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Exploring the Impact of SaaS Acceptance and Adoption on Faculty Performance in Libyan Higher Education Institutions

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Abstract

This study explores the impact of Software as a Service (SaaS) adoption in Libyan higher education institutions (HEIs) on faculty performance. Despite the numerous advantages of SaaS, such as reduced infrastructure costs and easier access to online applications, its adoption in many developing countries, including Libya, remains limited and largely confined to small-scale implementations. To address this gap, the study employs the Unified Theory of Technology Acceptance and Use (UTAUT) to examine the key determinants influencing SaaS adoption, including performance expectations, effort expectations, social influence, enabling conditions, and behavioral intent.

A quantitative approach was used, and data were collected through a questionnaire distributed to 120 faculty members across several HEIs in Libya. The study and its hypotheses were tested using partial least squares structural equation modeling (PLS-SEM) with SmartPLS software. The results showed that behavioral intention significantly and positively influences the adoption of Software as a Service (SaaS) application. Furthermore, both performance expectations and effort expectations significantly influence faculty members' behavioral intention to use SaaS technologies, while social influence and facilitating conditions showed no significant impact in this context. These findings highlight the importance of
perceived usefulness and ease of use in encouraging SaaS adoption. The study emphasizes the need for Libyan HEIs to enhance their technological infrastructure, provide training programs, and strengthen institutional support to facilitate faculty interaction with and adoption of cloud technologies, thereby improving their performance.

Keywords: *Cloud computing, SaaS, HEIs, Faculty performance, UTAUT, SEM, SmartPLS.*

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1. Introduction

Modern technologies have earned prominence in universities for advancing educational tools and communication, yet their high costs pose financial barriers for higher education institutions (Alhadad & Ertürk, 2019). Cloud computing (CC) emerges as a viable solution, delivering on-demand services such as storage, processing, and applications via the internet Core models include Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS), offering HEIs flexibility, affordability, and accessibility without substantial hardware investments (Xuan & Rana, 2024) (Fan & Rana, 2021). Cloud Computing (CC) is recognized as a dominant paradigm for delivering computing resources and services, driven by its flexibility, scalability, cost-efficiency, and support for collaboration (Qasem, Abdullah, Jusoh, Atan, & Asadi, 2019). These features make it particularly valuable for higher education institutions (HEIs), which face increasing demands related to student growth, IT infrastructure, and the need to maintain quality while reducing costs.(Alexander, 2008; Katz, 2010). CC has rapidly matured and been widely adopted across HEIs worldwide; however, retaining users remains a challenge for service providers (Qasem, Abdullah, Yaha, & Atana, 2020). Its ability to deliver on-demand access to software, platforms, and infrastructure reflects the concept of utility computing and has attracted significant interest in both academic and industrial sectors. (Motavaselalhagh, Safi Esfahani, & Arabnia, 2015). According to the National Institute of Standards and Technology (NIST), CC enables convenient, on-demand access to a shared pool of configurable resources with minimal management effort (Soinu, 2014). Its core characteristics include on-demand self-service, rapid elasticity, measured service, and resource pooling Among its service models, Software as a Service (SaaS) is widely used, as it reduces user technical requirements by placing greater responsibility on the service provider.(Kourik & Wang, 2012; Mell & Grance, 2011). (Erkoç & Kert, 2011). Libyan universities use SaaS solutions from local providers such as Libyan Spider and Al-Madar, as well as international companies, to facilitate quick and easy access to information for faculty and administrators (Yang, 2024). SaaS adoption is increasing in Libyan higher education due to the wide range of services it provides, including email systems, antivirus software, middleware, and firewall protection (Sharma & Ganpati, 2013).

1.1. Research questions and significances

This study examines the acceptance and adoption of SaaS and its impact on faculty performance in Libyan higher education. It further explores the use of SaaS-based collaboration applications in educational environments. To analyze the proposed relationships, Structural Equation Modeling (SEM) was employed. Accordingly, the main research questions are as follows:

(a) What are the significant factors that impact faculty members’ adoption of SaaS-based collaboration applications in higher education settings?

(b) How can the SEM method help to identify and predict the changes in adoption level of SaaS-based collaboration applications in higher education settings?

To answer these questions, an adoption model was based on the integration of the Unified Theory of Acceptance and Use of Technology (UTAUT) and collaboration-related constructs such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Behavioral Intention. The proposed model and hypotheses were then tested using the SEM.

2. Literature review

2.1. Collaborative Applications Based on (SaaS)

Cloud computing (CC) represents a modern evolution of the Internet, offering on-demand access to shared and scalable computing resources with minimal management effort. In higher education, Software as a Service (SaaS) reduces the cost and complexity of software installation, maintenance, and security management, while enabling flexible access to applications from any location(Deepa & Sathiyaseelan, 2012).. This flexibility supports lecturers in completing tasks efficiently and meeting academic deadlines. (Jula, Sundararajan, & Othman, 2014).

CC has become integral to teaching and learning processes, (Pardeshi, 2014). CC enables lecturers to access and complete their tasks from any location while maintaining data security and supporting timely task completion, which helps them meet deadlines (Yadav, 2014). enhancing engagement and facilitating collaboration among students, lecturers, and researchers(Budiawan, 2016). Widely used cloud-based tools such as Google Drive and Dropbox exemplify these benefits by supporting resource sharing and academic interaction(Tan & Kim, 2015). Furthermore, SaaS-based applications enable seamless collaboration across devices, overcoming geographical constraints and improving coordination (Taufiq-

Hail, Sarea, Mohd Yusof, Alsaidi, & Alenazi, 2021). Overall, CC adoption allows HEIs to optimize costs and reallocate resources to strategic priorities, while fostering knowledge sharing and innovation through collaborative cloud environments(Gohary, Hussin, & Razak, 2013).

