still under construction, calling for empirical studies in various cultural and institutional contexts. This fully justifies conducting targeted research in Moroccan universities, among teachers, to better understand their perceptions, uses and intentions towards ChatGPT. Having presented previous work on the educational use of ChatGPT, the perceived benefits, the risks, and the explanatory models used in previous research, it is now appropriate to propose a conceptual framework adapted to the context of this study. This research is based on the UTAUT model [11] which explores the factors influencing the adoption of ChatGPT by university teachers. Drawing on existing literature, four factors were identified as particularly relevant to this study :

- Expected performance (or perceived usefulness), which refers to the degree to which an individual believes that using ChatGPT improves his or her pedagogical performance.
- Expected effort (or perceived ease of use), which refers to the perceived ease with which ChatGPT can be used without requiring significant effort.
- Social influence, which measures the pressure or influence exerted by peers and the academic community to adopt ChatGPT.
- Facilitating conditions, which refer to the resources, institutional support and technological infrastructure available to facilitate the adoption of ChatGPT.

These variables are assumed to have a positive influence on the intention to use and the actual use of ChatGPT in a pedagogical context. Based on the theoretical framework thus defined, the following hypotheses are formulated :

H_1: *Effort expectancy has a positive impact on teachers' intention to adopt ChatGPT.*

H_2: *Facilitating conditions have a positive impact on teachers' intention to adopt ChatGPT.*

H_3: *Expected performance has a positive impact on teachers' intention to adopt ChatGPT.*

H_4: *Social influence has a positive impact* on teachers' intention to adopt ChatGPT.

The following figure illustrates the proposed conceptual model, based on the hypothetical relationships examined in this study.

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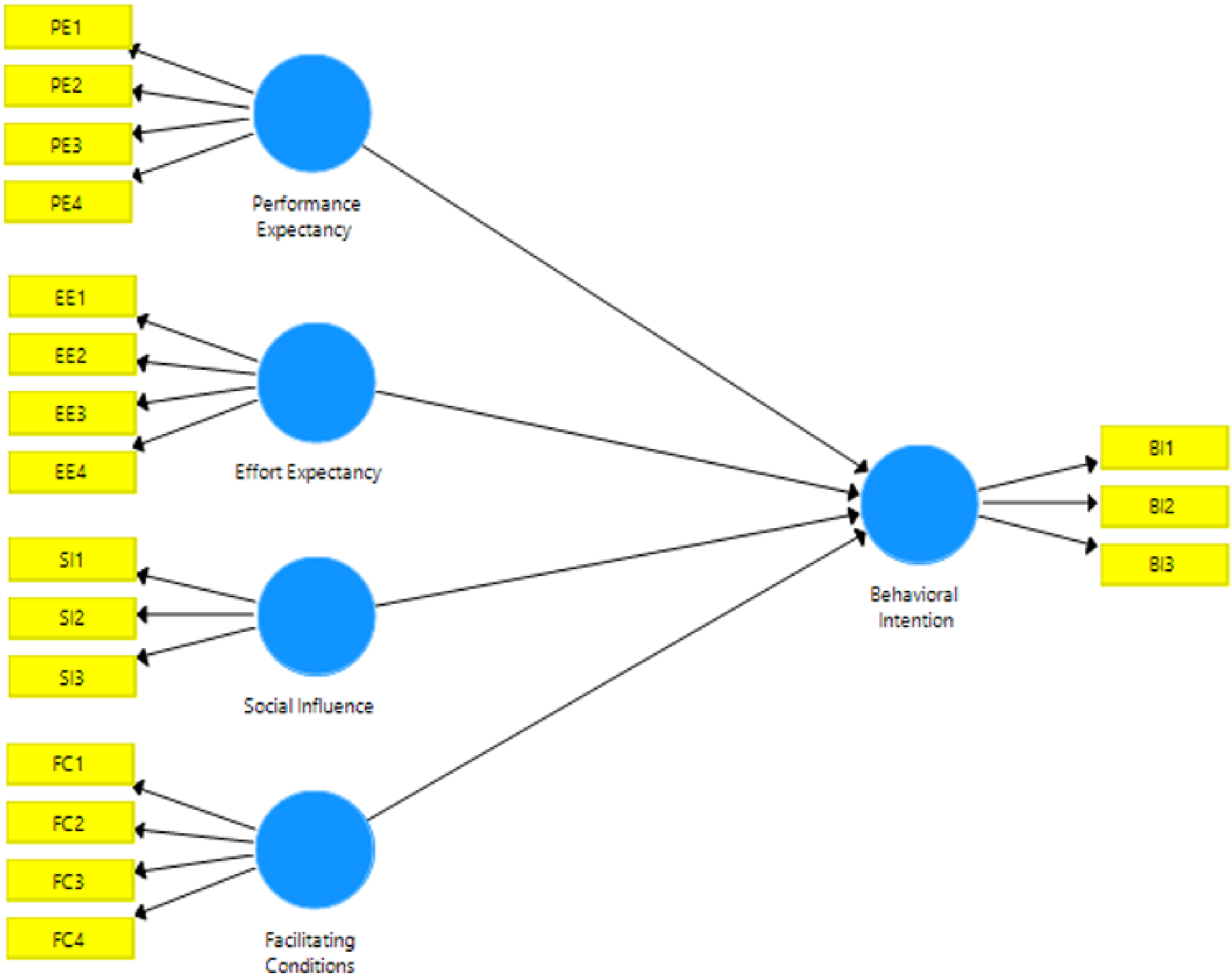

Figure 1.
Proposed conceptual model based on UTAUT.

