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SOFTWARE AS A SERVICE (SAAS) CLOUD COMPUTING: AN EMPIRICAL INVESTIGATION ON UNIVERSITY STUDENTS' PERCEPTION

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ABSTRACT

Aim/Purpose	This study aims to propose and empirically validate a model and investigates the factors influencing acceptance and use of Software as a Services cloud computing services (SaaS) from individuals' perspectives utilizing an integrative model of Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM) with modifications to suit the objective of the study.
Background	Even though SaaS cloud computing services has gained the acceptance in its educational and technical aspects, it is still expanding constantly with emerging cloud technologies. Moreover, the individual as an end-user of this technology has not been given the ample attention pertaining to SaaS acceptance and adoption (AUSaaS). Additionally, the higher education sector needs to be probed regarding AUSaaS perception, not only from a managerial stance, but also the individual. Hence, further investigation in all aspects, including the human factor, deserves deeper inspection.
Methodology	A quantitative approach with probability multi-stage sampling procedure conducted utilizing survey instrument distributed among students from three public

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Malaysian universities. The valid collected responses were 289 Bachelor's degree students. The survey included the demographic part as well as the items to measure the constructs relationships hypothesized.

Contribution

The empirical results disclosed the appropriateness of the integrated model in explaining the individual's attitude ($R^2 = 57\%$), the behavior intention ($R^2 = 64\%$), and AUSaaS at the university settings ($R^2 = 50\%$). Also, the study offers valuable findings and examines new relationships that considered a theoretical contribution with proven empirical results. That is, the subjective norms effect on attitude and AUSaaS is adding empirical evidence of the model hypothesized. Knowing the significance of social effect is important in utilizing it to promote university products and SaaS applications – developed inside the university – through social media networks. Also, the direct effect of perceived usefulness on AUSaaS is another important theoretical contribution the SaaS service providers/higher education institutes should consider in promoting the usefulness of their products/services developed or offered to students/end-users. Additionally, the research contributes to the knowledge of the literature and is considered one of the leading studies on accepting SaaS services and applications as proliferation of studies focus on the general and broad concept of cloud computing. Furthermore, by integrating two theories (i.e., TPB and TAM), the study employed different factors in studying the perceptions towards the acceptance of SaaS services and applications: social factors (i.e., subjective norms), personal capabilities and capacities (i.e., perceived behavioral control), technological factors (i.e., perceived usefulness and perceived ease of use), and attitudinal factors. These factors are the strength of both theories and utilizing them is articulated to unveil the salient factors affecting the acceptance of SaaS services and applications.

Findings

A statistically positive significant influence of the main TPB constructs with AUSaaS was revealed. Furthermore, subjective norms (SN) and perceived usefulness (PU) demonstrated prediction ability on AUSaaS. Also, SN proved a statically significant effect on attitude (ATT). Specifically, the main contributors of intention are PU, perceived ease of use, ATT, and perceived behavioral control. Also, the proposed framework is validated empirically and statistically.

Recommendations for Practitioners

The findings expected to support decision makers at universities, government higher education authorities, and cloud providers by highlighting the vital role of the factors that emerged in the study.

Recommendations for Researchers

The proposed model is highly recommended to be tested in different settings and cultures. Also, recruiting different respondents with different roles, occupations, and cultures would likely draw more insights of the results obtained in the current research and its generalizability

Future Research

Participants from private universities or other educational institutes suggested in future work as the sample here focused only on public sector universities. The model included limited number of variables suggesting that it can be extended in future works with other constructs such as trialability, compatibility, security, risk, privacy, and self-efficacy. Comparison of different ethnic groups, ages, genders, or fields of study in future research would be invaluable to enhance the findings or reveal new insights. Replication of the study in different settings is encouraged.

Keywords common method bias, PLS-SEM, SaaS cloud computing, subjective norms, technology acceptance, TPB and TAM integrated model

INTRODUCTION

A growing demand for high capability computing devices, high speed networks, and large storage capacity, combined with high memory capacity requirements, have made technology advancements a requirement to cope with these rapid changes in modern life. Additionally, the daily immense use of applications and services on computers or other smart devices (e.g., tablets, handphones, smart TVs, fridges, water boiler, ovens, etc.), have changed the way that technology is directed. Therefore, researchers, practitioners, and professionals have been considering a technology that can compete with these challenges. With the advent of virtualization, these challenges became manageable, especially with the growing high speed and smart network developments that have taken the burden of transporting the immense data volumes to meet the high demands. As an outcome, the cloud computing paradigm surfaced as a solution that utilizes virtualization at its core (Taufiq-Hail et al., 2017a). This technology made Software as a Service (SaaS) cloud computing accessible from anywhere, available at any time or place, reliable, and cost-effective, fostering a plausible solution to these issues with the new paradigm of pay-as-per-usage for the user.