2.2. Related work

The SaaS model is increasingly adopted in higher education for its ability to improve faculty efficiency and academic outcomes (P. Ertmer & A. Ottenbreit-Leftwich, 2010). Research indicates that SaaS applications enhance teaching effectiveness, student engagement, and resource management, while supporting collaborative learning environments (P. A. Ertmer & A. T. Ottenbreit-Leftwich, 2010). Effective integration, however, depends on faculty development and appropriate implementation strategies, which are closely linked to improved teaching performance (Wtang, 2021). Additionally, cloud-based platforms foster interactive learning and better student outcomes by creating more engaging educational environments. In the Libyan context, SaaS adoption offers practical solutions to challenges such as limited IT infrastructure by providing scalable and cost-efficient alternatives. (Q. Zhang, Cheng, & Boutaba, 2010).

A study conducted at the Surman College of Science and Technology (2025) demonstrated that SaaS tools positively impact students' academic performance by providing access to educational materials anytime and anywhere and enabling interactive learning experiences (Aladad, Gweder, Kashada, Snon, & Bisher, 2025). Despite the recognized benefits of SaaS in education, the specific context of Libyan higher education remains largely unexplored. Current studies mostly focus on institutions in developed countries, leaving a significant gap in the literature regarding the challenges and opportunities faced by Libyan universities in adopting SaaS technologies. Al-Shammari (2021) identifies several obstacles to technology adoption in educational environments in the Middle East, including inadequate training, limited infrastructure, and resistance to change obstacles particularly relevant to the Libyan context (Alshammari, 2021). This study explores the adoption of SaaS in Libyan HEIs, with a focus on faculty performance, to explore how educational technologies enhance institutional effectiveness and support faculty performance development.

2.3. Theoretical foundation

This study utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical framework to examine the adoption of SaaS and its subsequent impact on faculty performance in Libyan higher education (Venkatesh, Morris, Davis, & Davis, 2003a). The Unified Theory of Acceptance and Use of Technology (UTAUT) integrate several prior models to explain user acceptance and system usage. It identifies four key determinants performance expectancy, effort expectancy, social influence, and facilitating conditions that significantly influence technology adoption (Ayaz & Yanartaş, 2020). Despite this, empirical evidence on applying UTAUT to SaaS adoption in Libyan higher education remains limited, revealing a notable research gap. Accordingly, this study employs the UTAUT framework to examine the factors influencing SaaS adoption among faculty members and their impact on performance. It aims to contribute theoretically and provide practical insights for effective SaaS implementation in developing higher education institutions, where SaaS is increasingly used for academic tasks and e-learning communication(El Bilali, Hassen, Bottalico, Berjan, & Capone, 2021).

3. Hypotheses Development

3.1. Acceptance and Adoption SaaS on Faculty Performance in Libyan Higher Education

The UTAUT theoretical model proposes that actual technology use is determined by behavioral intention. The likelihood of adoption is influenced directly by four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. Additionally, the effects of these predictors are moderated by factors such as age, gender, experience, and voluntariness of use (Venkatesh, Morris, Davis, & Davis, 2003b). Acceptance refers to users' willingness to embrace new technologies, while adoption denotes the actual use and integration of these technologies within the educational context. In this study, the acceptance and adoption of SaaS concern the extent to which faculty members are willing and able to utilize SaaS applications and tools in their teaching activities. This is increasingly important for educational institutions seeking to enhance teaching and learning processes. According to the Unified Theory of Acceptance and Use of Technology (UTAUT), technology acceptance and adoption are influenced by four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, as shown in figure1. These constructs play a critical role in shaping users' attitudes and behaviors toward technology adoption. Numerous studies have highlighted the importance of SaaS. acceptance and adoption in education (Yadegaridehkordi, Nilashi, Shuib, & Samad, 2020).

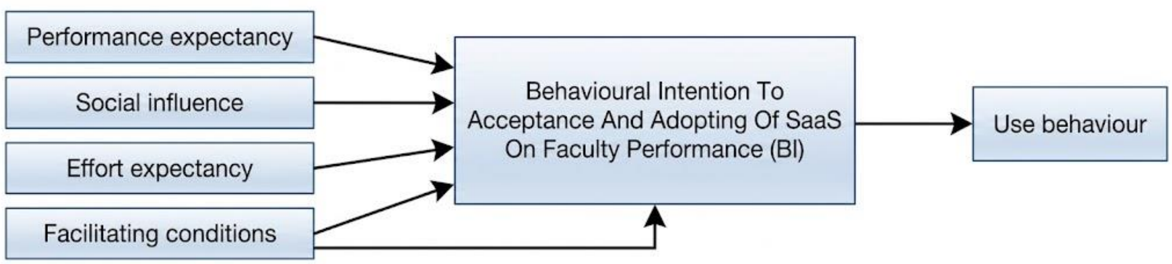

Figure 1. the Unified Theory of Acceptance and Use of Technology (UTAUT)

3.2. Behavior Intention's effects on Accepting and Adopting of SaaS on Faculty Performance

Behavioral intention (BI) to use SaaS-based applications reflects faculty members' conscious plans and willingness to integrate cloud-based tools into their teaching, research, and administrative activities. Empirical studies on learning management systems and cloud solutions indicate that BI is a strong predictor of actual system usage (Lavidas, Komis, & Achriani, 2022). When users perceive these technologies as useful and easy to use, their behavioral intention increases, which in turn promotes more frequent and sophisticated adoption in practice (Assalaarachchi, Silva, & Hewagamage, 2023). In higher education, such adoption has been associated with better course organization, increased interaction, and improved academic outcomes, indicating that stronger behavioral intention toward SaaS can indirectly enhance faculty performance and overall academic effectiveness (Sabi, Uzoka, Langmia, & Njeh, 2016). A suitable hypothesis that aligns with this paragraph could be written as:

H1: BI has a significant positive effect on acceptance and adoption of Saas by faculty members to enhance their performance.

