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Abstract

This study aims to investigate the factors influencing the various stages of Google Workspace adoption among academic staff at higher education institutions (HEIs). An expanded version of the "Unified Theory of Acceptance and Use of Technology" (UTAUT) served as the theoretical basis for the study. A quantitative research approach was employed, utilizing an online questionnaire completed by 416 academic members at higher education institutions (HEIs). A multinomial logistic regression technique was performed for data analysis. The findings revealed that distinct factors affect the different stages of SaaS adoption by academic members. Performance expectancy, facilitating conditions, social influence, perceived trust, and perceived security were positively associated with academic members' adoption stage of SaaS compared to their intention to adopt. In contrast, effort expectancy had no significant effect. The results also showed that all of the suggested factors had a significantly larger impact on academic members in the intention-to-adopt stage compared to post-adopters. Finally, performance expectancy, effort expectancy, social influence, and perceived trust had a significant positive effect on the post-adoption of SaaS among academic members compared to adopters. Facilitating conditions and perceived security were found not to be significant.

Keywords – Software as a Service (SaaS), Cloud computing, Google Workspace, Technology Acceptance, Technology in Higher Education

Introduction

Cloud computing is a new paradigm, which can help organizations to enjoy the entire range of software and hardware services via the internet. It has quickly become a necessity, with its most important benefits being cost effectiveness, scalability, high performance and operational efficiency (Low et al., 2011). With this model, companies are able to take advantage of high-quality applications and computing power without going through the high

monetary expenses of acquiring and sustaining tangible infrastructure. Cloud services include data storage, virtual servers, customer relationship management and enterprise resource planning made accessible by cloud vendors remotely (Oliveira et al., 2019). As a result, cloud computing is redefining the organizational functions as well as becoming a strategic force of customer engagement and business transformation (Dajani et al., 2022; Al-Okaily et al., 2023; Khalifeh et al., 2024).

There are usually three basic models of cloud-based services: the "Software as a Service" (SaaS), the "Platform as a Service" (PaaS), and the "Infrastructure as a Service" (IaaS). SaaS is the highest-layered model, which offers the on-demand software and application services to the users. Within this model, the service provider has all the applications to be installed, managed, and maintained all ready, and the user is given instant access without having to install or maintain the application locally. Located between the two layers is PaaS which offers a platform on which users can develop, test, and deploy apps. It also provides the required equipment, network and operating systems, which makes the management of the underlying infrastructure less complicated. IaaS is the third model; it provides the infrastructure needed for organizations to use servers, datasets, and network resources on a rental basis (Diaby and Rad, 2017; Safari et al., 2015). Among these models, SaaS is the leading type of cloud computing service for organizations, SMEs in particular, as it eliminates the need to install software, a common task for in-house IT. Most decision-makers in organizations are attracted to implementing SaaS because it is mature, friendly, and easy to use and offers flexible access through web-based user interfaces. SaaS is inherently different than other types of cloud services as it provides more opportunities for business growth, greater efficiency, and significant improvement in business performance, particularly for organizations. Nonetheless, although SaaS has offered many advantages to individuals, it has not been reached to a mature level. Therefore, the adoption of SaaS is considered a major challenge for the individuals, particularly when there are no specific attributes that can be taken into account when switching to SaaS (Changchit and Chuchuen, 2018; Majengo and Mbise, 2022).

The majority of literature on cloud computing adoption has tended to take the issue in general terms, and make no attempt to differentiate the special features of SaaS, PaaS, and IaaS. Nevertheless, the factors affecting adoption can be diverse in relation to those models because they are characterized by the different degrees of complexity (Martins et al., 2016; Oliveira et al., 2019). Whereas SaaS is end user oriented, PaaS and IaaS are more technical and thus aimed at IT specialists and hence relate to different adoption dynamics. In this respect, Senyo et al. (2018) highlighted the necessity of more profound studies to comprehend how cloud

computing, and, above all, SaaS are adopted in different settings. Moreover, a significant part of the current literature has focused on the immediate impacts of the suggested variables on the existing adoption without considering the other innovation diffusion phases. Therefore, the "intention-to-adopt (pre-adoption), adoption (decision), and post-adoption (implementation)" stages are considered very important areas of study to elucidate how end users integrate this technology into their business activities (Martins et al., 2016; Mathani et al., 2024; Wahshat et al., 2024). Also, although cloud computing has been gaining attention from researchers in the last decade and several studies have investigated the determinants of SaaS at an organizational level, a relatively limited number of studies have investigated SaaS adoption at an individual level. Therefore, more studies are needed to understand this topic (Oliveira, 2019; Al-Okaily et al., 2023; Qasim et al., 2025).

The usage of cloud computing and especially Software as a Service (SaaS) has not been embraced as fast as it should be since its benefits have been well documented. The advantages of cloud technologies are obvious: they are cost-effective, flexible, scalable, and can be accessed easily. However, they are still limited in the number of barriers to their widespread diffusion. The main concerns are such issues as data protection, the complexity of the system configuration, data recovery, and the possibility to monitor the services in real time. Institutional reluctance and slow adoption have also been contributed to by other factors such as facing difficulties in managing clouds, using external services providers, loss of organizational control, user awareness, privacy and unpredictable cost structures (Raza et al., 2015; Khalifeh et al., 2023; Khayer et al., 2020). The latter are particularly applicable to SaaS that delivers cloud-based apps to end users and is a major aspect of IT infrastructure modernization in other sectors, higher education being one of them.

SaaS can be very instrumental in transforming the academic set up by offering the ability of scalability, accessibility, and ease of use as solutions to deliver education, collaborative, and administrative services to the institution. One of the brightest examples is Google Workspace, which is a widely used SaaS platform and combines Gmail, Google Drive, Google Docs, Sheets, Meet, and Classroom apps, which are explicitly intended to support teaching, learning, communication, and overall academic productivity. However, despite its theoretical benefits, many higher education institutions (HEIs) remain hesitant to adopt SaaS solutions like Google Workspace. Al-Sharafi (2021) noted that even with the variety of services that cloud applications offer to end users in the academic field, traditional technology preferences do not disappear entirely. Similarly, Aviamu et al. (2019) found that African university academic libraries have been slow to adopt cloud computing, mostly because of issues of trust,

awareness, and authentication procedures. Such hesitation is even greater in the developing world, where the gap in studies on cloud computing adoption at the individual level continues to exist among institutions of higher education (HEIs) (Odeh, 2017). On this background, it is necessary to comprehend the particular issues that determine the adoption of SaaS, especially the adoption of Google Workspace by the academic employees. The current research aims to fill this gap by suggesting a conceptual framework that will analyze the intention-to-adopt, adoption, and post-adoption stages of Google Workspace by academic members. In contrast to much of the previous literature that has focused a lot on one of the stages, this study takes a holistic approach to the adoption behaviour of SaaS in HEIs. By so doing, it offers meaningful lessons to policymakers and technology vendors wishing to promote the effective and sustainable integration of cloud-based services in the higher education.

This paper is structured into eight sections. The following section presents an overview of SaaS. This is followed by a description of the theoretical background that supports this investigation in Section Three. Section Four proposes a conceptual model and provides hypothesis development. Research methods and design are delineated in Section Five, and Section Six presents the data analysis and results. The results of this study are discussed in Section Seven. Finally, the theoretical contributions, practical implications, and limitations are discussed, and the findings and conclusions derived from the study are presented in Section Eight.