The higher education sector converted to be an essential element in building modern societies, innovating industrial technologies, improving life standards by preparing future generations that would change the way of living. Therefore, higher education became a competitive and promising market (Dwaikat, 2020; Wilkins, 2020) that requires a lot of new innovative technology to meet the substantial demand of IT infrastructure, the increasing number of users, the enhancement of their process performance, education quality and services (Qasem et al., 2020). To cope with these new challenges, the role of cloud computing surfaced and became crucial as an integral element of higher education institutes due to its flexibility, innovation, reliability to meet the demand of the pedagogical process through its application (Ali et al., 2018). These features of cloud computing with its new paradigm made it easy for individuals as well as organizations to overcome the enormous running cost of having to periodically upgrade their devices and offer the mobility and flexibility of accessing online courses especially during disasters and pandemics.

BACKGROUND OF THE RESEARCH PROBLEM

Numerous studies have investigated the issues of cloud computing with regard to the contextual factors affecting its adoption (Oliveira et al., 2019), a specific service or model of cloud computing (Wu et al., 2011), or technological aspects of cloud computing adoption, such as complexity, compatibility, trust and privacy, interoperability, reliability, security requirements, and future expectancy of cloud computing (Low et al., 2011). Moreover, notwithstanding its popularity, usability, accessibility, and cost effectiveness, cloud computing technology is still in the infancy stage, and both the SaaS cloud computing users and providers face a steep learning curve (Lee et al., 2013). In addition, unlike other information technology services, the cloud computing phenomenon is at a relatively early stage of its existence in the majority of developing countries (Sharma et al., 2016) and has not reached a maturity level that needs further exploration on different aspects (Oliveira et al., 2019; Taufiq-Hail et al., 2017a). More importantly, although there are several studies covering cloud computing and its adoption, the minority of these studies derived the attention towards SaaS services and applications using a well-defined methodology, model, theory, or framework especially in the higher educational sector that suffers from a paucity of empirical studies (Senyo et al., 2018).

Cloud computing consists of three major service models, i.e., Software as a Service (SaaS), Platform as a Service (PaaS), and the Infrastructure as a Service (IaaS). SaaS services are less customizable, simple, and require less technical background to run by end users, while the other two service models require highly technical IT professionals to configure and customize (Schneider & Sunyaev, 2016). For this reason, it is assumed that the factors influencing SaaS adoption by far resemble the other

two (i.e., IaaS and PaaS) due to its nature of simplicity and usage by the end user. The recent works in literature asserted the lack of comprehensive studies and suggest developing sufficient understanding, enhancing our knowledge of this topic, and studying this nascent technology of SaaS from different angles (Oliveira et al., 2019). Additionally, Senyo et al. (2018) pointed out that the issues of cloud computing with respect to companies have been explicated and investigated in academia; however, the individual's view and attitude towards using cloud computing were overlooked. To explain, the majority of previous works in literature addressed the trends of SaaS cloud computing from organizational perspectives, migration process, and its developments (Jede & Teuteberg, 2016; Oliveira et al., 2019; Tomás et al., 2018; van de Weerd et al., 2016); however, the individual's perception is far less focused upon. For instance, Oliveira et al. (2019) addressed the importance of SaaS cloud computing and its dominance in the IT service delivery model based on the tangible benefits financially and operationally that garnered the interest. The authors tested in their research the contextual factors (i.e., technological, environmental, and organizational factors) influencing the adoption of SaaS cloud services in firms by utilizing technology-organization-environment (TOE) framework. However, their research did not turn the theoretical lenses towards the user's influential factors of adopting this technology. Another study by Tomás et al. (2018) proposed an integrated model of three theories to explain the adoption of SaaS cloud computing in firms. Firstly, constructs from the technology-organization-environment (TOE) were used to explain the intra-organizational factors; secondly, the institutional theory (INT) was used to explain the inter-organizational factors; and finally, the process virtualization theory (PVT) was utilized to test the processes' effect in the migration towards SaaS cloud computing. Although their results shadow the influential factors of the adoption of this innovative technology, they contend the need to intensively explore other factors. Also, their study overlooked the actual user of the technology and focused on the higher level of acceptance, i.e., the mezzo-level or the organizational level.