3.3. Social Influence's effects on Behavior Intention

Social influence (SI) captures the perceived expectations from influential peers, such as colleagues, department heads, or leaders, to adopt technologies like SaaS applications in higher education. These social and professional pressures shape faculty decisions, with peer and supervisory support enhancing perceived usefulness and bolstering behavioral intention (BI) for teaching and research integration. Grounded in TAM and UTAUT, empirical evidence underscores SI's positive impact on BI in educational contexts(Alyoussef, 2022). Institutional policies, training, and collaboration further reinforce this by normalizing SaaS adoption (Bahari, Arpaci, Azmi, & Shuib, 2023). Accordingly, this study positions SI as a core antecedent of BI, hypothesizing that stronger normative encouragement heightens faculty intentions.

H2: Social influence (SI) has a significant positive effect on behavioral intention (BI) to use SaaS-based applications among faculty members in Libyan HEIs.

3.4. Facilitating Condition's effects on Behavior Intention and Acceptance and Adopting of SaaS on Faculty Performance

Facilitating conditions (FC) refer to the extent to which faculty perceive that adequate organizational and technical support such as reliable internet, technical assistance, training, and clear policies exists to enable the use of SaaS applications (Venkatesh, Brown, Maruping, & Bala, 2008). Within the UTAUT framework, strong facilitating conditions enhance users' confidence, thereby increasing their behavioral intention (BI) to adopt and continuously use such technologies (Yadegaridehkordi et al., 2020). In higher education, FC serve as critical enablers that translate positive intentions into actual system use. When sufficient support is available, faculty can improve course delivery, strengthen student communication, and manage academic tasks more efficiently, ultimately enhancing performance. Accordingly, this study posits that facilitating conditions have a direct positive effect on behavioral intention and indirectly support the adoption of SaaS, contributing to improved teaching effectiveness and overall academic outcomes in Libyan HEIs (Y. Zhang, Chen, & Xu, 2025).

H3a: Facilitating Conditions (FC) have a positive and significant influence on faculty members' behavioral intention (BI) to accept and adopt SaaS (Ac_Saas)

H3b: Facilitating conditions (FC) have a positive and significant influence on faculty members' actual acceptance and adoption of SaaS (Ac_Saas).

3.5. Performance Expectancy's effects on Behavior Intention (BI)

Performance expectancy (PE) is defined as "the degree to which an individual believes that using a system will improve job performance". In the context of higher education, it refers to faculty members' perceptions that SaaS-based applications can enhance their work, such as improving teaching effectiveness, facilitating course management, and providing better support to students. When lecturers believe that these tools help organize learning materials, enable faster communication, and support effective assessment and feedback, their behavioral intention (BI) to use them increases. Therefore, PE is considered a key predictor of BI in many technology adoption models, as greater perceived performance benefits lead to stronger intentions to adopt the technology (Lew & Lau, 2020).

H4: PE has a significant positive effect on behavioral intention (BI) to use SaaS-based applications among faculty members in Libyan HEIs.

3.6. The Effort Expectancy's effects on Behavior Intention

Effort expectancy (EE) refers to the degree to which faculty members perceive SaaS-based applications as easy to learn and use. When these systems are viewed as simple, intuitive, and requiring minimal technical skills or time, lecturers are more likely to evaluate them positively. As a result, their behavioral intention (BI) to use these applications in daily academic activities increases (Roca, Chiu, & Martínez, 2006). In technology acceptance research, effort expectancy (EE) is considered a key determinant of behavioral intention (BI). This is particularly important in educational settings, where heavy workloads and limited technical support can make complex systems less appealing to potential users. When technologies are perceived as easy to use, faculty members are more likely to intend to adopt them (Almaiah et al., 2022).

H5: EE has a significant positive effect on behavioral intention (BI) to use SaaS-based applications among faculty members in Libyan HEIs.