LITERATURE REVIEW

The Concept of Software as a Service (SaaS)

In the late 1990s, the cost of the internet drastically decreased, internet speed increased, and security improved. This led to the emergence of the application service provider (ASP) as a new business model for enterprise software. According to Susarla et al. (2003), the "Application Service Provider Consortium" defined an ASP as an entity that "manages and delivers application capabilities to multiple entities from a data center across a wide area network (WAN)" (p. 91). This new business model has brought many advantages to organizations, including the ability to launch software applications in short time periods and with lower-cost implementation. However, the ASP approach has a significant customization challenge: since clients cannot undertake modifications independently, the demand for customization from diverse clients has an impact on the efficiency of vendor work (Li et al., 2012). The SaaS model was designed to meet customers' needs and overcome these limitations.

It solved the efficiency problem by allowing clients to customize the metadata layer to some extent.

SaaS is the top model for cloud computing and is an effective alternative approach to delivering software applications, enabling users to access them through the cloud platform (Gashami et al., 2013). In general, SaaS refers to software that is hosted on the internet (off the premises) rather than on a company's own servers (on the premises). ASPs are responsible for software application development and maintenance. SaaS has attracted organizations and end users because it is easy to use and allows them to access and use web-based applications through the internet using a web browser or other thin-client applications in exchange for subscription fees (Safari et al., 2015). SaaS has a substantial lead over other cloud services and kept its dominance in 2022. The rate of SaaS adoption by organizations and end users has also increased over the last decade because SaaS offers reduced setup costs, a higher rate of software quality improvement, and faster delivery of new features than software that requires on-premises installation. Also, SaaS is changing IT resources into a ubiquitous service due to the nature of its characteristic architecture. SaaS is predominately used by end users. It offers flexible and cost-effective software accessibility via internet servers and facilitates more effective collaboration between individuals (Tan and Kim, 2015; Siek and Wijaya, 2022).

SaaS is classified into two types, horizontal and vertical, each of which has distinct characteristics. Vertical SaaS refers to a software market that focuses on a specific user segment, domain, or industry. The vertical SaaS provider does not try to be everything to everyone or cover a wide range of products. Vertical SaaS, however, is industry- or niche-specific (like insurance industry (Guidewire Software), hospitality industry (Toast Software), pharmaceutical and life sciences industry (Veeva Software), and health and medical industry (Hakeem Software). Horizontal SaaS, in its turn, is created to accommodate a broad spectrum of business consumers, irrespective of their business sphere. It offers the solutions that could be implemented in different spheres with different business demands as well as goals. Horizontal SaaS therefore is a more established approach which serves a wide and diverse client base. Some such tools consist of QuickBooks (accounting software), Salesforce (customer relationship management software), Office 365 (productivity software), and Google Workspace (formerly referred to as G Suite) (Martins et al., 2019; Tan and Kim, 2015; Ha et al., 2020).

Google Workspace in Higher Education

The transformation towards the use of cloud-based systems as opposed to traditional ones by higher education institutions (HEIS) is driven by the benefits of long-term sustainability,

operational efficiency, ease of implementation, and cost-effectiveness. Among the biggest advantages of cloud computing is the possibility of improved collaboration which is especially important in academic circles. Cloud technologies make the exchange of educational resources and learning materials between lecturers and students, as well as between institutions, possible, which makes it possible to enhance inter-institutional cooperation and positively impact the overall quality of education (Qasem et al., 2020; Alharthi et al., 2017; Qasim and Khalifeh, 2025).

Out of the variety of SaaS tools, Google Workspace can be regarded as one of the most complete, trustworthy, and popular application in the higher education sphere. It provides a bundle of cloud-based services, such as Google Docs, Sheets, Drive, Gmail, Meet, Classroom, Forms, Groups, Calendar, and Tasks, each of which is critical towards improving communication, enhancing collaboration, and managing assignments, as well as the overall goals of the digital learning settings. Its main benefits include real time editing, automatic saving, version control, and accessibility via the cloud which enable students and academic staff to work together as a team without having been limited by time or location. Moreover, the interoperability of the platform with other educational technologies and Learning Management Systems (LMSs) makes it more versatile, which contributes to its scalability and allows the institution of various sizes and needs to use it (Sopwandin and Junaidi, 2024; Emilzoli et al., 2025).

Google Workspace Education Google Workspace Education is a version designed specifically with academic use in mind, available in a range of levels, including Fundamentals, Standard, Teaching and Learning Upgrade, and Education Plus, with varying amounts of functionality and administrative control applicable by different institutions. It is more inclusive and flexible because it can be used in both web browsers and mobile applications, thereby, reaching a large number of learners and educators. In addition, its affiliation with other software such as Google Scholar and other learning extensions complements its use in other areas of communication and file sharing such as research, evaluation, and analytics. Due to all these features, it has integrated itself into virtual classes, blended learning, administrative management, and online tests. The simple interface of Google Workspace and low learning curve further make it easy to adopt, particularly when the user has less technical expertise (Lake, 2022; Siek and Wijaya, 2022).

Google Workspace enhances student learning outcomes, further underscoring its pedagogical value and potential to enrich instructional quality. As such, understanding the

dynamics behind its adoption is crucial, particularly in the context of higher education institutions transitioning from traditional systems to cloud-based infrastructures.

Theoretical Framework

While extensive research has been conducted to understand the adoption of cloud services, few studies have addressed specific categories of cloud computing. There has been little research on SaaS adoption, although many previous studies have confirmed that the factors affecting SaaS adoption are different than those for IaaS and PaaS (Martins et al., 2019; Oliveira et al., 2019; Li et al., 2012). Also, most studies have focused on SaaS as a global concept, and limited attention has been given to the specific types of SaaS adoption (vertical or horizontal). Moreover, the majority of studies related to SaaS adoption examined the issue from the vendors' perspective, and few have focused on the end users' perspective. Surprisingly, most studies have investigated the current state of cloud services adoption, and few have focused on the factors affecting different stages of SaaS adoption. For example, according to Martins et al. (2016), the determining factors for SaaS adoption have different effects on individuals in the intention-to-adopt (pre-adoption), adoption (decision), and post-adoption (implementation) stages.

According to the literature, SaaS adoption has been linked to numerous factors derived from a variety of well-known models and theories that have been used to understand technology adoption. Alrousan et al. (2020) explain that the choice of a suitable theoretical framework has always been a decisive issue among the information systems (IS)-researchers. The most common models and theories used to explain personal acceptance and use of technology are the "Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), the Diffusion of Innovation Theory (DoI), the Expectation Confirmation Model (ECM), Institutional Theory (INST), and the Unified Theory of Acceptance and Use of Technology (UTAUT)" (Al-Mamary et al., 2016; Oliveira et al., 2019; Tarhini et al., 2016).