Furthermore, van de Weerd et al. (2016) investigated in their work the factors impacting the adoption of SaaS in Indonesia as perceived by companies. The outcome of the study shows that the small to medium-sized enterprises are adopting SaaS more than the larger ones. Also, top management support has been found to be an enabler of the adoption, whereas the organizational readiness is not. Despite these findings, the user perceptions in terms of technology usage, easiness, usefulness, attitude, or social factors were neglected. Additionally, the work of Jede and Teuteberg (2016) focused on the IT professionals in organizations before and after SaaS cloud computing implementation as well as the end users. They utilized a mixed method; firstly, they examined the perception of the IT professionals before and after the implementation, and then conducted interviews with a group of users and IT professionals. The results shed light on the socio-technical effects on the job outcome and individual performance. Also, the focus of their study turned into exploring the change of the interface configuration, IT architecture change, organizational change, and IT technical radicality change. However, their work investigated the early stage of using the technology and did not reach to probe the real factors influencing the adoption nor the easiness, usefulness, and the attitude of the end-user toward the acceptance. Hence, their research is focused on the organization interest not end-user interest and perceptions.

Based on these delineated examples on the organizational level of acceptance of the SaaS adoption and acceptance, it is clear that the higher education sector and the end-user were lent less attention in terms of the salient factors affecting the acceptance. Specifically, the comprehensive review of literature conducted by Senyo et al. (2018) addressed the dire need to conduct more research on the higher education sector and to direct more attention toward the individuals. In addition, former works believe the notion that challenges surrounding cloud computing adoption are not the technical-based aspects, but user-based behavior aspects (Kayali & Alaaraj, 2020). Therefore, a number of studies investigated the behavioral factors from business organizational perspectives and less attention turned to higher education universities (Gohary et al., 2013; Kayali & Alaaraj, 2020; Lim et al., 2015). Besides, the role of cloud computing in the learning process is apparent at universities as students access different resources, upload their assignments, and communicate with other peers or exchange

thoughts and experience in group-assignment tasks inside or outside the campus. Additionally, they can interact with courses-related tasks and assignments from any device, anywhere, and any time to continue the pedagogical process inside or outside the campus. Further, using the services provided by SaaS cloud computing enables the students to access their online courses and lecturers to manage the contents of the offered courses, the student activities, and the evaluation of the students' performance (L.-Y.-K. Wang et al., 2019). More importantly, when identifying the factors that engender the acceptance of SaaS cloud-based applications and services that are used in the daily tasks by the students, this would create the opportunities to further develop the pedagogies that are aligned with SaaS cloud technology to serve the development of the educational institutes. This view has been articulated by H. H. Yang et al. (2019) as students' involvement is vital and their learning gains from such SaaS cloud-based services are critical to the success of the educational process. Despite these benefits for the higher educational institutes and students, studying the adoption factors as perceived by the university students remains scarce or in the early phases in developing countries (Huang, 2016; Kayali & Alaaraj, 2020; Okai et al., 2014; Ratten, 2013; Sabi et al., 2016; H. H. Yang et al., 2019). As such, it is indispensable and plausible to explore these factors that warrant more efforts to explore and gain more insights.