The Conceptual Framework of the Study

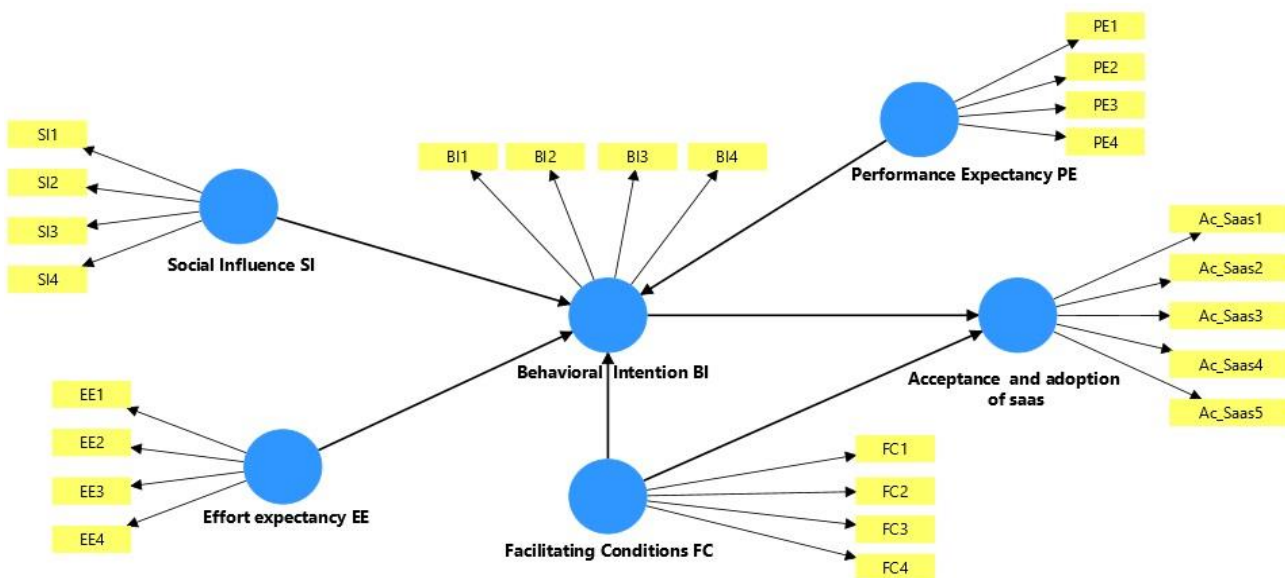

Figure 2. Conceptual Framework

4. Research Methodology

This study investigates the impact of Software as a Service (SaaS) on faculty acceptance and adoption in Libyan higher education institutions using the UTAUT framework. The research targets faculty members who use SaaS applications in teaching activities across universities in Libya. A quantitative approach was employed, using convenience non-probability sampling and a survey questionnaire for data collection. The questionnaire was developed using Google Forms and included an introduction explaining the study objectives and inviting participants to take part. Ethical considerations were ensured by protecting participants' privacy and maintaining anonymity. The questionnaire measured the independent variables: Social Influence (SI), Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Behavioral Intention (BI) as well as the dependent variable(Ac_Saas).

This exploratory study collected a modest number of responses (120 responses), effectively manageable by SmartPLS 4.0, which offers a good level of statistical power. To determine the minimum recommended sample sizes, G Power Analysis was used according to the recommendations and guidelines of Sarstedt et al.'s (Sarstedt, Ringle, & Hair, 2021). Employing the G*power software analytical tool (Faul, Erdfelder, Buchner, & Lang, 2009) resulted in a minimum sample size of 116, factoring in a power level of 0.90, an alpha error probability of 0.05, and a medium effect size of 0.15 (Sarstedt et al., 2021). Refer to Figure 3 for G*power output.

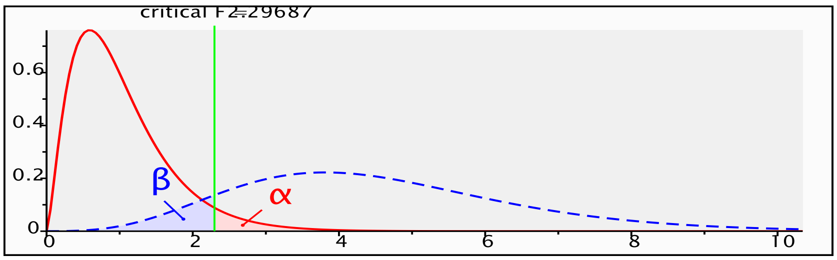

Figure 3. G*Power Sample size output

SmartPLS, a non-parametric PLS-SEM technique, mitigates issues of data normality, missing values, and scale variations, making it ideal for exploratory, prediction-oriented studies (Al-Mamary, 2022, Samsudeen, Selvaratnam, & Hayathu Mohamed, 2022). It excels in simultaneously assessing explanatory and predictive model capabilities, enabling analysis of complex latent relationships in emerging frameworks (Almaiah, Alamri, & Al-Rahmi, 2019; Kaya, Behravesh, Abubakar, Kaya, & Orús, 2019). This study employs PLS-SEM to evaluate the measurement model via internal consistency (Cronbach's $\alpha \geq 0.7$, or ≥ 0.6 for exploratory work), indicator loadings ≥ 0.708, (AVE ≥ 0.5 for convergent validity)followed by structural model assessment and hypothesis testing (Sarstedt et al., 2021). Discriminant validity is confirmed through higher indicator loadings on assigned constructs and the Fornell-Larcker criterion (square root of AVE exceeding inter-construct correlations, Fornell & Larcker, 1981 (Sarstedt et al., 2021). The full methodology is (Fornell & Larcker, 1981)depicted in Figure 4.