The TRA model, which was introduced by Martin Fishbein and Icek Azjen (1975), demonstrated that the attitude of an individual and his subjective norm values were important predictors of the behavioral intention and later, immediate, predictors of his actual use. Ajzen (1991) incorporated TRA into TPB through the addition of the construct of perceived behavioral control to overcome limitations to TRA and enhance its explanatory power. The third model is TAM that was developed by Davis (1989) based on the original adaptation of TRA with certain differences. Perceived ease of use and perceived usefulness were introduced

as the determinants of intention to use and subjective norms were not included in this model as they were not significantly influencing technology adoption. Actual use of technology is a function of intention to use. TAM was found to be a robust conceptual model, and it has been widely used to study user acceptance of information technology. However, TAM had some limitations, so it was extended to TAM2, which further emphasizes the important role of social influence and cognitive instrumental processes on technology adoption (Venkatesh et al., 2003). Rogers (2003) proposed the DoI model in an attempt to explain the process that occurs as individuals decide whether or not to adopt new technology. In this model, the innovation elements are determined by five dimensions: compatibility, relative advantage, observability, complexity, and trialability.

The "Unified Theory of Acceptance and Use of Technology" (UTAUT) by Venkatesh et al. (2003) is a model that was created with the help of a systematic synthesis of eight frameworks that are dominant. These were the above mentioned models and the combined TAM-TPB model and the Motivational Model, the "Model of PC Utilization" (MPCU) and the Social Cognitive Theory. UTAUT was meant to counter the shortcomings of these models when used alone and its aim was to offer a more detailed explanation of technology acceptance and actual use. UTAUT model consists of four important constructs namely, "performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC)" that directly influence behavioral intention and actual usage. Moreover, effects of these constructs are moderated by gender, experience, age, and willfulness of use. Performance expectancy includes the aspects of perceived usefulness, relative advantage, and job-fit (based on TAM, DoI, and MPCU). Effort expectancy covers the same dimensions as perceived ease of use in TAM and complexity construct in DoI.

The SI construct covers the TRA's subjective norms construct and the MPCU's social factors construct. Finally, the FC construct is similar to the perceived behavioral control, compliance, and facilitating the situation constructs from the TRA, PCIM, and MPCU models, respectively.

Consequently, UTAUT is regarded as one of the most effective models to use to forecast technology adoption and use. It has a better explanation capability compared to the other known models and has the ability to explain 70 percent of the intention to use (Venkatesh et al., 2003). Thus, UTAUT has been extensively used in other areas of technology adoption like mobile learning (Chao, 2019; Almaiah et al., 2019), e-learning (Abbad, 2021; Tan, 2013), e-government (Ahmad et al., 2013), e-commerce (Cabrera-Sánchez et al., 2020; Sim et al., 2018; Ofori et al., 2018), and cloud computing (Kh Thus, the UTAUT framework was utilized as the

theoretical basis of the current research to allow explaining the elements that can influence the adoption of SaaS educational resources, and specifically Google Workspace, by academic members.

Yet, the initial variables of the UTAUT model were determined to be not enough to describe technology acceptance and utilization (Oliveira et al., 2019; Gupta et al; 2019). As Venkatesh et al. (2012) observed, the majority of the technology adoption studies merely applied a part of the UTAUT model and omitted the moderators. Dwivedi et al. (2019) also established this by conducting a meta-analysis of 162 previous studies of technology use that had considered UTAUT as a theoretical framework, following which most studies had not identified any important effects among moderators of the original UTUAT. Also, numerous previous research works have established that the constructs of this model were inadequate to determine technology adoption; they expanded the initial model with the addition of other constructs in order to have a holistic view of technology adoption. Thus, moderators of the UTAUT model were eliminated through this study. Table (1) presents an overview of the literature available on SaaS uptake amongst the individuals.

Table 1: A summary of previous research studies

Author(s)	Theory/Model	Factors Identified	Participants	SaaS Type
Tan and Kim (2015)	ECM	"Confirmation, expectation, perceived usefulness, and satisfaction"	MBA students	Group support systems
Hussein and Hilmi (2020)	TAM	"Perceived usefulness, perceived ease of use, trust and security, and need"	Students	Cloud-based e-learning systems
Yadegaridehkordi et al. (2019)	UTAUT	"Task-technology fit, performance expectancy, effort expectancy, social influence, facilitating conditions, peer and superior influence, self-efficacy, collaboration technology experience, and familiarity with group members"	Students/Malaysia	SaaS-based collaboration services in higher education
Lawkobkit and Speece (2012)	TAM	"Usefulness, confirmation, continuance intention, satisfaction, structural fairness, and social fairness"	Full-time employees/USA	Customer relationship management SaaS
Pańkowska et al. (2020)	TAM	"Perceived usefulness, perceived availability, service and system quality, and attitude"	College students	
Chang et al. (2013)	UTAUT	"Performance expectancy, effort expectancy, social influence, and users' behavioral intention"	Individuals	Google SaaS
Arpaci (2016)	TAM	"Perceived ease of use, perceived ubiquity, perceived security, perceived privacy, perceived usefulness, trust, subjective norm, and attitude"	Students	Mobile cloud computing
Al-Sharafi et al. (2021)	TOE DoI, FVM, and INST	"Task, relative advantage, compatibility, complexity, security, fitness, technology readiness, cost, top management support, cloud knowledge, viability, coercive pressures, normative pressures, and mimetic pressures"	Academics and IT staff	Cloud-based e-learning systems

Based on the findings, perceived trust, perceived privacy, perceived risk, and security are the dominant and most frequent significant factors explaining and affecting technology adoption. Many previous studies have demonstrated the importance of security and trust factors in the adoption of SaaS; they have emphasized the necessity of including these factors in a study model focusing on SaaS adoption because SaaS is relatively new and not widely recognized (Almaiah et al., 2019; Alassafi et al., 2019; Al-Okaily, 2023). Therefore, these factors were added to the proposed conceptual framework. Also, this study attempts to understand the relationship between these factors and the different stages of users' SaaS adoption (intention-to-adopt, adoption, and post-adoption). The proposed conceptual framework is presented in Figure 1.