THE RATIONALE BEHIND STUDYING THE STUDENTS' PERCEPTIONS OF SAAS ACCEPTANCE

In principle, the selection focuses on university communities represented by students, as these communities with a mixture of different races, cultures, languages, and beliefs, offer respondents from different areas in Malaysia. These cultural differences are more likely to influence the perceptions, attitudes, and behaviors of the individuals (Hofstede, 1984). In this way, the differences in culture creates differences in the way that an individual thinks and acts and, accordingly, affects behaviors that are socially acceptable or not (Sang et al., 2015). Consequently, the respondents from universities offer an appropriate mixture that can be expected to provide a clear clue of the phenomena investigated because different cultures provide different perceptions, opinions, and attitudes towards a behavior (i.e., adopting and using SaaS cloud computing services). In other words, the opinions gained from this study would likely provide a wider view of different perceptions from different social and ethnic groups regarding acceptance and adoption factors. This would, in turn, help SaaS vendors, higher education authorities, and universities to focus on the main factors affecting the adoption and acceptance of this innovative technology. Furthermore, the students are one of the main pillars that intensely use SaaS innovative technologies inside or outside the campus to access the various resources, interact with online courses, and their learning gains from such SaaS cloud-based services are critical to the success of the educational process (H. H. Yang et al., 2019). Moreover, when the students inculcate the SaaS cloud computing culture, education, knowledge combined by skills and opportunities offered at the university campus, this would urge them – when leaving the university – to use and encourage others to adopt these services and applications. Also, it is more likely that once they join the cadre in different organizations, this culture would be reflected in their working environment and urge the management to use such handy, affordable, flexible, and reliable services provided by SaaS providers. Consequently, this would increase the likelihood of dispersing cloud computing usage, acceptance, and adoption and, therefore, would create multifold benefits for the SaaS cloud computing service vendors, the organization adopting it, and the users who are already familiar and have accepted this innovative technology. From a different perspective, the researchers may consider that the low adoption rate of cloud computing services would be likely improved, and the service providers can obtain more revenue in a win-to-win strategy if the salient factors are known from different people with a variety of beliefs, cultures, backgrounds, and mindset. This proliferation can be found at university campuses and concentrated in student communities. Noteworthy, major theories in information technology (i.e., Diffusion of Innovation theory (DOI), the decomposed theory of planned behavior (DTPB), and TAM) that focus on the usage, acceptance, and adoption of

systems have been developed in campus, which infer that students are a testbed and an important element in perception studying and diffusion of innovative systems.

Drawing on the extant cloud computing literature reviews discussed so far, the main objective of this study is to fill the abovementioned issues highlighted to provide more attention – especially in the higher education sector represented by universities – by developing and evaluating a framework. In addition, the researchers argue that the inclusion of social factors (i.e., subjective norms), personal capabilities and capacities (i.e., perceived behavioral control), technological factors (i.e., perceived usefulness and perceived ease of use), and attitudinal factors in the current model is worthwhile to explore their expected vital roles in the acceptance process of SaaS cloud computing. To accomplish the inclusion of these constructs to attain the intended hypotheses, the researchers employed two theories, i.e., TAM and TPB. The rationale behind the selection is that both theories gained popularity and dissemination in various assortments of users and technologies in various empirical studies. However, each has its own limitations. That is, TAM posits that intention is determined jointly by attitude and perceived usefulness and that perceived ease of use affects the usefulness and attitude towards the adoption of technology under consideration. However, TAM in its original form overlooks the requisite resources or skills needed for performing the behavior (i.e., Perceived Behavior Control) and the influence of others (i.e., subjective norms) in the social circle of individuals on performing the behavior under study. TPB, on the other hand, included these two constructs to overcome the limitations of TAM but neglects the crucial role and significant effect of perceived ease of use (PEU) and perceived usefulness (PU) in shaping the attitude of individuals to adopt innovative technologies. Therefore, the integrated model suggested utilizes TAM (Davis, 1989) and TPB (Ajzen, 1985) constructs and is tested empirically to determine its applicability in the higher education setting at Malaysian university campuses. Also, it uses the strength of both theories in achieving the goal of the study. More precisely, this paper is an endeavor to explore the factors influencing the acceptance and adoption process from the individual's perspective as no deep substantial focus on individual's perception – especially students at higher education institutes – has yet been made to investigate the usage and adoption process of SaaS cloud computing by this category.

Other sub-objectives include the exploration of the relationships between subjective norms and attitude towards intention and the direct relationship of perceived usefulness and the adoption of SaaS cloud computing. These relationships have not been included in the original theories' framework and scarcely used in the prediction of cloud-based acceptance models. This is considered one of the unique contributions, to the best of the researchers' knowledge, in the area of SaaS cloud computing adoption models. Besides, the scope of this current research includes university students from three public universities resides in northern Malaysian context.

The last objective considered is to conduct intensive and rigorous survey design and analysis beyond the regular analysis followed in previous empirical research by not only examining the direct effects of the respective constructs, but also the detailed analyses that cover, where many previous works neglect due to paper length, the measurement and structural model analyses, such as the inclusion of Heterotrait-Monotrait ratio of correlation, and approximate model fit analysis. Furthermore, common method bias analysis is overlooked in many recent empirical studies in education, technology, banking, and business. Hence, this study explains these issues related to it briefly and summarized its role in empirical studies. In this way, this research paper is considered one of the leading comprehensive studies in the field of empirical studies in the context of SaaS cloud computing. The results that emerge in this current study is expected to contribute to the body of knowledge and draw more insights for the business strategists, the government legislators, cloud providers, and the university rectors for building their future plans, as well as the higher education authorities. The remainder of the paper is structured as follows. First, the literature review provides an overview of the theoretical background, followed by the background of cloud computing concept and its classification. Then, the hypotheses development with constructs of the model are delineated. After that, the

methodology section is presented, followed by findings and discussion. Implications and limitations and future directions sections are presented along with conclusion.