2. Methodology

The fieldwork for this research was carried out with a targeted sample of teachers affiliated with the Faculty of Legal, Economic and Social Sciences at Sidi Mohamed Ben Abdellah University in Fez, Morocco. This choice was justified by the strategic positioning of this faculty within the Moroccan university landscape, and by its teachers' growing interest in innovative educational technologies, in particular generative artificial intelligence tools such as ChatGPT. The faculty's disciplinary diversity, notably in law, economics and management, has ensured a wealth of analysis in the exploration of digital practices in a university context. Data collection was carried out in April 2025 using a self-administered online questionnaire. This survey instrument was designed on the basis of the UTAUT (Unified Theory of Acceptance and Use of Technology) theoretical model proposed by Venkatesh, et al. [11] recognized for its robustness in the study of technology acceptance. The study focused on the model's four main variables: performance expectancy (equivalent to perceived usefulness), expected effort (equivalent to perceived ease of use), social influence and facilitating conditions, in order to better understand the determinants of intention to adopt ChatGPT in a Moroccan academic context. The questionnaire link was disseminated via recognized institutional channels, including professional e-mail and WhatsApp groups used by teachers for pedagogical communication, in line with methodological recommendations for dissemination in educational research [36]. Of the 465 teachers contacted, 230 responded to the survey. Following a rigorous verification process to eliminate incomplete or inconsistent responses, 202 valid responses were retained for statistical analysis. This data cleaning process is an essential step in guaranteeing the scientific rigor and reliability of statistical inferences [37].

2.1. Measures

This study is based on the analysis of four key variables from the Unified Technology Acceptance and Use Model (UTAUT), namely: performance expectancy (PA), expected effort (EA), social influence (SI) and facilitating conditions (CF). These dimensions were selected for their theoretical relevance to understanding the mechanisms of acceptance of an emerging technology such as ChatGPT in a university environment. The conceptual constructs were operationalized in accordance with the definitions proposed by Venkatesh, et al. [11] within the framework of the UTAUT model. Performance expectancy refers to the perception that using ChatGPT can improve teachers' pedagogical performance. Expected effort measures the perceived ease of use of this tool. Social influence captures the degree to which teachers feel that their professional environment (colleagues, administration, institution) encourages or motivates them to use ChatGPT. Finally, the facilitating conditions concern the resources, technical support and institutional environment perceived as favorable to the adoption of this technology. All items were measured using a five-point Likert-type scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"), providing a nuanced picture of respondents' perceptions and intentions. To ensure the questionnaire's content validity and contextual appropriateness, a pre-test was carried out with a panel of ten teachers from the same faculty. This pre-test enabled certain formulations to be adjusted to improve clarity, semantic relevance and comprehensibility, in line with methodological recommendations established in the literature [38]. Table 1 below presents a summary of the variables mobilized and associated items, in relation to the dimensions of the UTAUT model.

Table 1.
Summary of construct with measurement items.

Variable	Code	Item	Reference
Performance Expectancy (PE)	PE1	I find using ChatGPT useful for improving the quality of my teaching.	Davis [39]
	PE2	Using ChatGPT allows me to complete my teaching tasks more quickly (e.g. preparing lessons, assessing assignments).	Davis [39]
	PE3	L'utilisation de ChatGPT augmente ma productivité dans la gestion et l'élaboration de mes cours	Moore and Benbasat [40].
	PE4	If I use ChatGPT, I'll be able to communicate more effectively with my students (for example, answer their questions more quickly).	Compeau and Higgins [41]
effort Expectancy (EE)	EE1	My interaction with ChatGPT is clear and easy to understand.	Davis [39]
	EE2	It's easy for me to become proficient in using ChatGPT for my teaching tasks.	Davis, et al. [42]
	EE3	I find ChatGPT easy to use in my courses.	Davis, et al. [42]
	EE4	It's easy for me to learn how to use ChatGPT to improve my teaching practices.	Moore and Benbasat [40]
Social Influence (SI)	SI1	The people who influence my behavior (colleagues, mentors, etc.) think I should use ChatGPT in my teaching.	Davis, et al. [42]
	SI2	The people who are important to me (colleagues, academics, etc.) feel that I should integrate ChatGPT into my teaching practices.	Taylor and Todd [43]
	SI3	The university administration facilitated the use of ChatGPT in my teaching.	Thompson, et al. [44]
	SI4	In general, the university supports the adoption of ChatGPT in teaching.	Thompson, et al. [44]
Facilitating Conditions (FC)	FC1	I have the resources I need to use ChatGPT in my teaching.	Ajzen [45]
	FC2	I have the knowledge to use ChatGPT effectively in my teaching.	Taylor and Todd [43]
	FC3	ChatGPT is compatible with the other tools and systems I use in my academic work.	Taylor and Todd [46]
	FC4	There are people or groups available to help me solve technical problems related to the use of ChatGPT in my teaching.	Thompson, et al. [44]
Behavioral Intention (BI)	BI1	I intend to use ChatGPT in the coming months.	Venkatesh, et al. [11]
	BI2	I plan to use ChatGPT in the coming months.	Venkatesh, et al. [11]
	BI3	I plan to use ChatGPT regularly over the coming months.	Venkatesh, et al. [11]

2.2. Data Analysis

Statistical analysis of the empirical data was carried out using SmartPLS software, version 3.3.9, mobilizing the partial least squares-based structural equation modeling (PLS-SEM) approach. This method is particularly recommended for examining complex theoretical models and predicting causal relationships in emerging research contexts [47]. The measurement model was rigorously evaluated for reliability and construct validity. Internal reliability was verified using Cronbach's alpha and composite reliability (CR). Convergent validity was measured through Average Variance Extracted (AVE). Discriminant validity was examined according to the Fornell and Larcker criterion [48] to ensure conceptual distinction between the different constructs of the model. In line with current methodological standards [37] only items with factor loadings above the 0.70 threshold were retained.