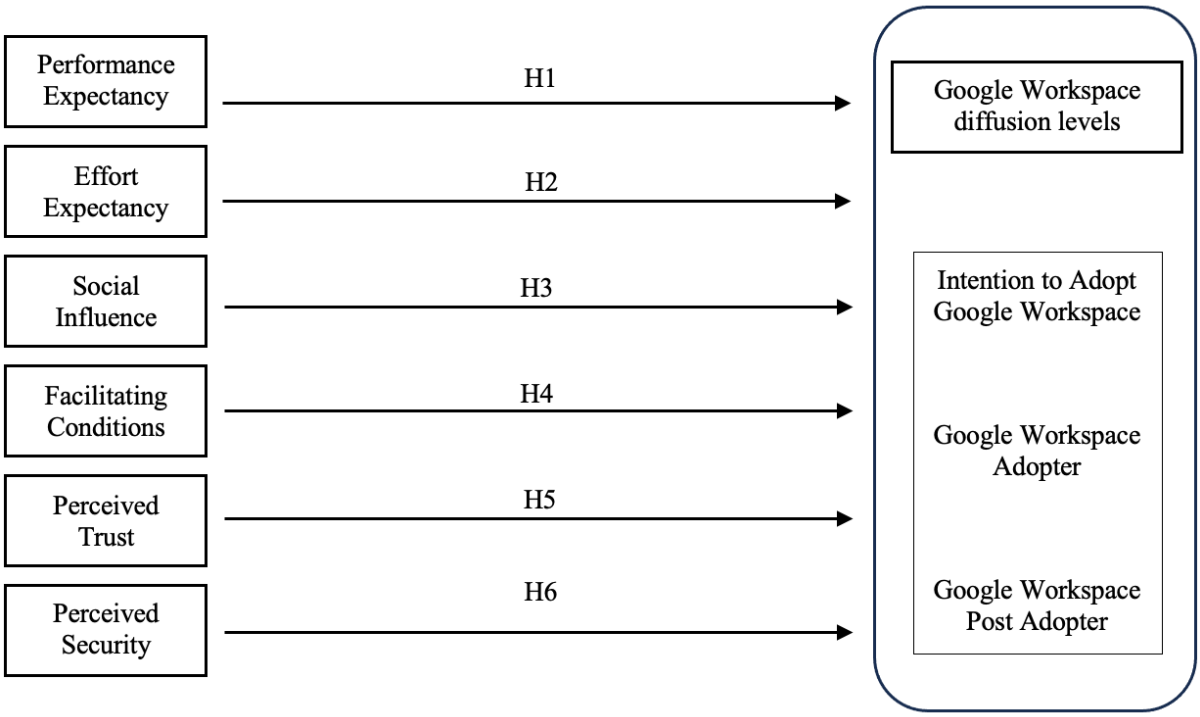


Figure 1: Research Model

HYPOTHESIS DEVELOPMENT

Performance Expectancy

According to Venkatesh et al. (2003), performance expectancy (PE) is the strongest factor in predicting technology acceptance in the UTAUT model. It is defined as "the degree to which an individual believes that the system helps to improve job performance." In this study, PE measures the extent to which the end user believes that using cloud applications will help them enhance their task performance. The existing literature demonstrates that PE has a

significant positive influence on technology adoption. For example, PE has been found to have significant effects on the adoption of online banking (Tarhini et al., 2016; Rahi et al., 2019), e-learning (Tan, 2013; Kabra et al., 2023), and e-government services (Imarah et al., 2013; Zeebaree et al., 2022).

A number of studies have explored the effect of PE on SaaS adoption by individuals. To illustrate, Yadegaridehkordi et al. (2019) discovered that PE plays a major role in the adoption of SaaS-based collaboration applications. In addition, Alotaibi (2016) investigated the issues influencing the adoption of the SaaS technology and discovered PE directly influences the behavioral intention to adopt SaaS. Furthermore, Martins et al. (2016) discovered that PE plays a significant role in SaaS diffusion, especially the intention to adopt SaaS, in a study on the factors that influence the stages of the SaaS diffusion process. Therefore, the following hypothesis was proposed:

H1: Performance expectancy has a positive effect on Google Workspace diffusion levels.

Effort Expectancy

Effort expectancy (EE) is an individual's perception of the amount of effort required to use a new technology. Venkatesh et al. (2003) referred to EE as "the degree of ease associated with the use of the system" (p. 450). Effort expectancy is similar to the "ease of use in TAM" and the complexity in the DoI theory. The literature on technology adoption has demonstrated that EE has a significant impact on the adoption of new technology (Soong et al., 2020; Chen and Hwang, 2019). According to previous studies on SaaS adoption, EE is considered one of the strongest predictors of SaaS adoption by individuals (Yadegaridehkordi et al., 2019; Alotaibi, 2016). Also, Martins et al. (2016) found this factor to be important to the adoption of SaaS, particularly at the initial stage of adoption. Hence, the following hypothesis was proposed:

H2: Effort expectancy has a positive effect on Google Workspace diffusion levels.

Social Influence

Social influence (SI) refers to the extent to which individuals' attitudes or actions are influenced by others. It reflects the aspects of an individual's social environment, such as friends or superiors, that may influence their decision to take part in a certain action. In this

study, SI refers to the information and motivations offered by those who surround end users that could have a significant impact on the adoption of SaaS. Alrousan (2016) addressed the adoption levels of e-commerce at the level of firms. He found that the degree of adoption is affected by the social environment. This has been confirmed by other scholars who have demonstrated the importance of social influence in determining the rate of technology adoption or diffusion (Batucan et al., 2022). SI was found to be the key determinant of SaaS adoption because end users' degree of SaaS use is influenced by the surrounding social environment (Al-Okaily et al., 2023; Alotaib, 2016; Kabra et al., 2023). Thus, the following hypothesis was proposed:

H**3:** Social influence has a positive effect on Google Workspace diffusion levels.

Facilitating Conditions

Venkatesh et al. (2003) defined facilitating conditions (FCs) as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (p. 453). A technology or service's usability greatly improves if the necessary environment, tools, and support are readily available. In the context of SaaS, FCs reflect end users' perceptions regarding the availability of the support and technical infrastructure necessary for the use of SaaS applications. The literature indicates that FCs play a significant role in the actual use and adoption of technology, such as mobile banking payment (Oliveira et al., 2014; Tarhini et al., 2016), e-learning (Tan, 2013; Abbad, 2021), and e-government (Imarah et al., 2013; Hooda et al., 2022). Yadegaridehkordi et al. (2020) examined the effect of FCs on SaaS-based collaboration services in HEIs but did not find any significant support for their impact. However, several studies have found a significant effect of FCs on usage behavior surrounding SaaS (Alotaibi, 2016; Kabra et al., 2023). Hence, this study proposes the following hypothesis:

H4: Facilitating conditions have a positive effect on Google Workspace diffusion levels.

Perceived Trust

Perceived trust (PT) is defined as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer

et al., 1995, p. 712). In SaaS studies, PT refers to the extent to which end users believe that the service offered by cloud vendors meets their expectations and is reliable and high quality. The existing literature indicates that PT has been identified as one of the key factors in determining the diffusion of technology adoption. Moreover, Gefen et al. (2003) indicated that trust not only has a significant impact on technology adoption but also has a significant influence on continuous usage. Alemneh et al. (2020) confirmed that trust is a key element for the fast adoption and expansion of cloud computing. Also, perceived trust has been found to be a crucial factor influencing SaaS uptake (Arpaci, 2016; Al-Okaily et al., 2023). Hence, the following hypothesis is formulated:

H5: Perceived trust has a positive effect on Google Workspace diffusion levels.

Perceived Security

The role of security in adopting technology has been studied widely by many past studies (Yuen et al., 2010; Alassafi et al., 2019). Rahi and Ghani (2018) found that security was the most important consideration when defining the intention of users to embrace internet banking. In cloud computing terms, they defined the concept of security as a process of securing data against unauthorized practices, such as data erasure, manipulation, and forgery. Perceived security and privacy in the present study means that the user believes that his/her use of SaaS is secure against unauthorized intrusion and loss of data among other internal and external risks. Chen and Zhao (2012) say that the primary factor discouraging people to use cloud computing services is security. Furthermore, among 96 published studies devoted to cloud computing, Pisirir et al. (2019) discovered that security is the most common aspect to be used in determining the context of cloud computing. They also discovered that security and privacy are the most important that have significant impact on the adoption of cloud services leading to 84.3% of their reviewed studies. This aspect has been defined in different ways by different researchers with some stating it as an inhibitory factor, others presenting it as a positive factor which lessens the uncertainty of adopting new technology (Low et al., 2011). Past research has shown that security factors are significant to the adoption rate of SaaS (Martins et al., 2019; Qasem et al., 2020). As a result, the following hypothesis is proposed:

H6: Security has a positive effect on Google Workspace diffusion levels.