4.1. Analyses and Discussions of Results

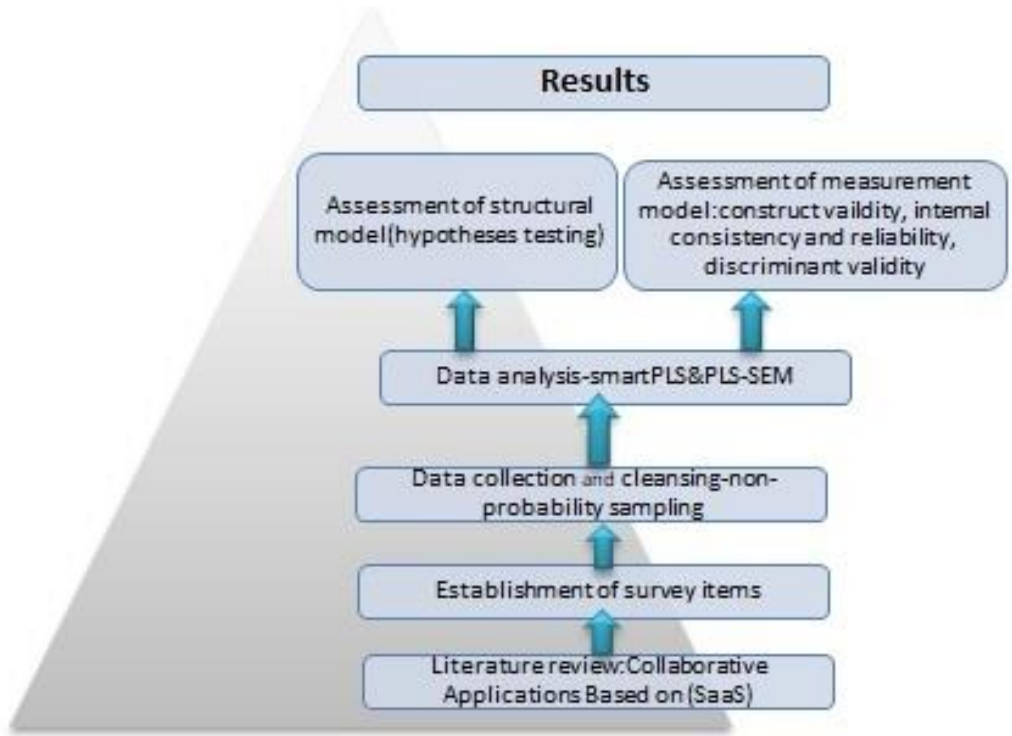

Figure 4. Overall Research Methodology Flowchart

4.1.1. Model Measurement Evaluation

The measurement model underwent a comprehensive evaluation, encompassing convergent validity, outer loadings, internal consistency, and discriminant validity. Convergent validity, assessed through Average Variance Extracted (AVE) with a threshold of 0.5 or higher (Sarstedt et al., 2021), met the criterion with values ranging from 0.51 to 0.80 (Table 2). Outer loadings of items were examined, surpassing the recommended threshold of 0.6 (Chin, 1998), thus confirming structural convergence validity.

Internal consistency and reliability were scrutinized using Composite Reliability (CR) and Cronbach's alpha. All latent variables exceeded the CR cut-off of 0.7, and Cronbach's alpha values surpassed the recommended range of 0.60 to 0.70. Consequently, both convergent validity and internal consistency/reliability were established. In summary, the measurement model shows adequate reliability and validity across all evaluated criteria, as presented in Table 1.

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Table 1. Internal consistency and reliability and convergent validity

Latent construct	Items	Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavior Intention (BI)	BI1	0.774	0.743	0.763	0.842	0.578
	BI2	0.540				
	BI3	0.887				
	BI4	0.797				
Effort Expectancy (EE)	EE1	0.716	0.758	0.778	0.845	0.579
	EE2	0.716				
	EE3	0.873				
	EE4	0.727				
Facilitating Conditions (FC)	FC1	0.859	0.739	0.739	0.828	0.549
	FC2	0.747				
	FC3	0.691				
	FC4	0.649				
Performance Expectancy(PE)	PE1	0.848	0.783	0.817	0.863	0.618
	PE2	0.771				
	PE3	0.576				
	PE4	0.910				
Social Influence (SI)	SI1	0.924	0.722	0.877	0.842	0.646
	SI3	0.847				
	SI4	0.607				
Acceptance and adopting of Saas	Ac_Saas 1	0.616	0.821	0.836	0.875	0.588
	Ac_Saas 2	0.775				
	Ac_Saas 3	0.830				
	Ac_Saas 4	0.898				
	Ac_Saas 5	0.682				

Note: AVE: Average Values Extracted; CR: Composite Reliability

As a final step in evaluating the measurement model, discriminant validity is assessed(Figure 4). His analysis involves two main steps. First, the Fornell-Larcker criterion is examined, where the square root of the AVE on the diagonal should be greater than the correlations with other constructs (Fornell & Larcker, 1981). As shown in Table 2, this requirement is satisfied.

Table 2. Discriminant validity with Fornell-Larker criterion analysis

Latent construct	1	2	3	4	5	6
Acceptance and adopting of Saas	**0.767**					
Behavioral Intention BI	0.577	**0.760**				
Effort expectancy EE	0.548	0.525	**0.761**			
Facilitating Conditions FC	0.334	0.349	0.194	**0.741**		
Performance Expectancy PE	0.316	0.442	0.313	0.301	**0.786**	
Social Influence SI	0.256	0.389	0.311	0.336	0.288	**0.804**

Note: Square root values (in bold) of AVE in the diagonal demonstrate values higher than off-diagonal.

Second, the cross-loading values are examined. Each item should load more strongly on its own construct than on other constructs to confirm discriminant validity. As shown in Table 3, the results satisfy this criterion.

Table 3. Discriminant validity with cross-loading analysis

	Acceptance of adopting Saas	Behavior Intention (BI)	Effort Expectancy (EE)	Facilitating Conditions (FC)	Performance Expectancy(PE)	Social Influence (SI)
Ac_Saas1	0.616	0.462	0.578	0.379	0.359	0.352
Ac_Saas2	0.775	0.364	0.378	0.161	0.152	0.157
Ac_Saas3	0.830	0.452	0.353	0.238	0.274	0.161
Ac_Saas4	0.898	0.503	0.452	0.265	0.229	0.189
Ac_Saas5	0.682	0.264	0.238	0.172	0.119	0.031
BI1	0.479	0.774	0.494	0.317	0.374	0.244
BI2	0.410	0.540	0.229	0.356	0.203	0.311
BI3	0.430	0.887	0.440	0.232	0.429	0.340
BI4	0.356	0.797	0.387	0.150	0.302	0.293
EE1	0.356	0.318	0.716	0.097	0.202	0.285
EE2	0.513	0.481	0.716	0.123	0.331	0.249
EE3	0.457	0.444	0.873	0.232	0.292	0.237
EE4	0.272	0.293	0.727	0.118	0.049	0.167
FC1	0.296	0.253	0.190	0.859	0.228	0.246
FC2	0.290	0.282	0.214	0.747	0.281	0.237
FC3	0.227	0.270	0.070	0.691	0.229	0.310
FC4	0.148	0.222	0.071	0.649	0.127	0.198
PE1	0.185	0.304	0.216	0.204	0.848	0.198
PE2	0.278	0.362	0.308	0.224	0.771	0.184
PE3	0.329	0.276	0.197	0.380	0.576	0.312
PE4	0.222	0.422	0.253	0.182	0.910	0.233
SI1	0.262	0.423	0.283	0.370	0.325	0.924
SI3	0.170	0.239	0.231	0.271	0.112	0.847
SI4	0.155	0.210	0.234	0.099	0.207	0.607

The results of the two discriminant validity tests support the adequacy of all constructs in the proposed model. Therefore, the findings of the previous analyses justify proceeding to hypothesis testing in the next section.