LITERATURE REVIEW

THEORETICAL BACKGROUND

Notwithstanding that a number of theories and models used to investigate the adoption of technology or information system innovations – such as theory of reasoned action (TRA) (Fishbein & Ajzen, 1975), TAM (Davis, 1989), and TPB (Ajzen, 1991) – are apparently similar, they seem to have distinctive variables to explain and predict the behavior of interest (Püschel et al., 2010). TRA was a leading approach and inspired many theories and models that are based on it with extensions. For example, TAM was primarily aimed at predicting the adoption of information systems, and TPB was developed to provide a special focus on the intention and subsequent behaviors in using IS (Information System) (Glavee-Geo et al., 2017). In addition, Leung and Chen (2017) reported the importance of the concept that the prudent considerations of available information and motivations from the perspective of the adopter are elements that drive human behavior, which TRA and TPB are derived from. Moreover, TPB is considered as an augmentation of TRA (Ajzen & Fishbein, 1977) and was developed to overcome its limitations as emphasized by Alzahrani et al. (2017). Therefore, TPB extended TRA with perceived behavioral control, which gave it strength over TRA and provided further insight to explain the behavior under consideration.

An extensive literature review shows a well-documented explanation in which theories are integrated in many studies (Hsu et al., 2014; M. Jain et al., 2014; Joglekar, 2014) as they complement each other, provide richer and potentially more explanatory power (Hsu et al., 2014), and therefore provide a wider view and more insights of the innovative technology acceptance, usages, or adoption under consideration. Glavee-Geo et al. (2017) pointed out that the integration provides more exploratory power and predictability over the individual use of a single theory and further identifies cross-correlation of the predictive variables of the investigated behavior (Püschel et al., 2010). Hence, the suggested integrated model of the current study, using a single model framework, provides the estimated strength of both theories and enhances our standing regarding the behavior of interest, taking advantage of both theories with a wider view of different factors.

Based on the above, the theoretical framework proposed departs from TPB and is augmented by including constructs from TAM, i.e., the perceived ease of use and perceived usefulness, and their relationships to bring insightful understanding on the innovative services of SaaS cloud computing and better understand the perception of individuals regarding the adoption and acceptance of this technology.

Also, other new relationships not in these original theories cover various beliefs and aspects of the individual and give strength of the research framework. They cover the technological, social, attitudinal beliefs in addition to personal capabilities. This holistic model that includes this variety is expected to introduce a wider scope of the phenomenon under investigation.

BACKGROUND ON CLOUD COMPUTING

Cloud computing is, in its simplest definition, an IT-related capability that is provisioned as a service, which has advantages of higher performance, scalability, and availability, together with a low-cost service that has better features compared with conventional data centers (Bhardwaj et al., 2010; Sarea & Taufiq-Hail, 2021). These data centers connect many of its servers together locally and connect with other data centers together by the Internet and cloud computing technology to provide IT services and resources to consumers. The consumers may be close or far away from these scattered data centers, without having knowledge of the underlying technology infrastructure. The proliferation of smart mobile devices, the increasing need for high performance computing, the high growth of the

Internet usage with Internet of Things (IoT), and the need to reduce cost and energy paved the way for a new and different computing model that provisioned IT-related resources as a utility (Bhardwaj et al., 2010). More importantly, the cloud concept shadows the green computing concept, in which a cluster of servers can be built near inexpensive electricity sources (Marston et al., 2011).

In another aspect, various studies in the area of cloud computing adopted the definition of the U.S. National Institute of Standards and Technology (NIST) from its final draft (Ghosh et al., 2012; Mitchell & Meggison, 2014; Sarea & Taufiq-Hail, 2021; Simamora & Sarmedy, 2015). In this study, the definition of cloud computing is also adopted from NIST, which defines it as, “a model for enabling ubiquitous, convenient, on demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction. This cloud model is composed of five essential characteristics, three service models, and four deployment models” (Mell & Grance, 2011), which are explained in the following section.