Methodology

Research Design

This study adopted a quantitative strategy by utilizing a questionnaire survey. The sample was chosen using a convenience sampling technique. The respondents targeted by this study were academic members of Jordanian universities. Academics represent a mature sample whose daily tasks include using the internet; therefore, understanding their views and perceptions will elucidate end users' perspectives and assist in the improvement of SaaS services. Hair et al. (2022) recommended the use of the 10 times rule for minimum sample size, thus a sample size of 416 was appropriate and valid for analysis. A total of 731 responses were received; 43 were removed from the study due to a large number of missing data points and outliers.

The questionnaire consisted of three sections. The first section gathered demographic information about the respondents. The second section addressed the dependent variables, including the current stage of Google Workspace adoption (intention-to-adopt, adoption, post-adoption), while the third section addressed the factors that affect SaaS adoption. The dependent and independent variables in this study were adapted from previous studies related to UTAUT, cloud computing, and technology adoption. All obtained measurements were modified to meet the needs of this study. As shown in Table (2), the "performance expectancy, effort expectancy, social influence, and facilitating conditions" constructs were adapted from Venkatesh et al. (2003). The perceived trust construct was adapted from a related study by Kabra et al. (2023), while the perceived security construct was adapted from Pańkowska et al. (2020) and Siagian et al. (2022). The dependent variables, "the intention-to-adopt, adoption, and post-adoption constructs", were adapted from Chan and Chong (2013, cited in Martins et al., 2016). The items of the dependent variable were measured on a nominal scale using a multichotomous question, while the independent constructs were measured using a "five-point Likert scale ranging from strongly disagree to strongly agree." A committee of five IS experts, all professional researchers in the cloud computing field, evaluated the questionnaire items for content validity, and revisions were made based on their feedback. The pilot study was conducted with 30 participants; this sample was excluded from the final analysis. The results supported the instruments' reliability and validity.

The link to the online survey was shared with respondents through official channels, such as emails provided by universities and LinkedIn. The online survey contained an explanation of the purpose of the study. The participants were assured that their identities would remain

confidential and that their responses would only be used for research purposes. In addition, they were advised that their participation was voluntary and that they could withdraw from the study at any moment.

Table 2: Measurement Items

Constructs	Items	Measurement items	Reference
Performance Expectancy (PE)	PE1	Using Google Workspace allows me to improve my job performance.	Venkatesh et al. (2003)
	PE2	Using Google Workspace allows me to accomplish tasks faster.	
	PE3	Using Google Workspace advances my productivity.	
	PE4	Using Google Workspace is helpful in carrying out my tasks.	
Effort Expectancy (EE)	EE1	I find Google Workspace easy to use.	
	EE2	My engagement with Google Workspace would be simple and straightforward.	
	EE3	It is simple for me to learn how to use Google Workspace.	
Social Influence (SI)	SI1	People whose opinions that I value prefer that I use Google Workspace.	
	SI2	People who are important to me think that I should use Google Workspace.	
	SI3	People who influence my behavior think that I should use Google Workspace.	
Facilitating Conditions	FC1	I have the resources necessary to use Google Workspace.	
	FC2	I have the knowledge necessary to use software-as-a-service.	
	FC3	Google Workspace is compatible with other systems I use.	
	FC4	A specific person (or group) is available for assistance with Google Workspace difficulties.	
Perceived Trust	PT1	The Google Workspace application is trustworthy.	Kabra et al. (2023)
	PT2	I believe that using Google Workspace is reliable.	
	PT3	I believe that using Google Workspace is guaranteed.	
Perceived Security	PS1	I believe that using Google Workspace is confidential.	Siagian et al. (2022)
	PS2	I believe that using Google Workspace is safe.	Pańkowska et al. (2020)
	PS3	I believe that using Google Workspace is protected and not shared by third party.	
	PS4	I believe that using Google Workspace cannot be modified by others.	
Intention to Adopt Google Workspace	I intend to use Google Workspace if possible.		(Chan and Chong, 2013) cited in Martins et al. (2016)
Google Workspace Adoption	I am currently using the Google Workspace application.		
Post Google Workspace Adoption	I am using applications other than Google Workspace, such as Microsoft 365, Zoho Workplace, or another application.		

Sample Profile

Descriptive analysis was utilized to determine the demographic characteristics of the respondents. As shown in Table (3), 70.2% of the sample consisted of respondents between the ages of 31 and 60; respondents between the ages of 22 and 30 accounted for 16.8%, and 13% of the sample was above 60 years old. Male respondents accounted for 74.3% of the sample, and the remaining 25.7% of respondents were female. Regarding participants' academic rank, most respondents had PhD degrees (90.1%) and were either assistant, associate, or full professors. Another 8.9% of respondents had a master's degree. Most respondents were from private universities (72.6%), while 27.4% were from public universities.

Table 3: Sample demographic profile

Categories	Description	(%)	Frequency
Age	22–30	16.8	70
	31–60	70.2	292
	60+	13.0	54
Gender	Male	74.3	309
	Female	25.7	107
Academic Rank	Lecturer	8.9	37
	Assistant Professor	41.3	172
	Associate Professor	31.7	132
	Professor	18.0	75
University Type	Public University	27.4	114
	Private University	72.6	302

Results

Data Analysis Method

As mentioned before, six factors (PE, EE, SI, FC, PT, and PS) were identified and tested to determine whether they are significant predictors of the dependent variable, namely the level of SaaS innovation (intention-to-adopt, adoption, post-adoption). Multinomial logistic regression analysis was employed to validate the research model. Multinomial logistic regression is recommended for the examination of multiple outcomes, such as categorical dependent variables based on different variables. Moreover, logistic regression is more flexible than discriminant analysis since it does not require certain assumptions regarding the independent variable, like normal distribution, laniary related, and equal variance across all groups. Finally, when the dependent variable has less than three categories, logistic regression can provide a more flexible interpretation of the data than discriminant analysis (Tabachnick and Fidell, 2019; Ananzeh et al., 2024).

Measurement Model

It is essential to assess the reliability and validity of proposed constructs before testing the hypotheses on the proposed model. Cronbach's alpha and composite reliability were used to evaluate the constructs' reliability. According to Hair (2022), Cronbach's alpha and composite reliability should be greater than 0.7 to be considered satisfactory. As shown in Table (4), all constructs were greater than 0.7, indicating sufficient reliability. Construct validity was also applied to verify that the items of the scale measured the same construct

(Khalifeh et al., 2025). In order to test the construct validity, a factor analysis that utilizes the principal-component factoring methods with varimax rotation was implemented. Hair et al. (2022) suggest that the Kaiser-Meyer-Olkin test (KMO) and Bartlett test of sphericity must be conducted initially in order to ascertain that the factor analysis is satisfactory. They recommended that the threshold value of KMO that is acceptable to proceed with factor analysis is a minimum of 0.5 and the p-value of the test of Bartlett sphericity must be below 0.05. As indicated in Table (5), KMO was 0.771 with Bartlett test of sphericity was significant, showing that the factor analysis was adequate.