For the structural model, the analysis focused on regression coefficients (β), t-values obtained by bootstrapping (with 5,000 samples), and coefficients of determination (R^2), with a view to assessing the explanatory power of the model. This methodological approach is in line with the recommendations of Henseler, et al. [49] and Ketchen [50] who highlight the relevance of PLS-SEM in applied social sciences. Furthermore, the final sample size (n = 80) is deemed sufficient with regard to the "ten times" rule, which advocates a minimum of ten observations for each structural relationship directed towards a given construct [51].

3. Results

Evaluation of the proposed structural model was carried out using SmartPLS 3 software, applying the partial least squares-based structural equation modeling (PLS-SEM) technique. This method is particularly suited to exploratory research and theoretical development contexts [47]. PLS-SEM is distinguished by its flexibility with respect to sample size and non-normal distributions, making it an appropriate approach for complex models or data that do not meet normality assumptions [51]. Furthermore, this method is less prone to problems such as factor indeterminacy or inadmissible solutions, often encountered in covariance-based approaches [52]. These advantages explain its growing popularity in various fields such as management, marketing and information systems [53].

3.1. Measurement Model

3.1.1. Reliability and Convergent Validity Analysis

In line with the recommendations of Hair, et al. [47] the measurement model was evaluated on indicators of internal reliability and convergent validity. The majority of standardized factor loadings exceeded the minimum threshold of 0.70, indicating satisfactory convergent validity [51]. However, two items, one relating to facilitating conditions (CF3) and the other to behavioral intention (BI2), displayed loadings below this threshold. Despite this, the average extracted variance (AVE) of these constructs remained above 0.50, confirming acceptable convergent validity at the overall level. Table 1 details the factor loadings, as well as internal reliability indices such as Cronbach's alpha, rho_A and composite reliability. Internal reliability was confirmed using several indices. Cronbach's alpha (α) values for all latent constructs were above 0.70, a threshold generally considered acceptable even in exploratory research Nunnally [54]. In addition, composite reliability (CR) values also exceeded the recommended threshold of 0.70, indicating strong internal consistency between items [41]. Discriminant validity was verified through the HTMT (Heterotrait-Monotrait) ratio of correlations. All HTMT values were below the conservative threshold of 0.85, as recommended by Henseler, et al. [52] attesting that each construct measures a distinct concept. Finally, the rho_A indicator, used as an additional measure of reliability, showed values above 0.70, reinforcing the robustness of the measurement model.

Table 2.
Factor loadings, reliability, and convergent validity.

Latent variable	Indicator	Load factor	Cronbach's Alpha	rho_A	Composite Reliability (CR)	Average Extrinsic Variance (AEV)
Performance Expectancy (PE)	PE1	0.752	0.847	0.854	0.898	0.689
	PE2	0.937				
	PE3	0.801				
	PE4	0.818				
Effort Expectancy (EE)	EE1	0.948	0.951	0.952	0.964	0.871
	EE2	0.955				
	EE3	0.909				
	EE4	0.920				
Social Influence (SI)	SI1	0.799	0.883	0.930	0.927	0.810
	SI2	0.954				
	SI3	0.939				
Facilitating Conditions (FC)	CF1	0.800	0.795	0.87	0.868	0.629
	CF2	0.879				
	CF3	0.556				
	CF4	0.891				
Behavioral Intention (BI)	BI1	0.943	0.752	0.938	0.843	0.662
	BI2	0.431				
	BI3	0.955				

3.2. Structural Model
3.2.1. Discriminant Analysis of Variables
Discriminant validity aims to verify the extent to which each construct in the model is distinct from the others. It ensures that each variable measures a single dimension of the phenomenon under study, without conceptual redundancy with other constructs. Two methods commonly used to assess this validity are the Fornell-Larcker criterion and the cross-loading matrix.

3.2.1.1. Fornell-Larcker Criterion
The Fornell-Larcker criterion consists in comparing the square root of the average variance extracted (AVE) of each construct with its correlations with the other constructs in the model. A construct satisfies discriminant validity if the square root of its AVE is greater than its correlations with any other construct [48]. As Table 3 shows, all constructs meet this methodological criterion, confirming the discriminant validity of the model. Intention to use ChatGPT (BI) has a square root AVE of 0.814, higher than its correlations with other constructs, such as Expectation of Effort (EE) (r = 0.371) and Facilitating Conditions (FC) (r = 0.649), confirming its conceptual specificity. Facilitating Conditions (FC) show a square root of AVE of 0.793, also higher than their correlations with BI (r = 0.649), EE (r = 0.723), and Performance Expectation (PE) (r = 0.721), attesting to their conceptual distinction.Similarly, Expectation of Effort (EE) has a square root of AVE of 0.933, significantly higher than its correlations with FC (r = 0.723), PE (r = 0.629), and BI (r = 0.371), demonstrating strong discriminant validity. Finally, Performance Expectancy (PE) achieves an AVE square root of 0.830, well above its correlations with EE (r = 0.629) and BI (r = 0.575), also validating its conceptual specificity. Social Influence (SI) has an AVE square root of 0.900, higher than its correlations with BI (r = 0.619), EE (r = 0.383), FC (r = 0.469), and PE (r = 0.577), which also confirms its discriminant validity. These results confirm that each of the model's constructs captures a unique concept, as recommended by Fornell and Larcker [48]. Consequently, the measurement structure can be considered robust, reliable and conceptually coherent for assessing university teachers' adoption of ChatGPT.

Table 3.
Fornell-Larcker Criterion correlation matrix.