CLOUD COMPUTING CLASSIFICATIONS

Cloud computing is classified based on two models, i.e., the deployment model and the service model. In the service model, there are three types. First, Software-as-a-Service (SaaS) is the topmost layer of this classification and is simply explained as using the applications on the cloud infrastructure of the service provider by the consumer (Mell & Grance, 2011). In addition, SaaS applications, which are provided through a technology coined as multi-tenancy technology, provision the software and data to many users at the same time on a single instance of the software (Bhardwaj et al., 2010). More importantly, SaaS services garnered the attention of researchers, practitioners, and IT business and became an online-centric functional software entity (Tomás et al., 2018).

The second layer of the service model is the Platform as a Service (PaaS), which is the middleware layer, where programmers can have more control over it and use the programming tools and packages to develop software. Finally, the Infrastructure as a Service (IaaS) is the bottom layer of the service level model, where users can have control over the hardware resources, such as memory, disk space or processors to use or release on the basis of pay-as-you-use. The invention of virtualization made it possible for these hardware resources to be used, shared, managed, and scaled up or down as needed by the consumer.

The second classification of cloud computing is the deployment model, of which there are four types. First, public cloud computing allows access to the data center from an outsider. In the public cloud, the infrastructure and services are provisioned for open use by the general public over the Internet on the basis of pay-per-use (W. Y. C. Wang et al., 2011). This model of cloud computing is owned, managed, administered, and operated by organizations in government, academic institutions, or businesses (Mell & Grance, 2011). The next type of deployment model is private cloud computing, where access is limited to insiders of an exclusive organization that has different business units (Mell & Grance, 2011; W. Y. C. Wang et al., 2011) and offers more security. The third type of deployment model is community cloud computing, in which different entities having the same interests – such as security requirements, shared policies, and common mission interests – are connected in a way to share resources among the members of this community (Jlelaty & Monzer, 2012; W. Y. C. Wang et al., 2011). Finally, hybrid cloud computing is a mixture of any of the abovementioned deployment models.

It is noteworthy that many services implemented at universities are deployed at the top of the SaaS cloud computing layer with hybrid cloud computing. These services include but are not limited to hosting services for university students as well as academic and non-academic staff, e-learning resources, digital archiving of records, and portals that cater to the students, academic staff, and administration and non-academic staff.

HYPOTHESES DEVELOPMENT AND RESEARCH MODEL

Behavior intention (BI)

Behavior intention is considered the major factor that predicts the behavior in question, and it gauges the person's relative strength to perform a certain behavior (Shin, 2013). Reviewing the literature, different definitions for BI in different contexts can be identified. For example, the following definition in the context of cloud computing defines BI as "the degree to which a student has formulated conscious plans to use or not use cloud services in the future" (Arpaci et al., 2015, p. 95). Another more comprehensive and adopted definition is reported by Taufiq-Hail et al. (2017a, p. 38) in which they defined BI as, "the degree in which the individual, student & academic staff, using SaaS cloud computing services has formulated conscious plans to use/accept 'or adopt' SaaS cloud computing services in their academic studies or communications with others inside or outside the campus." It is worthwhile to note that behavior intention (BI) is widely adopted in the literature in different contexts and models and is found to be a strong and significant predictor of behavior, adoption process, or acceptance of certain services or technologies (Alalwan et al., 2017; Dong et al., 2017). Additionally, the inclusion of BI is apparent in many models and theories; for example, TRA (Fishbein & Ajzen, 1975), TAM (Davis, 1989), TPB (Ajzen, 1991), and the decomposed theory of planned behavior (DTPB) (Taylor & Todd, 1995), in which they affirm that BI is the main driver of behavior. Hence, the following hypothesis is postulated:

***H1.** BI positively and significantly impacts accepting and using SaaS cloud computing.*

Subjective norms (SN)

Considerable work has been done in the literature to investigate the impact of subjective norms in the social sciences and was given special attention in academia. It has been identified as "a specific individual expects one to perform or not to perform the behavior combined with one's motivation to comply with these specific individuals" (Bagozzi, 1992, p. 180). In the context of this study, the subjective norms (SN) construct is defined as the extent to which the SaaS services users urge others to adopt/accept (or not to adopt/accept) SaaS cloud computing services in their daily academic routine/tasks combined with the motivation that those others would comply with them.