Table 4: Reliability and Validity Measurements

Construct	Items	Factor Loading	AVE	Cronbach's Alpha	Composite Reliability
Performance Expectancy (PE) (eigenvalue = 5.866, variance = 27.933)	PE1	0.700	0.566	0.863	0.838
	PE2	0.765			
	PE3	0.794			
	PE4	0.748			
Effort Expectancy (EE) (eigenvalue = 2.406, variance = 11.459	EE1	0.888	0.647	0.757	0.844
	EE2	0.847			
	EE3	0.662			
Social Influence (SI) (eigenvalue = 1.839, variance = 8.757)	SI1	0.664	0.613	0.718	0.824
	SI2	0.840			
	SI3	0.833			
Facilitating Conditions (eigenvalue = 2.011, variance = 9.575)	FC1	0.690	0.658	0.859	0.844
	FC2	0.737			
	FC3	0.887			
	FC4	0.804			
Perceived Trust (eigenvalue = 1.412, variance = 6.723)	PT1	0.787	0.606	0.782	0.820
	PT2	0.690			
	PT3	0.850			
Perceived Security (eigenvalue = 1.229, variance = 5.853)	PS1	0.554	0.617	0.719	0.825
	PS2	0.834			
	PS3	0.880			
	PS4	0.619			

Table 5: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.771
Bartlett's Test of Sphericity	Approx. Chi-Square	4443.733
	df	210
	Sig.	.000

Convergent validity was measured with the average variance extracted (AVE). As shown in Table (4), the AVE values were greater than 0.5 for all constructs, which meets the minimum criterion for convergent validity (Hair et al., 2022; Fornell and Larcker, 1981). Another measurement of convergent validity was used to confirm that the expected factors for all items were equal to or above 0.5 (Tabachnick and Fidell, 2019). The results in Table (4) confirmed

convergent validity, as the factor loading for all items was higher than the recommended value of 0.5.

Regarding the measurement of discriminant validity, Fornell and Larcker (1981) suggested that discriminant validity is achieved when the square root of the AVE of each construct is greater than the correlation between other constructs. The results in Table (6) demonstrate that this was the case for the current study.

Table 6: Discriminant Validity

Variables	PE	EE	SI	FC	PT	PS
Performance Expectancy	**0.752**					
Effort Expectancy	0.207	**0.804**				
Social Influence	0.240	0.144	**0.783**			
Facilitating Conditions	0.616	0.156	0.226	**0.797**		
Perceived Trust	0.455	0.099	0.233	0.454	**0.778**	
Perceived Security	0.093	0.072	0.023	0.012	0.085	**0.785**
Note: Diagonal elements indicate the square root of the AVE, while off-diagonal indicates the correlations between constructs						

The results of these analyses indicate that all assessments of construct reliability and validity were satisfactory, enabling further assessment of the conceptual research model.

Hypothesis Testing Results

Multinomial logistic regression was used to test the proposed hypotheses. However, testing for multicollinearity assumption was necessary before hypothesis testing to make sure that the interpretation of the model was meaningful. Tabachnick and Fidell (2019) suggested that the absence of multicollinearity is indicated when the squared correlations between variables are less than 0.9. A Person Correlation Matrix was used to determine whether multicollinearity could be a potential problem. The absence of multicollinearity was indicated, as all squared correlations among predictor variables were less than 0.9, as shown in Table (7).

Table 7: Pearson and Spearman Correlations

Variables	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Perceived Trust	Perceived Security
Performance Expectancy	1	0.207**	-0.240**	0.616**	0.455**	-0.093
Effort Expectancy	0.207**	1	-0.144**	0.156**	0.099*	0.072
Social Influence	-0.240**	-0.144**	1	-0.226**	-0.233**	0.023
Facilitating Conditions	0.616**	0.156**	-0.226**	1	0.454**	-0.012
Perceived Trust	0.455**	0.099*	-0.233**	0.454**	1	-0.085
Perceived Security	-0.093	0.072	0.023	-0.012	-0.085	1

*Significant at 0.10. **Significant at 0.05.

The variance inflation factor (VIF) and tolerance value were also calculated to provide additional support for the multicollinearity assessment. Hair et al. (2022) suggested that the VIF value should be less than 10 and the tolerance value should not exceed 0.10; values within these limits indicate the absence of multicollinearity. Table 8 shows that the VIF values were between 1.025 to 1.782, indicating the absence of multicollinearity in this study.

Table 8: Collinearity Results

Variable	Tolerance	VIF
Performance Expectancy	.561	1.782
Effort Expectancy	.939	1.065
Social Influence	.910	1.099
Facilitating Conditions	.576	1.736
Perceived Trust	.730	1.370
Perceived Security	.976	1.025

Goodness-of-fit assesses whether the model adequately fits the data. Field (2009) claimed that the model is a good fit if the Pearson and deviance tests are not be significant from the observed value. Table (9) shows that the model adequately fits the data. The 2 log likelihood (-2LL) and Nagelkerke pseudo-R-squared were also analyzed to show the model's ability to explain the data variation. Field (2009) stated that if the full model's -2LL is lower than that of the null model, it indicates a better model fit. As shown in Table (10), the -2LL of the full model is lower than that of the null model. The model fit was statistically significant ($\chi^2(12) = 355.564$, $p < 0.05$), indicating that the full model was significantly outperformed by the null model. Finally, the pseudo-R-squared was also used to present the proportion of variance in the dependent variable explained by the model. As shown in Table (11), three different pseudo-

R-squared metrics have been used to represent the overall fit. The Cox and Shell value was 57.5%, the Nagelkerke value was 65.2%, and the McFadden value was 40.1%, indicating that the model utilized in this study is adequate and useful in predicting SaaS adoption.

Table 9: Goodness of Fit of the Model

	Chi-Square	Df	Sig.
Pearson	786.726	440	.000
Deviance	531.972	440	.002

Table 10: Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	Df	Sig.
Intercept Only	887.536			
Final	531.972	355.564	12	.000

Table 11: Pseudo R-Square

Cox and Snell	.575
Nagelkerke	.652
McFadden	.401

Two separate runs of multinominal logistic regression were used to compare different stages of SaaS adoption. In the first run, the intention to use Google Workspace was selected as a reference against the Google Workspace adopter and Google Workspace post-adopter stages, while the Google Workspace adopter stage was used in the second run as a reference against the Google Workspace post-adoption stage. Table (12) shows the results of the multinomial logistic regression and the influence of the independent variables on the different adoption levels of SaaS (intention-to-adopt, adoption, post-adoption).