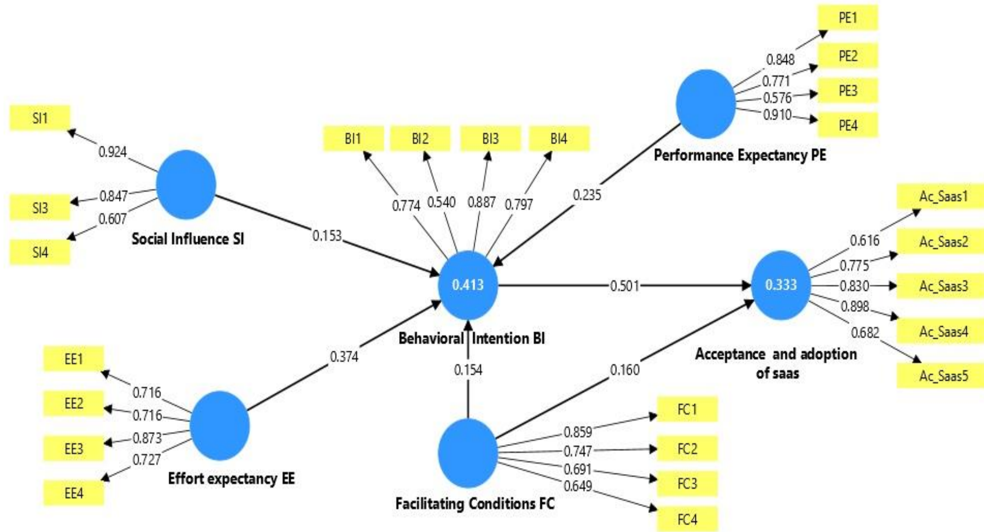

Figure 4. illustrates the results of the measurement model analyses

4.2. Hypotheses Testing via Structural Model Evaluation

Before conducting the structural model evaluation, collinearity was examined to ensure there were no potential issues. The results showed that all constructs had Variance Inflation Factor (VIF) values below 5, indicating that collinearity was not a concern (see Table 4).

Table 4. Collinearity issues evaluation with VIF analysis

Latent construct	1	2	3	4	5	6
Ac_Saas						
BI	1.138					
EE		1.181				
FC	1.138	1.191				
PE		1.214				
SI		1.240				

Note: The recommended threshold of Variance Inflation Factor (VIF) ≤ 5.

4.2.1. The Coefficient of Determination (R^2) Analysis

The coefficient of determination (R^2) or out-of-sample prediction measures the proportion of variance in the dependent variable that is predictable from the independent variables in a regression model. In our study, the R^2 values for Behavioral Intention (BI) and the acceptance and adoption of SaaS applications and tools (Ac_Saas).

are 0.413 and 0.333, respectively. According to Cohen (Cohen, 1988), R^2 values can be categorized as $R^2 < 0.02$(small effect), $0.02 \leq R^2 < 0.13$ (medium effect), $R^2 \geq 0.13$ (large effect). Our findings reveal a substantial effect size for both BI and Ac_Saas, suggesting that the independent variables collectively account for a substantial portion of the variance observed in the dependent variables. Furthermore, to assess the magnitude of the relationship between the independent and dependent variables, the effect size (f^2) is calculated. Effect sizes quantify the strength of the relationship between variables and are categorized as $0.02 \leq f^2 < 0.15$ (small) , $0.15 \leq f^2 < 0.35$ (medium), $f^2 \geq 0.35$ (large), according to Joseph F.Hair (Hair, Ringle, & Sarstedt, 2011) . In our study, the effect size for BI on Ac_Saas is ($f^2 = 0.33$), indicating a medium effect size and suggesting a strong relationship between behavioral intention and the acceptance and adoption of SaaS. This finding underscores the significant influence of behavioral intention on the willingness of faculty members to adopt innovative educational technologies.

On the other hand, the effect size of Effort Expectancy (EE) and Performance Expectancy (PE) on BI is ($f^2 = 0.20$) and ($f^2 = 0.07$), respectively, indicating a Medium effect size of EE and a small effect of PE on BI, therefore, PE does not significantly contribute to (Ac_Saas). Facilitating Conditions (FC) and Social Influence (SI) exhibit varying degrees of influence on (Ac_Saas). FC effect size ($f^2 = 0.03$) exerts on BI and ($f^2 = 0.04$) on (Ac_Saas), respectively, indicating small and moderate effect sizes. On the other hand, SI shows an effect size ($f^2 = 0.09$) on BI, as well as an indication and strong relationship with BI. These findings highlight the importance of considering multiple factors, including behavioral intention, facilitating conditions, and social influence, when examining the adoption of SaaS by faculty members in Libyan HEIs. Refer to Table 5 for more details.

Table 5. Coefficients of determination R² and effect size f

Latent Constructs	Behavior Intention BI	Acceptance and adoption of Saas (Ac_Saas)
Coefficient of Determination R^2	0.413	0.333
Effect size f^2 of antecedent and driving constructs		
Ac_Saas		
BI		0.331
EE	0.201	
FC	0.034	0.044
PE	0.077	
SI	0.092	

Examining the outcomes in Table 6 reveals insightful results regarding the impact of various factors on users' behavioral intentions and the subsequent acceptance and adoption of Saas. In the following subsections, a detailed explanation and interpretation of the relationship between the postulated in the current research.