	BI	EE	FC	PE	SI
BI	**0.814**				
EE	0.371	**0.933**			
FC	0.649	0.723	**0.793**		
PE	0.575	0.629	0.721	**0.830**	
SI	0.619	0.383	0.469	0.577	**0.900**

3.2.1.2. Heterotrait-Monotrait criterion (HTMT)

In addition to the Fornell-Larcker criterion, the discriminant validity of the model was also assessed using the Heterotrait-Monotrait ratio (HTMT), known for its heightened sensitivity to conceptual overlaps between constructs [52]. According to these authors, a maximum threshold of 0.90 is generally accepted; higher values may indicate a lack of discriminant validity. In studies requiring enhanced methodological rigor, a more conservative threshold of 0.85 is often recommended [55]. Analysis of the HTMT values, presented in Table 4, shows that all coefficients are below the 0.85 threshold, with ratios ranging from 0.398 (between Effort Expectancy (EE) and Social Influence (SI)) to 0.870 (between Performance Expectancy (PE) and Facilitating Conditions (FC)). These results suggest an adequate level of differentiation between the constructs in the model. In particular, the low values observed for the EE-SI (0.398) and FC-SI (0.526) pairs confirm the conceptual distinction between these variables. Other pairs also show HTMT values below 0.85, such as BI-EE (0.493), BI-FC (0.760), PE-EE (0.685), and PE-BI (0.719), reinforcing discriminant validity between constructs. Overall, the results from the HTMT analysis confirm the discriminant validity of the measurement model and support the methodological robustness of this study on the adoption of ChatGPT by university teachers.

Table 4.
Heterotrait-Monotrait criterion (HTMT).

	BI	EE	FC	PE	SI
BI					
EE	0.493				
FC	0.760	0.833			
PE	0.719	0.685	0.870		
SI	0.656	0.398	0.526	0.689	

3.2.1.3. Cross-Loading Matrix

Another tool for assessing discriminant validity is the cross-loading matrix. It compares the loadings of each item on the construct to which it is supposed to relate, with its loadings on the other constructs in the model. In concrete terms, an item must have a higher loading coefficient on its associated construct than on any other construct. This ensures that the item actually measures the concept it is supposed to represent. Analysis of the results (Table 5) shows that, for each item, saturation is significantly higher on the construct to which it is attached than on the others. These results confirm that each item correctly measures its target construct, validating the discriminant validity of all the constructs in the model studied.

Table 5.
Matrix of crossover loads.

	BI	EE	FC	PE	SI
BI1	0.943	0.329	0.598	0.594	0.702
BI2	0.431	0.352	0.293	0.238	-0.024
BI3	0.955	0.345	0.634	0.492	0.509
EE1	0.348	0.948	0.744	0.52	0.386
EE2	0.331	0.955	0.73	0.531	0.365
EE3	0.372	0.909	0.583	0.694	0.318
EE4	0.331	0.92	0.648	0.594	0.362
FC1	0.384	0.633	0.8	0.335	0.221
FC2	0.376	0.678	0.879	0.515	0.216
FC3	0.434	0.319	0.556	0.798	0.444
FC4	0.71	0.644	0.891	0.594	0.494
PE1	0.428	0.249	0.501	0.752	0.506
PE2	0.498	0.663	0.638	0.937	0.469
PE3	0.523	0.617	0.576	0.801	0.372
PE4	0.447	0.518	0.674	0.818	0.59
SI1	0.4	0.149	0.384	0.537	0.799
SI2	0.63	0.26	0.358	0.472	0.954
SI3	0.603	0.574	0.528	0.575	0.939

The results indicate that each item has a higher factor loading on its respective construct than on the others, thus confirming the factorial structure of the model.

3.2.2. Principle of Collinearity

The Variance Inflation Factor (VIF) is used to examine potential interactions between explanatory variables within a predictive model. A VIF score below 5 is generally considered indicative of low multicollinearity, meaning that there is no excessive correlation between independent variables. In this study of university teachers' intention to adopt ChatGPT, the internal VIF values of the different constructs of the UTAUT model were analyzed (see Table 6). The results show that all VIF values are below the critical threshold of 5, suggesting the absence of significant multicollinearity between the constructs studied. These results confirm the methodological robustness of the model, as well as the reliability of the measures used, reinforcing the validity of subsequent structural analyses.

Table 6.
Internal VIF values.

	BI	EE	FC	PE	SI
BI					
EE	2.21				
FC	2.802				
PE	2.578				
SI	1.513				

3.2.3. Hypothesis Testing Results

The objective of hypothesis validation is to examine the direct causal relationships between the elements influencing the adoption of educational technologies. The results of testing hypotheses H1, H2, H3, and H4 are presented below.

Table 7.
Hypothesis testing results.

Assumptions	Structural links	Original value (O)	Observed average (M)	Standard deviation	Measurement T (|O/standard deviation|)	Statistical significance (p)	Confirmation
H1	EE → BI	-0.261	-0.258	0.082	3.18	0.002	Accept
H2	FC → BI	0.593	0.593	0.098	6.049	0.000	Accept
H3	PE →BI	0.086	0.086	0.07	1.217	0.224	Reject
H4	SI →BI	0.392	0.396	0.063	6.218	0.000	Accept