Table 12: Multinominal Regression Statistics for the Hypotheses

	Model 1 Google Workspace Adopter vs. Intention to adopt Google Workspace [a]				**Model 2 Google Workspace Post adoption vs. Google Workspace Intention to adopt [a]**				**Model 3 Google Workspace Post adoption vs. Google Workspace Adopter [b]**			
	B	Exp(B)[c]	Wald	p-value	B	Exp(B)	Wald	p-value	B	Exp(B)	Wald	p-value
Intercept	-20.033		63.051	.000	21.854		65.812	.000	-1.821		.703	.402
Performance Expectancy	1.093	2.984	13.433	.000**	2.274	9.715	47.846	.000**	1.180	3.256	12.265	.000**
Effort Expectancy	.107	1.113	.242	.623	0.997	2.711	18.641	.000**	.890	2.436	18.292	.000**
Social Influence	1.824	6.198	16.711	.000**	1.096	2.993	6.040	.014*	.728	2.070	4.976	.026*
Facilitating Conditions	1.994	2.538	42.127	.000**	0.931	7.341	11.383	.001**	.381	1.691	.647	.421
Perceived Trust	.620	1.858	6.120	.013*	1.410	4.094	32.385	.000**	.790	2.203	12.646	.000**
Perceived Security	1.043	2.838	13.671	.003**	1.238	3.450	14.358	.000**	0.195	1.216	.387	.534
	a. The reference category is Intention to adopt Google Workspace b. The reference category is Google Workspace adopter c. Exp(B) = Odds ratio * Significance at < 0.05 level, ** Significance at < 0.01 level											

The results in Table (12) indicate that the hypothesis results were not similar across all models, as a single set of the proposed hypotheses was used to examine the different stages of SaaS adoption. In the case of Model 1 (Google Workspace Adoption vs. Intention to Adopt Google Workspace), the results show that five of six factors were significant (p values < 0.05). These factors were: performance expectancy, social influence, facilitating conditions,

perceived trust, and perceived security. They were all positively associated with academic members' adoption of Google Workspace compared to intention to use. Effort expectancy was found to be not significant. The predictor with the highest significance in Model 1 was social influence, with an odds ratio of 6.198. This was followed by performance expectancy, facilitating conditions, perceived trust, and perceived security, with odds ratios of 2.984, 2.538, 1.858, and 0.282, respectively. This suggests that these factors encourage academic members to adopt Google Workspace, since increases in these factors are connected with increases in the likelihood that academic members are in the adoption stage.

In the case of Model 2 (Post Google Workspace Adoption vs. Intention to Adopt Google Workspace), the results show that all factors were positively significant with academic members' post-adopter of Google Workspace compared to intention to use. The results in Table (12) show that performance expectancy was the highest predictor in Model 2, with an odds ratio of 9.715. This was followed by social influence, perceived trust, perceived security, effort expectancy, and facilitating conditions, with odds ratios of 7.341, 4.094, 3.450, 2.993, 2.711, and 0.282 respectively. This suggests that these factors facilitate academic members' implementation of Google Workspace, as an increase in these factors correlates with an increase in the likelihood of academic members being in the post-adoption stage.

Finally, the results for Model 3 (Post-Adoption of SaaS vs. Adoption) show that four of six factors were significant (p values < 0.05). Performance expectancy, effort expectancy, social influence, and perceived trust were found to be significantly positively correlated with the post-adoption status of academic members compared to the adoption stage, while facilitating conditions and perceived security were found to be non-significant. The results in Table (12) indicate that the strongest predictor in Model 3 was performance expectancy, with an odds ratio of 3.256. This was followed by effort expectancy, perceived trust, and social influence, with odds ratios of 2.436, 2.203, and 2.070, respectively. These results indicate that these factors are able to differentiate post-adopters from adopters among academic members.

Discussion

This study aimed to identify the factors affecting different stages of SaaS adoption by academic members in Jordanian universities, looking specifically at the case of Google Workspace. Multinomial logistic regression was applied to predict the adoption of SaaS technologies. The results indicate that five of the six hypothesized factors were able to distinguish between the adoption and intention-to-adopt stages. These significant factors were performance expectancy, social influence, facilitating conditions, perceived trust, and

perceived security. In addition, four determining factors (performance expectancy, effort expectancy, social influence, and perceived trust) have a direct effect in differentiating between the post-adoption and adoption of Google Workspace stages. All suggested factors had a direct effect in differentiating between the post-adoption and intention-to-use stages.

The results indicate a significant positive relationship of performance expectancy in all stages of SaaS adoption by academic members. This throws the importance of the performances expectancy into the limelight, especially when the academic members realize that there are unmistakable benefits of using technology applications more than using traditional methods. The findings also show that academic staff in the adoption phase were 2.984 times more likely to use Google Workspace than the academic members in the intention-to-adopt phase and were even more likely to incorporate Google Workspace into their professional activities than the adoption phase and the intention-to-adopt phase. These results are consistent with the previous studies in the adoption literature, which also support the significance of the performance expectancy in determining technology adoption and continued use (Kabra et al., 2023; Alotaibi, 2016; Zeebaree et al., 2022).

Effort expectancy was found to be relevant and positively related with Google Workspace adoption by academic members, although it was only significant when comparing between the Models 2 and 3. The findings indicate that the academic members who were in the post-adoption phase were discovered to use Google Workspace 2.711 times as compared to members in the intention phase. Conversely, academic members in the adoption stage were found to be 2.436 times less likely to use Google Workspace than those in the post-adoption stage. Effort expectancy is viewed as using tools and services provided by Google Workspace is easy and does not require hard effort from academic members in the educational environment. Contrary to expectation, effort expectancy was found to be non-significant when differentiating Google Workspace Adopter vs. Intention to adopt Google Workspace. This finding indicates that in the intention phase of implementing Google Workspace, the academic members could express overconfidence towards the usefulness of the technology, thinking that cloud-based systems can be readily used. They however might experience unexpected complexities as they go through the actual adoption phase thus limiting the scope of successful implementation. This trend was also established on comparing post-adopters and intention-stage users as well as adopters. Therefore, the results also show that the ease of use rating decreases as people start using the system in real life, which means that there is a disconnect between expectations and real experience. This finding is consistent with the previous research,

which found that the struggle of technology usage intensifies at higher adoption levels (Nguyen and Liaw, 2022; Lee and Shin, 2018).

The findings show that social influence is a constructive and useful element during every phase of adopting SaaS by academics. In addition, the outcomes indicate that academic members have higher probability to affect the intention of other people to adopt Google Workspace compared to other adoption phases. This means that the academic members can be influenced by referent group, like coworkers, family, and friends. The results of the study are also aligned with the results of other studies, which have shown that social influence has a significant impact on cloud computing adoption (Al-Okaily et al. 2023; Yadegaridehkordi et al., 2020).

With respect to the facilitating conditions factor, the findings indicate that this dimension influences the diffusion rate of SaaS adoption among academic members, exerting greater effects at higher stages of Google Workspace adoption. The results show that academic staff in the adoption stage were 2.538 times more likely to use Google Workspace compared to those in the intention stage, while those in the post-adoption stage were 7.371 times more likely than intention-stage users. However, in Model 3, facilitating conditions were found to have a non-significant effect in distinguishing between adopters and post-adopters. This suggests that once adoption has taken place, facilitating conditions remain equally important for both groups. These findings suggest that the academic members in higher levels of adoption are more aware and understand how to take advantage of the offered tools, guidance, assistance, and technical support provided by Google Workspace, and people in the intention stage might not be that familiar with it. This outcome correlates with the existing research on the use of the cloud computing system (Alotaibi, 2016; Kabra et al., 2023).