Table 6. Path coefficient and hypotheses testing

Path	Path Coefficients Beta	Sample Mean	STDEV	t values	p values	LL CI 2.5%	UL CI 97.5%	Hypotheses Remarks
BI->Ac_Saas	0.50	0.50	0.90	5.49	0.00	0.32	0.67	Supported
EE-> BI	0.37	0.38	0.09	3.89	0.00	0.19	0.56	Supported
FC-> Ac_Saas	0.16	0.17	0.10	1.52	0.12	-0.05	0.36	Not Supported
FC-> BI	0.15	0.14	0.09	1.68	0.09	-0.03	0.32	Not Supported
PE->BI	0.23	0.23	0.07	2.96	0.03	0.08	0.40	Supported
SI->BI	0.15	0.16	0.09	1.55	0.12	-0.03	0.35	Not Supported

Note: CI: confidence interval; LL: lower limit; UL: upper limit, * $p < 0.10$; ** $p < 0.01$.

4.2.2. *Behavioral Intention's* effects on Acceptance and adopting of Saas(Ac_Saas)

The results presented in Table 7 provide important insights into the relationship between different factors and the behavioral intentions of faculty members in Libyan HEIs regarding the acceptance and adoption of SaaS. The analysis shows a statistically significant relationship between behavioral intention (BI) and the acceptance and adoption of SaaS (Ac_Saas) among faculty members ($\beta = 0.50$, $p \leq 0.05$, $t = 5.49$). This result supports Hypothesis H1, which states that BI has a significant positive effect on the acceptance and adoption of SaaS to enhance faculty performance. It indicates that when faculty members have stronger intentions to use SaaS applications, they are more likely to adopt and integrate these technologies into their teaching and academic activities.

In the context of improving higher education in Libya, these findings highlight the importance of aligning institutional strategies with faculty members' intentions to use digital technologies. When instructors perceive technological tools as useful and are willing to adopt them, their teaching performance and academic practices are more likely to improve. Therefore, understanding faculty members' behavioral intentions is essential for promoting digital transformation in Libyan universities. Furthermore, the consistency of these results with previous studies that have shown that behavioral intention strongly influences the actual use of technology (Al-Momani, Mahmoud, & Ahmad, 2016; García Botero, Questier, Cincinnato, He, & Zhu, 2018), supports the reliability of our current study's findings and confirms that behavioral intention plays a pivotal role in encouraging the adoption of cloud CC and SaaS applications in HEIs.

Overall, these results suggest that universities and policymakers in Libya should focus on strengthening positive attitudes and intentions among faculty members toward SaaS and cloud technologies. Such efforts can enhance faculty performance, improve teaching effectiveness, and support the development of modern and technology-driven HEIs.

4.2.3. Social Influence's effects on Behavioral Intentions

The analysis of the relationship between Social Influence (SI) and Behavioral Intention (BI) among faculty members in Libyan HEIs revealed an unexpected result. Contrary to the proposed hypothesis (H2), Social Influence did not have a significant effect on Behavioral Intention ($\beta = 0.15$, $p = 0.12$, $t = 1.55$). This finding suggests that the opinions or expectations of colleagues, administrators, or the academic environment do not play a decisive role in shaping faculty members' intentions to adopt SaaS-based applications. According to previous studies, Social Influence (SI) does not have a significant effect on Behavioral Intention (BI)(García Botero et al., 2018; Matheis, Lehnhart, Costa, Tontini, & Vieira, 2026), which supports and confirms the results of our current study.

One possible explanation for this result is that faculty members tend to rely more on their personal evaluation of the technology rather than on external social pressure or recommendations. In academic environments, lecturers often have a high level of professional autonomy, which may reduce the influence of social factors on their technology adoption decisions. Therefore, their intention to use SaaS applications may be driven primarily by individual perceptions such as usefulness, ease of use, or personal experience with the technology rather than by the influence of others.

4.2.4. Facilitating condition's effects on Behavioral Intentions Acceptance and adopting of Saas(Ac_Saas)

The analysis of the relationship between Facilitating Conditions (FC) and both Behavioral Intention (BI) and the acceptance and adoption of SaaS applications (Ac_Saas) revealed non-significant results. The findings indicate that Facilitating Conditions do not have a statistically significant effect on Behavioral Intention ($\beta = 0.15$, $p = 0.09$, $t = 1.86$) or on the acceptance and adoption of SaaS applications ($\beta = 0.16$, $p = 0.12$, $t = 1.52$). Therefore, Hypotheses H3a and H3b are not supported.

This result may be explained by the current context of Libyan HEIs, where technological infrastructure and institutional support for digital technologies remain limited. In many universities, reliable internet connectivity, modern digital infrastructure, and structured technical support systems are insufficient. Additionally, formal training programs that help faculty members effectively use modern digital technologies, including SaaS-based applications, are often limited or inconsistent. Under such circumstances, facilitating conditions may not be perceived as an enabling factor that encourages technology adoption.

Facilitating conditions (FC) encompassing organizational infrastructure, technical support, and resources support system use but often falter in weak environments, hindering adoption despite positive user attitudes (Venkatesh et al., 2003; Venkatesh et al., 2003b). In developing contexts, inadequate resources constrain digital uptake, even with recognized benefits (Alenezi, Karim, & Veloo, 2011). Empirical evidence shows inconsistent FC effects on behavioral intention, particularly where support is underdeveloped (Alblooshi & Abdul Hamid, 2021) aligning with this study's null finding For Libyan HEIs, bolstering infrastructure, ongoing training, and technical aid is crucial to promote faculty SaaS adoption.