In adopting innovative technologies, Pedersen (2005) explained that the role of SN was not comprehensively explained and well-defined in ICT research due to the nature and type of applications and services provided or offered of innovative technologies. This role may vary from one type of technology to another. Apart from that, colleagues, classmates, friends, and lecturers who are in the same social circle inside/outside the university campus can be potential users/adopters of SaaS cloud-based services. They may exhibit a significant influence on the student to use, accept, or adopt the services and applications offered freely in the campus portal or in the internet space. Based on human nature, when one expects risks or a potential uncertainty and fear, he/she may seek a second opinion from others and not relying on one's own opinion (Sharma et al., 2017), especially when it comes to a new technology service such as SaaS cloud-based applications. Therefore, students in their daily academic life tend to gather together to listen, learn, discuss, and exchange new experiences, ideas, practices, and knowledge within their social circle in addition to the role of supervisors and lecturers to open their minds and asking to adhere to use such technology to comply with university regulations in using online SaaS cloud-based portals.

Reviewing the literature shows that there is a paucity of studying the direct relationship between SN and the actual behavior in general, and specifically in the area of SaaS cloud computing. However, there are a limited number of studies that have postulated the significant effect of SN on the actual behavior. The findings emerged from these studies with no significant relationship between the two constructs. For example, Janmaimool (2017) postulated that individuals will engage in waste management behavior (WMB) if others (i.e., referents) will be engaged in WMB. On the other hand, the findings did not reveal a significant direct impact with WMB; rather, it shows this significance

indirectly through organizational norms, which is a category of social norms. Similarly, another study by Mafabi et al. (2017) conducted in the area of knowledge sharing revealed that the relationship SN → knowledge sharing (i.e., the actual behavior) appears to be nonsignificant against the hypothesis of the researchers. Therefore, these findings draw more ambiguity on the direct relationship between SN and behavior in what is posited and what is empirically found. In comparison, a study conducted by Alzahrani et al. (2017) found a significant and positive direct relationship between SN and the actual use of online game playing.

Based on the above literature review and justifications, the researchers argue that the effect of SN has a crucial influence on the decision to adopt SaaS cloud-based services and applications; hence, the following hypothesis is presented:

H2-1. *The SN latent construct is expected to have a direct, positive, and statistically significant effect with AUSaaS.*

In another aspect, some previous work investigated the relationship between SN and attitude (ATT) of the respondents. For instance, H. C. Yang and Zhou (2011), in their study on mobile viral marketing utilizing young American consumers, found that SN exert an empirically significant and positive relationship with the consumers' attitude. Likewise, another study conducted by Hamari and Koivisto (2013) to investigate the role of social factors on the attitude towards gamification services, revealed a significant and positive effect of SN on ATT. In the same token, a study conducted to investigate the influence of SN on ATT towards buying organic food found a statistical and significant positive correlation between the two constructs (Al-Swidi et al., 2014). Similarly, Pedersen (2005) in his work indicated the importance of adding SN → ATT relationship in the modified version of decomposed theory of planned behavior (DTPB) toward the adoption of mobile services and the final model revealed a statistical positive and significant relationship between SN and ATT. Interestingly, more recent studies (Arpaci, 2016; Taufiq-Hail et al., 2017a) confirmed the positive and significant role of SN on ATT towards the adoption of cloud computing services.

In the context of the current study, the researchers articulate that the students are assumed to adopt SaaS cloud computing services as a result of receiving positive feedback from their friends and companions who are using it, talking about it positively, touching the tangible benefits, and urging them to use these innovative services (Hernandez et al., 2011). Consequently, as a result of this social influence in their university community circle, students would be more willing and more likely to accept, use, and adopt SaaS services and applications. In principle, in collectivist societies, people rely on other referents to do specific behavior, especially when it comes to decision taking. The fear of risk in doing the specific behavior is mitigated or at least avoided when other referents in the social circle had a positive outcome of practicing the behavior in question. Malaysian culture is in this category where social influence is strong and in general collectivist societies tend to exchange experiences among its individuals. Based on the abovementioned literature review, the researcher assumes that the said relationship has received strong support and the conceptual reasoning underlying the relationship between SN and ATT. Accordingly, the following hypothesis is formulated:

H2-2. *The SN latent construct is expected to have a direct significant and positive relationship with ATT.*

Perceived behavior control (PBC)

The intention to use any technology is driven and predicted by three different beliefs: attitudinal belief, normative belief, and control beliefs, as stipulated in TPB (Ajzen, 1991) and DTPB (Taylor & Todd, 1995). PBC can be said to be, “the perceived ease or difficulty of performing the behavior and it is assumed to reflect past experience as well as anticipated impediments and obstacles.” (Ajzen, 1991, p. 188). For the purpose of this research, PBC can be defined as the perceived ease or difficulty in performing different tasks using SaaS cloud computing services, and it is assumed to reflect the past experience of the university student to use technology skills they possess, in addition to the anticipated obstacles to perform such tasks with SaaS cloud-based services.