The results of the PLS-SEM analysis, presented in the table above, offer relevant insights into the relationships between the factors influencing Moroccan university teachers' intention to use ChatGPT. Firstly, Facilitating Conditions (FC) exert a positive and significant effect on intention to use (β = 0.593; p = 0.000). This result highlights the importance of technical resources, training and institutional support in promoting the adoption of ChatGPT by teachers. Facilitating Conditions prove to be a crucial predictor, as suggested by numerous studies in the field of technology adoption. Secondly, Social Influence (SI) also shows a positive and significant effect on intention to use (β = 0.392; p = 0.000). This factor highlights the impact of social expectations and interactions within the academic community on teachers' decision to adopt ChatGPT. Social influence therefore plays a key role in the formation of intention to use, corroborating the findings of previous research on social pressure in digital educational environments. In contrast, Expectation of Effort (EE) had a negative, but significant, effect on intention to use (β = -0.261; p = 0.002). This suggests that the perceived ease of use of ChatGPT could, paradoxically, reduce teachers' intention to adopt it. Such a dynamic may indicate that teachers perceive the use of ChatGPT as potentially less demanding, which may lead to less motivation to fully integrate it into their pedagogical practices. Finally, Performance Expectation (PE) showed no significant effect on intention to use (β = 0.086; p = 0.224). This result suggests that, in this context, teachers do not sufficiently perceive the concrete benefits of ChatGPT in terms of improved pedagogical effectiveness or teaching support. This finding is in line with the work of Bervell and Umar [56] who showed that perceived performance alone is not sufficient to stimulate an intention to adopt a technology without a clear incentive context. In sum, the results show that organizational and social factors, such as Facilitating Conditions and Social Influence, have a significant impact on intention to use ChatGPT, while Effort Expectation and Performance Expectation play a more modest role. These findings provide a better understanding of the levers to be activated to encourage the adoption of this technology by Moroccan university teachers.

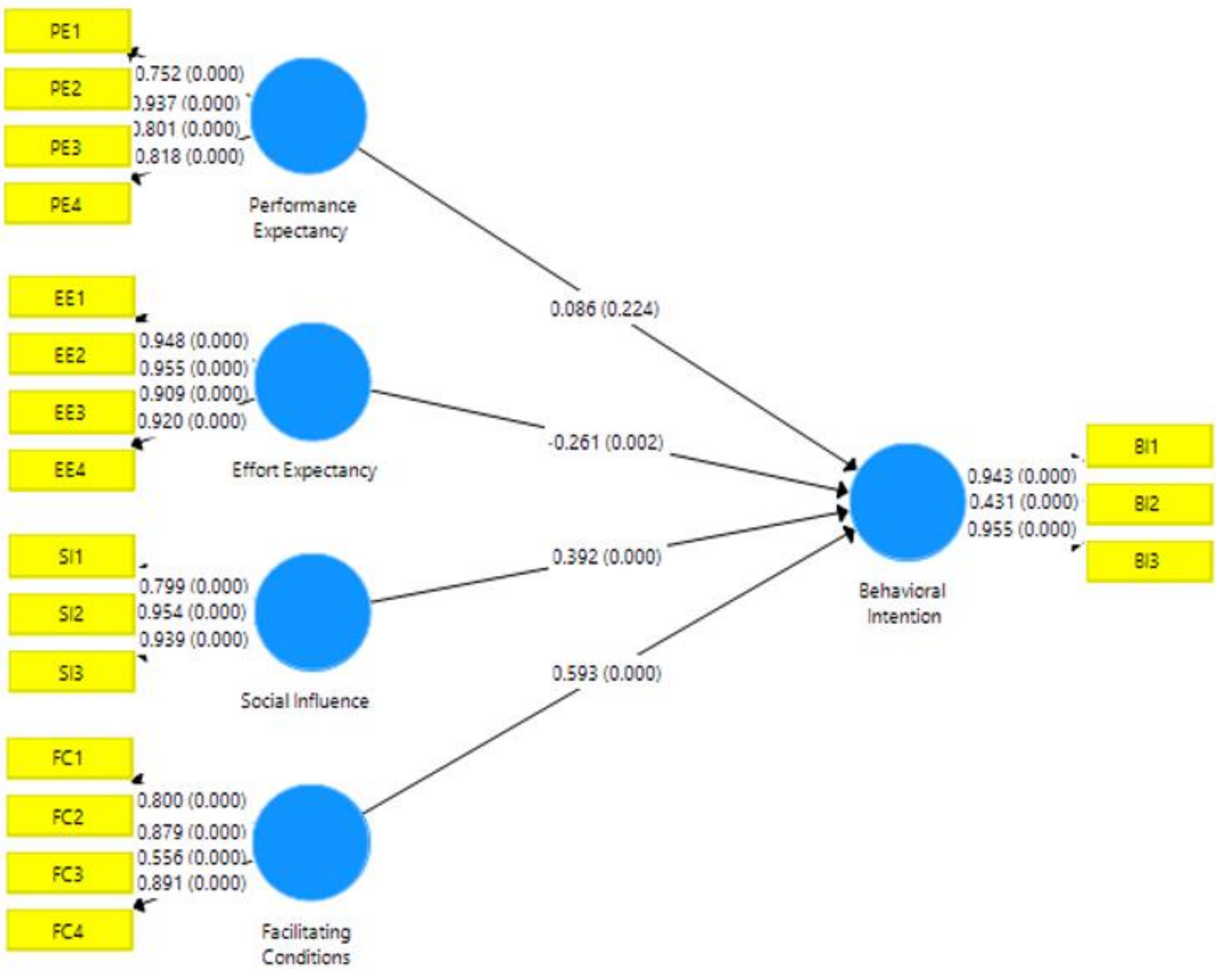

Figure 2.
Conceptual framework for the effect of elements on intention to use.