4.2.5. Performance Expectancy's effects on Behavioral Intentions Relationship

The analysis of the relationship between Performance Expectancy (PE) and users' behavioral intentions (BI) regarding the adoption and acceptance of SaaS in Libyan HEIs yielded positive results. Lend support to hypotheses (H4). It refers to Performance Expectancy (PE), which demonstrates a significant influence on BI ($\beta = 0.23$, $p = 0.03$, $t = 2.96$). This finding suggests that faculty members' perceptions of the performance benefits associated with SaaS applications and tools play a decisive factor in shaping their behavioral intentions towards adoption and acceptance. In other words, the potential advantages and perceived usefulness of these technologies, Faculty members' intentions to utilize them in their educational activities and performance expectancy have been significantly influenced by their expectations of performance outcomes.

According to previous studies, which indicate that Performance Expectancy is the strongest variable affecting Behavioral Intention to Use Technology(Chen, Jia, & Wu, 2023; Tusyanah, Wahyudin, & Khafid, 2021; Venkatesh et al., 2003b). In a study on the use of digital educational resources, the results indicated that performance expectancy has a statistically significant positive effect on users' intention to use digital educational resources(Liu, Wang, & Luo, 2025). All these results from previous studies strongly support the results of our current study.

4.2.6. . Effort Expectancy's effects on Behavioral Intentions Relationship

Analyzing the relationship between Effort Expectancy (EE) and users' behavioral intentions (BI) regarding the acceptance and adoption of SaaS applications and tools among faculty members in Libyan HEIs yielded significant results. Specifically, the path from Effort Expectancy (EE) to Behavioral Intention (BI) was found to be statistically significant ($\beta = 0.37$, $p = 0.00$, $t = 3.89$), thus providing support for Hypothesis 5 (see Figure 5). This result underscores the importance of faculty members' perceived ease of use and interaction with SaaS applications and tools in shaping their behavioral intentions.

These findings highlight effort expectancy (EE) perceived ease of use and interaction with SaaS tools as a pivotal driver of faculty behavioral intention (BI). When technologies feel intuitive, users gain stronger incentives to adopt them, enhancing performance in educational contexts. This aligns with prior studies confirming EE's robust link to BI in technology adoption (Abdekhoda, Dehnad, & Zarei, 2022; Hossain, Salam, & Akhond, 2024; Raheem Ahmed, Streimikiene, Streimikis, & Khouri, 2024).

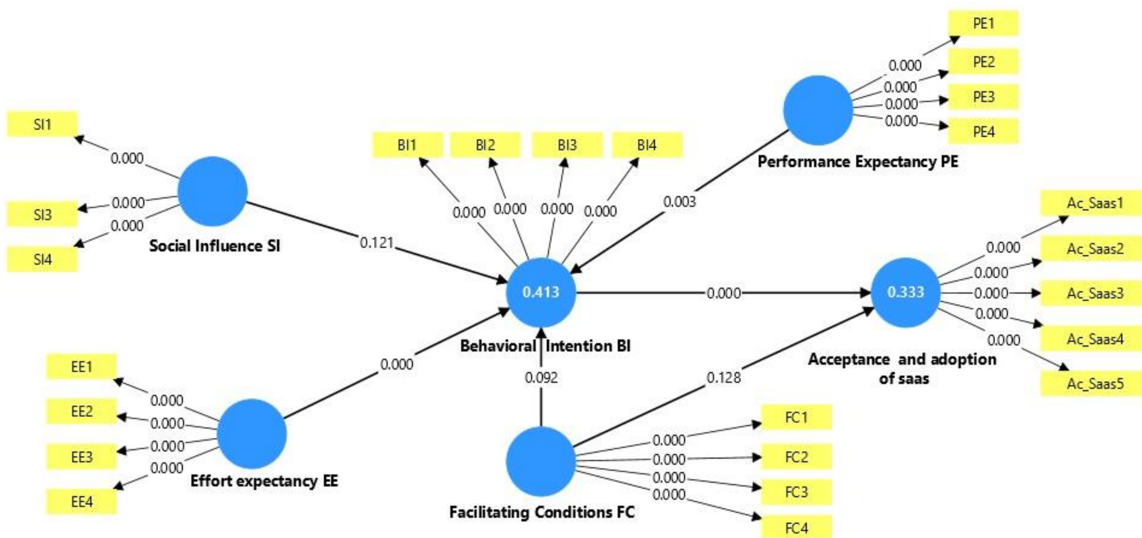

Figure 5. Hypotheses Analysis' Results

5. Contribution of the Study

This study advances SaaS adoption literature in Libyan higher education institutions (HEIs) through four key contributions. First, it extends UTAUT to the underexplored context of Libyan faculty, addressing a gap in empirical research on developing nations (unlike prevalent studies in developed settings). Second, it elucidates UTAUT constructs' impacts: performance expectancy and effort expectancy significantly predict behavioral intention (BI), whereas social influence and facilitating conditions do not, informing debates on factor salience in educational contexts. Third, it confirms BI as a robust antecedent of actual SaaS adoption, linking it to enhanced faculty performance, collaboration, and efficiency. Finally, it offers practical guidance for Libyan policymakers, administrators, and vendors emphasizing user-friendly designs, training, and awareness campaigns to foster adoption.

6. Conclusion

This study investigated SaaS adoption factors and their effects on faculty performance in Libyan HEIs using UTAUT, analyzed via PLS-SEM on quantitative data. It examined links among performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), behavioral intention (BI), and actual adoption. In this section, we will address the research questions:

Research Question 1: What are the important factors influencing faculty members' adoption of SaaS-based collaboration applications in HEIs?
PE and EE significantly positively affect BI, indicating faculty favor user-friendly tools that enhance academic performance. BI robustly predicts adoption, but SI and FC show no significant impact in this context.
Research Question 2: How can the SEM method help to identify and predict the changes in adoption level of SaaS-based collaboration applications in higher education settings?

PLS-SEM effectively modeled multifaceted relationships, pinpointing PE and EE as primary BI drivers while validating the framework. These insights guide Libyan HEIs toward digital transformation via intuitive, benefit-focused SaaS integration.

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