Regarding the perceived trust, the findings show that this measure positively affects each of the adoption stages of SaaS among academic members. Specifically, academic staff members at the intention stage expressed 1.858 times less amounts of trust than the adoption stage, and 4.094 times less than the post adoption stage. In addition, academic members at the adoption stage had low levels of trust also by 2.203 times relative to the post adoption stage. Such results indicate that mistrust is among the factors that explain resistance to the adoption of SaaS platforms such as Google Workspace, particularly during the early stages of adoption. Conversely, the findings have shown that academic faculty would be more willing to use SaaS application when the faculty believes that the application would be able to deliver quality, effective, and timely services. This result is consistent with previous studies that found that

trust has a positive impact on the success of SaaS acceptance and usage (Alemneh et al., 2020; Arpaci, 2016).

The results indicate that perceived security positively influences the SaaS adoption rate among academic members. Perceived security was significant in Models 1 and 2, while it was found to be not significant in Model 3. The results show that academic members feel less confident and more careful regarding the protection of their data when they are in the intention stage (i.e., 2.838 times less than when they are in the adoption stage and 3.450 times less than when they are in the post-adoption stage). The findings from Model 3 reveal that security has no significant effect in distinguishing adopters from post-adopters. This implies that security plays a critical role in adopting Google Workplace in educational environments, particularly in the intention stage of adoption. Also, this result suggests that security concerns such as security threats, cyberattacks, identity theft, and privacy violations are more relevant for academic members in the intention stage than among those in the adoption and post-adoption stages. This result is in line with earlier studies that found security is one of the most challenging factors in the adoption of cloud computing (Martins et al., 2018; Qasem et al., 2020; Pisirir et al., 2019).

Theoretical and Practical Implications

This study has numerous implications for theory and practice. In terms of theoretical implication, this study has effectively extended and implemented the UTAUT model to a new context, namely SaaS adoption in Jordan. Moreover, this study seeks to provide a comprehensive model that best explains SaaS adoption using Google Workspace by users, particularly in higher education sectors. The proposed model was based on an extended version of the UTAUT model and included significant and frequent factors in the context of cloud adoption literature (i.e., perceived trust and perceived security). Also, most of the previous studies focused on cloud computing in general, whereas SaaS is different than other types of cloud services due to its unique characteristics. Additionally, as far as we know, this study is the first to focus on the deeper insights that may be achieved by examining the distinct factors affecting different stages of SaaS adoption rather than narrowly examining one level of adoption, such as the intention-to-adopt stage. Finally, the proposed model was validated and determined to be useful in explaining all stages of technology adoption by users in general, specifically within the context of cloud computing.

The current study provides many practical contributions by offering a unique roadmap and important insights to academics, HEIs, and SaaS providers interested in advancing the usage of SaaS adoption in higher education institutions in Jordan and other developing

countries. First, SaaS such as Google Workspace offers a wide range of tools, services, and collaboration applications to academic members and contribute substantially to the educational environment. The results of this study reveal the core factors affecting the different stages of SaaS adoption among academic members. For example, academic members in the early stage of adoption were resistant to the use of SaaS due to security and trust concerns as well as a lack of knowledge or awareness of the valuable advantages of using the technology. As a result, rather than focusing on the ease of using SaaS tools, which was found to be partially non-significant in the early stage of adoption, SaaS providers should highlight the reliability and security of using SaaS. Also, the facilitating conditions should be prioritized by SaaS providers because of their importance in increasing the rate of adoption by academic members. In this regard, SaaS providers should offer valuable information and technical support to help end users effectively resolve any technical problems they may face. This will make them more productive and efficient and hence more interested in using this technology. The findings of this paper provide HEIs with improved insights on the utilization of cloud computing by academic members as regards to teaching and learning. Thus, HEIs would need to establish measures to enhance their capacity to utilize cloud computing like Google Workplace in learning and motivate academic participants to adopt such technology as a student teaching device. To take an example, in selling SaaS to academic members, HEIs need to be sure that there is sufficient training provided to foster confidence in the use of this technology. Additionally, instead of requiring the academic members to purchase SaaS, HEIs ought to seek alternative methods of encouraging them to use this technology; this is by demonstrating to them how the new SaaS tools in education can enhance teaching and learning. Lastly, social influence was identified to positively significantly impact all phases of SaaS adoption by members of the academic community. Therefore, HEIs should foster positive social influence to motivate the academic members to consider SaaS in their teaching process as a handy tool. For example, HEIs should ask academic members who have already adopted SaaS to share their experiences with their colleagues and show the benefits gained from using this technology. This may increase the adoption rate among other academics, particularly in the early stage of adoption.

Conclusion

Most studies on SaaS adoption contexts have addressed the current stage of adoption of the technology, while very few studies have focused on factors affecting the different stages of SaaS adoption. As a result, the primary objective of this study was to develop a robust model

to investigate the factors affecting the different stages of SaaS adoption, using Google Workspace as an example of SaaS. These factors were identified based on extended UTAUT and were selected to examine the different stages of using SaaS among academic members in HEIs. Multinomial logistic regression was employed to examine the proposed hypotheses and determine their relationship to the study model. The results indicate that performance expectancy, social influence, facilitating conditions, perceived trust, and perceived security were significant in differentiating between academic members' adoption of Google Workspace compared to intention-to-adopt, while effort expectancy was found not to be significant. The results also indicate that all proposed factors were significantly positively correlated with academic members' status of post-adoption of Google Workspace compared to the intention-to-adopt stage. Finally, the results found that performance expectancy, effort expectancy, social influence, and perceived trust had significant positive effects on the differentiation between the post-adoption and adoption stages for academic members using Google Workspace, while facilitating conditions and perceived security were found to be non-significant. Given these findings, this study indicates that the proposed model has significant explanatory power. By integrating perceived trust and security with the original model of UTAUT, it explains greater variation in the different factors affecting the stages of SaaS adoption compared with previous studies in the context of technology adoption. Furthermore, the results have significant practical implications for academics, HEIs, and SaaS providers and can aid them in developing a strategic roadmap to enhance the implementation of SaaS in education.

Limitations and Future Research

This study has several limitations that should be considered and addressed in future research. First, the current study investigated educational SaaS adoption by academic members at HEIs. It was limited to the individual level, and the organizational level (adoption by HEIs) was not considered. Therefore, future research should focus on the factors affecting the different stages of adoption by organizations such as HEIs. Second, this study focused on Google Workspace as an example of educational SaaS. The proposed model should be investigated in other SaaS platforms to make additional contributions. Third, the sample of this study was from Jordan. Thus, the proposed model should be examined in other countries to improve the generalizability of the findings. Finally, a cross-sectional method was applied to examine the proposed model. In future work, a longitudinal method should be applied to provide a better understanding and explanation of SaaS adoption and its diffusion stages among academics over time.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethical Approval Declaration

This study was conducted in accordance with the Declaration of Helsinki. Under the guidelines of the Scientific and Research Ethics Committee of Al-Zaytoonah University of Jordan, formal ethical approval was waived for this research as it involved a non-clinical, low-risk survey and collected no sensitive personal data. Informed consent was obtained electronically from all individual participants included in the study.

Consent to Participate

Written informed consent was obtained from all participants before they took part in the study. Participants were informed of the study purpose and assured that their responses would be anonymous and kept confidential. Participation was voluntary, and participants could leave the survey incomplete or withdraw without penalty.

Consent to Publish

Not applicable. The manuscript reports aggregate findings and contains no identifiable participant information.

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