4. Discussion

The results of this study reveal crucial information about the factors influencing Moroccan university teachers' behavioral intention to adopt ChatGPT. Among the hypotheses tested, facilitating conditions (H2: $\beta = 0.593$; $p = 0.000$) were found to be the most influential factor in behavioral intention to adopt ChatGPT. This suggests that factors such as technical support, resource availability and infrastructure are essential to encourage technology adoption by teachers, which is in line with the findings of Venkatesh, et al. [11] who highlighted the importance of facilitating conditions in technology adoption processes. In contrast, effort expectancy (H1: $\beta = -0.261$; $p = 0.002$) showed a significant negative relationship with intention to adopt ChatGPT. This result indicates that perceived ease of use, while useful, is not enough on its own to motivate teachers to adopt this tool. The negative effect could be due to a low perception of the need to use the tool in the current pedagogical context, despite its ease of use. Performance expectancy (H3: $\beta = 0.086$; $p = 0.224$), on the other hand, had no significant effect on adoption intention, suggesting that teachers do not necessarily perceive ChatGPT as a tool with a direct impact on their performance or effectiveness. This lack of effect could stem from a lack of tangible demonstration of the tool's benefits in the pedagogical setting. Finally, social influence (H4: $\beta = 0.392$; $p = 0.000$) had a positive and significant effect. This shows that the expectations of colleagues, superiors and the university community have a significant impact on teachers' decision to adopt ChatGPT. This could reflect a dynamic of social pressure or encouragement in academia that drives teachers to adopt digital tools, even if these don't always meet their immediate needs. These findings have several implications for institutional strategies. It is vital that Moroccan universities, such as Sidi Mohamed Ben Abdellah University, invest in appropriate technical and pedagogical resources to facilitate the adoption of educational technologies. In addition, the role of facilitating conditions in the adoption of ChatGPT highlights the importance of a robust support infrastructure that includes practical and ongoing training for teachers. In conclusion, the study shows that it is not enough to focus solely on perceptions of usefulness or ease of use of technologies to encourage adoption. Institutions need to take into account the organizational and techno-pedagogical factors that influence teachers' commitment, and enable them to fully integrate these tools into their teaching practices.

5. Conclusion

This study explored the factors influencing the adoption of ChatGPT by Moroccan university teachers in higher education. The empirical results obtained highlighted aspects crucial to the success of this adoption, in particular the role of facilitating conditions. Adequate infrastructure, technical support and ongoing training are key factors in encouraging teachers to effectively integrate ChatGPT into their teaching practices. The study also revealed that factors such as effort expectancy and performance expectancy did not have the expected impact, suggesting that the perceived simplicity of the tool and its theoretical benefits are not sufficient to encourage its adoption. This finding underlines the importance of not reducing the adoption of educational technologies to a simple question of user-friendliness or perceived effectiveness. Teachers need to see concrete added value in the use of these technologies if they are to become a genuine pedagogical lever. In addition, social influence showed significant importance, reflecting social or institutional pressure to adopt these digital tools. This phenomenon can be interpreted as a positive factor, insofar as it encourages the integration of technology into teaching. However, it is essential to go beyond this social logic and create environments where adoption relies more on the personal conviction of teachers as to the real and contextual benefits of the tool.The results of this research also highlight the need for higher education institutions, notably at Sidi Mohamed Ben Abdellah University, to rethink their strategies for supporting the integration of educational technologies. Investing in technical resources, offering targeted in-service training and establishing partnerships with industry players to co-design appropriate pedagogical solutions are essential avenues for ensuring the sustainable and successful adoption of digital tools. Thus, this study calls for a systemic approach to the integration of educational technologies, where institutional issues, pedagogical needs and labor market expectations are articulated to foster adoption fully aligned with professional standards. Ultimately, the adoption of educational technologies should not be seen simply as a process of technological modernization, but as a strategic lever for the professionalization of training in the context of current developments in higher education. However, this study is not without limitations. First, the sample was limited to a single Moroccan university, which may restrict the generalizability of the findings to other institutions or regions. Second, the use of a cross-sectional design does not allow for the observation of changes in perceptions or behaviors over time. Finally, the study focused solely on self-reported measures, which may be subject to biases such as social desirability or misinterpretation of items. Future research could address these limitations by extending the study to multiple universities across different regions or countries, adopting longitudinal approaches to track the evolution of adoption behaviors, and combining quantitative findings with qualitative insights to better capture teachers' lived experiences and contextual realities. Moreover, it would be valuable to explore the actual pedagogical impact of ChatGPT use in the classroom, as well as the ethical and regulatory dimensions of its integration into educational settings.

Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

References

[1] S. Grassini, "Shaping the future of education sciences," *Education Sciences*, vol. 13, no. 7, p. 522, 2023. https://doi.org/10.3390/educsci13070522
[2] P. P. Ray, "ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope," *Internet of Things and Cyber-Physical Systems*, vol. 3, pp. 121-154, 2023. https://doi.org/10.1016/j.iotcps.2023.04.003
[3] OpenAI L.L.C, *ChatGPT: Optimizing language models for dialogue*. San Francisco, CA: OpenAI Blog, 2022.
[4] E. Kasneci *et al.*, "ChatGPT for good? On opportunities and challenges of large language models for education," *Learning and Individual Differences*, vol. 103, p. 102274, 2023. https://doi.org/10.1016/j.lindif.2023.102274
[5] A. Zirar, "Exploring the impact of language models, such as ChatGPT, on student learning and assessment," *Review of Education*, vol. 11, no. 3, p. e3433, 2023. https://doi.org/10.1002/rev3.3433
[6] J. Rudolph, S. Tan, and S. Tan, "ChatGPT: Bullshit spewer or the end of traditional assessments in higher education?," *Journal of Applied Learning & Teaching*, vol. 6, no. 1, pp. 342-363, 2023. https://doi.org/10.37074/jalt.2023.6.1.9
[7] M. Es-Sanoun, M. Elmoukhtar, F. Mohammed, N. Yassine, and B. Mounir, "Modeling the impact of exchange rate fluctuations on agricultural performance: Evidence from Morocco during the period 2000-2023," *Edelweiss Applied Science and Technology*, vol. 8, no. 6, pp. 7939-7950, 2024. https://doi.org/10.55214/25768484.v8i6.3731
[8] E. A. Van Dis, J. Bollen, W. Zuidema, R. Van Rooij, and C. L. Bockting, "ChatGPT: five priorities for research," *Nature*, vol. 614, no. 7947, pp. 224-226, 2023. https://doi.org/10.1038/d41586-023-00288-7
[9] X. Zhai, "ChatGPT user experience: Implications for education," *Available at SSRN 4312418*, 2022. https://doi.org/10.2139/ssrn.4312418
[10] E.-S. Mohamed, H. Hind, K. Abdellah, E. A. Maryem, and B. Mounir, "Manufacturing sector performance in Morocco: What role do exchange rate fluctuations play?," *Journal of Posthumanism*, vol. 5, no. 1, pp. 540–554, 2025.
[11] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Quarterly*, vol. 27, no. 3, pp. 425-478, 2003. https://doi.org/10.2307/30036540
[12] V. Venkatesh, J. Y. Thong, and X. Xu, "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology," *MIS Quarterly*, vol. 36, no. 1, pp. 157-178, 2012. https://doi.org/10.2307/41410412
[13] J. Park, J. Ahn, T. Thavisay, and T. Ren, "Examining the role of anxiety and social influence in multi-benefits of mobile payment service," *Journal of Retailing and Consumer Services*, vol. 47, pp. 140-149, 2019. https://doi.org/10.1016/j.jretconser.2018.11.015
[14] S. F. Ahmad, M. M. Alam, M. K. Rahmat, M. S. Mubarik, and S. I. Hyder, "Academic and administrative role of artificial intelligence in education," *Sustainability*, vol. 14, no. 3, p. 1101, 2022. https://doi.org/10.3390/su14031101
[15] L. Bishop, "A computer wrote this paper: What chatgpt means for education, research, and writing," *SSRN Electronic Journal*, 2023. https://doi.org/10.2139/ssrn.4338981
[16] M. Farrokhnia, S. K. Banihashem, O. Noroozi, and A. Wals, "A SWOT analysis of ChatGPT: Implications for educational practice and research," *Innovations in Education and Teaching International*, vol. 61, no. 3, pp. 460-474, 2024. https://doi.org/10.1080/14703297.2023.2195846
[17] A. Korinek, "Generative AI for economic research: Use cases and implications for economists," *Journal of Economic Literature*, vol. 61, no. 4, pp. 1281-1317, 2023.
[18] O. Ali, P. A. Murray, M. Momin, Y. K. Dwivedi, and T. Malik, "The effects of artificial intelligence applications in educational settings: Challenges and strategies," *Technological Forecasting and Social Change*, vol. 199, p. 123076, 2024. https://doi.org/10.1016/j.techfore.2023.123076
[19] E. H. Almansor and F. K. Hussain, "Survey on intelligent chatbots: State-of-the-art and future research directions," in *Complex, Intelligent, and Software Intensive Systems: Proceedings of the 13th International Conference on Complex, Intelligent, and Software Intensive Systems (Cisis-2019)*, 2020: Springer, pp. 534-543.
[20] Y. K. Dwivedi *et al.*, "Opinion Paper:"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy," *International Journal of Information Management*, vol. 71, p. 102642, 2023. https://doi.org/10.1016/j.ijinfomgt.2023.102642

[21] S. A. Bin-Nashwan, M. Sadallah, and M. Bouteraa, "Use of ChatGPT in academia: Academic integrity hangs in the balance," *Technology in Society*, vol. 75, p. 102370, 2023. https://doi.org/10.1016/j.techsoc.2023.102370
[22] D. Lindebaum and P. Fleming, "ChatGPT undermines human reflexivity, scientific responsibility and responsible management research," *British Journal of Management*, vol. 35, no. 2, pp. 566-575, 2024. https://doi.org/10.1111/1467-8551.12781
[23] F. Farhi, R. Jeljeli, I. Aburezeq, F. F. Dweikat, S. A. Al-shami, and R. Slamene, "Analyzing the students' views, concerns, and perceived ethics about chat GPT usage," *Computers and Education: Artificial Intelligence*, vol. 5, p. 100180, 2023. https://doi.org/10.1016/j.caeai.2023.100180
[24] M. A. Camilleri, "Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework," *Technological Forecasting and Social Change*, vol. 201, p. 123247, 2024. https://doi.org/10.1016/j.techfore.2024.123247
[25] R. Sabherwal and V. Grover, "The societal impacts of generative artificial intelligence: A balanced perspective," *Journal of the Association for Information Systems*, vol. 25, no. 1, pp. 13-22, 2024. https://doi.org/10.17705/1jais.00860
[26] M. Firat, "What ChatGPT means for universities: Perceptions of scholars and students," *Journal of Applied Learning and Teaching*, vol. 6, no. 1, pp. 57-63, 2023. https://doi.org/10.37074/jalt.2023.6.1.22
[27] C. K. Y. Chan and W. Hu, "Students' voices on generative AI: Perceptions, benefits, and challenges in higher education," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, p. 43, 2023. https://doi.org/10.1186/s41239-023-00411-8
[28] J.-M. Romero-Rodríguez, M.-S. Ramírez-Montoya, M. Buenestado-Fernández, and F. Lara-Lara, "Use of ChatGPT at university as a tool for complex thinking: Students' perceived usefulness," *Journal of New Approaches in Educational Research*, vol. 12, no. 2, pp. 323-339, 2023. https://doi.org/10.7821/naer.2023.7.1458
[29] H. Yilmaz, S. Maxutov, A. Baitekov, and N. Balta, "Student attitudes towards Chat GPT: A technology acceptance model survey," *International Educational Review*, vol. 1, no. 1, pp. 57-83, 2023. https://doi.org/10.58693/ier.114
[30] M. S. Rahman, M. M. Sabbir, J. Zhang, I. H. Moral, and G. M. S. Hossain, "Examining students' intention to use ChatGPT: Does trust matter?," *Australasian Journal of Educational Technology*, vol. 39, no. 6, pp. 51-71, 2023. https://doi.org/10.14742/ajet.8956
[31] A. Barrett and A. Pack, "Not quite eye to AI: Student and teacher perspectives on the use of generative artificial intelligence in the writing process," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, p. 59, 2023. https://doi.org/10.1186/s41239-023-00427-0
[32] A. Strzelecki, "Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology," *Innovative higher education*, vol. 49, no. 2, pp. 223-245, 2024. https://doi.org/10.1007/s10755-023-09686-1
[33] D. R. Cotton, P. A. Cotton, and J. R. Shipway, "Chatting and cheating: Ensuring academic integrity in the era of ChatGPT," *Innovations in Education and Teaching International*, vol. 61, no. 2, pp. 228-239, 2024. https://doi.org/10.1080/14703297.2023.2190148
[34] A. Abadie, S. Chowdhury, and S. K. Mangla, "A shared journey: Experiential perspective and empirical evidence of virtual social robot ChatGPT's priori acceptance," *Technological Forecasting and Social Change*, vol. 201, p. 123202, 2024. https://doi.org/10.1016/j.techfore.2023.123202
[35] C. R. Rogers, *Freedom to learn*, 3rd ed. Columbus, OH: Merrill Prentice Hall, 2003.
[36] R. Gomm, *Social research methodology: A critical introduction*, 2nd ed. Palgrave Macmillan. https://doi.org/10.1007/978-0-230-22911-2, 2008.
[37] J. F. Hair, C. M. Ringle, and M. Sarstedt, "PLS-SEM: Indeed a silver bullet," *Journal of Marketing theory and Practice*, vol. 19, no. 2, pp. 139-152, 2011. https://doi.org/10.2753/MTP1069-6679190202
[38] D. A. Dillman, J. D. Smyth, L. M. Christian, and J. Wiley, *Internet, phone, mail, and mixed-mode surveys: The tailored design method*, 4th ed. Hoboken, NJ: Wiley, 2016.
[39] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319-340, 1989. https://doi.org/10.2307/249008
[40] G. C. Moore and I. Benbasat, "Development of an instrument to measure the perceptions of adopting an information technology innovation," *Information Systems Research*, vol. 2, no. 3, pp. 192–222, 1991. https://doi.org/10.1287/isre.2.3.192
[41] D. R. Compeau and C. A. Higgins, "Computer self-efficacy: Development of a measure and initial test," *MIS Quarterly*, vol. 19, no. 2, pp. 189–211, 1995. https://doi.org/10.2307/249688
[42] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User acceptance of computer technology: A comparison of two theoretical models," *Management Science*, vol. 35, no. 8, pp. 982–1003, 1989. https://doi.org/10.1287/mnsc.35.8.982
[43] S. Taylor and P. A. Todd, "Assessing IT usage: The role of prior experience," *MIS Quarterly*, vol. 19, no. 4, pp. 561–570, 1995a. https://doi.org/10.2307/249633
[44] R. L. Thompson, C. A. Higgins, and J. M. Howell, "Personal computing: Toward a conceptual model of utilization," *MIS Quarterly*, vol. 15, no. 1, pp. 125–143, 1991. https://doi.org/10.2307/249443
[45] I. Ajzen, "The theory of planned behavior," *Organizational Behavior and Human Decision Processes*, vol. 50, no. 2, pp. 179–211, 1991. https://doi.org/10.1016/0749-5978(91)90020-T

[46] S. Taylor and P. A. Todd, "Understanding information technology usage: A test of competing models," *Information Systems Research*, vol. 6, no. 2, pp. 144–176, 1995b. https://doi.org/10.1287/isre.6.2.144

[47] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "The results of PLS-SEM article information," *European Business Review*, vol. 31, no. 1, pp. 2-24, 2019.

[48] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, pp. 39-50, 1981. https://doi.org/10.1177/002224378101800104

[49] J. Henseler, C. M. Ringle, and R. R. Sinkovics, *The use of partial least squares path modeling in international marketing* (New challenges to international marketing). Emerald Group Publishing Limited. https://doi.org/10.1108/S1474-7979(2009)0000020014, 2009.

[50] D. J. Ketchen, "A primer on partial least squares structural equation modeling," *Long Range Planning*, vol. 46, no. 1-2, pp. 184-185, 2013. https://doi.org/10.1016/j.lrp.2013.01.002

[51] J. F. Hair Jr, M. Sarstedt, L. Hopkins, and V. G. Kuppelwieser, "Partial least squares structural equation modeling (PLS-SEM)," *European Business Review*, vol. 26, no. 2, p. 106, 2014.

[52] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science*, vol. 43, pp. 115-135, 2015. https://doi.org/10.1007/s11747-014-0403-8

[53] A. A. Alalwan, Y. K. Dwivedi, N. P. Rana, B. Lal, and M. D. Williams, "Consumer adoption of Internet banking in Jordan: Examining the role of hedonic motivation, habit, self-efficacy and trust," *Journal of Financial Services Marketing*, vol. 20, pp. 145-157, 2015. https://doi.org/10.1057/fsm.2015.5

[54] J. C. Nunnally, "Review of psychometric theory," *Educational and Psychological Measurement*, vol. 60, no. 2, pp. 313–315, 1995. https://doi.org/10.1177/0013164495602008

[55] N. Tabri and C. M. Elliott, "Principles and practice of structural equation modeling," *Canadian Graduate Journal of Sociology and Criminology*, vol. 1, no. 1, pp. 59-60, 2012. https://doi.org/10.15353/cgjsc-rcessc.v1i1.25

[56] B. Bervell and I. N. Umar, "Validation of the UTAUT model: Re-considering non-linear relationships of exogeneous variables in higher education technology acceptance research," *Eurasia Journal of Mathematics, Science and Technology Education*, vol. 13, no. 10, pp. 6471-6490, 2017. https://doi.org/10.12973/ejmste/78076