Moreover, PBC has received theoretical support in TPB (Ajzen, 1991) and DTPB (Taylor & Todd, 1995) theories, respectively, as well as empirical support in different contexts (Chang et al., 2016; Yeap et al., 2016), in which a significant and positive directional relationship $PBC \rightarrow BI$ is established. However, other previous works in the literature reveal a nonsignificant relationship between PBC and BI (S. Jain et al., 2017; Renda dos Santos & Okazaki, 2016). These inconsistencies raise a cautionary concern to investigate the said relationship in the context of the Malaysian higher education sector, represented by the students at a university level in the area of SaaS cloud computing.

Reviewing the literature with respect to the relationship $PBC \rightarrow$ actual behavior, it is found that there is a scarcity of previous works that study this direct relationship of PBC – as a single construct – empirically, although theoretically supported by TPB. In addition, a majority of research papers neglected and overlooked the direct relationship from $PBC \rightarrow$ AUSaaS (i.e., the actual behavior) and only focused on its relationship with BI instead of studying both directions; that is, $PBC \rightarrow BI$ and $PBC \rightarrow$ AUSaaS. However, some studies revealed the positive and significant relationship between PBC and the actual use or behavior (Alzahrani et al., 2017; Cheung & To, 2016; S. Jain et al., 2017). Additionally, the results of the study by Mafabi et al. (2017), in which the results reveal full mediation between PBC and the actual behavior, implies a nonsignificant relationship between PBC and the actual behavior because, in the full mediation case, the mediator tries to absorb the direct effect between PBC and the actual behavior (Hair et al., 2014; Nitzl et al., 2016). Therefore, we assume a nonsignificant relationship between PBC and the actual behavior in this research. In addition, it is worth understanding that PBC is determining both the intention and the interested behavior because when doing something is easier, within the ability, and under control, the behavior perceived would be more likely to influence future behavior or have the intention to perform that behavior or adopt the behavior in question (Smith & McSweeney, 2007). Based on the contradictory findings combined with the scarcity of studying the PBC effect on AUSaaS directly, this study postulates the following two hypotheses:

H3-1. *The PBC latent construct is expected to have a nonsignificant relationship with AUSaaS.*

H3-2. *The PBC latent construct is expected to have an empirically significant relationship with BI.*

Attitude (ATT)

Attitude is given a remarkable amount of attention for predicting BI and actual behavior in different theories; namely, TRA (Fishbein & Ajzen, 1975), TPB (Ajzen & Fishbein, 1980), DTPB (Taylor & Todd, 1995), and TAM (Davis, 1989). It is defined as “the degree to which a person has a favorable or unfavorable evaluation of the behavior in question.” (Ajzen & Madden, 1986, p. 454). Aligned with the above definition, ATT is defined in the current study as the degree of favorable or unfavorable assessment felt by the individual at the university level regarding the adoption, acceptance, or usage of SaaS cloud computing services and applications. In addition, TPB by Ajzen (1991) implies that the positive ATT that the individual possesses forms the future intention to embrace a specific behavior. Additionally, ATT is found to be a strong and robust antecedent of BI in various studies, especially those related to ICT and innovative technologies, and it exerts a positive and significant relationship with BI (Arpaci, 2016; Gao & Huang, 2019; Salahshour Rad et al, 2019; Taufiq-Hail et al., 2017b). It is worthwhile to note the positive advantages of SaaS cloud computing to the students of this innovative technology for accomplishing their academic tasks, which would most likely shape their intention towards the adoption of this technology. That is, the context of SaaS cloud computing online services, the around the clock access to applications, storage, and other SaaS services – regardless of location, time, or device – make it advantageous compared with other conventional methods. Hence, these tangible benefits of SaaS services presumed by the students in their academic life would likely affect their ATT and, therefore, influence their intention to perform the behavior in question. Following this line of reasoning, this hypothesis is considered:

H4. *ATT has a direct and positive influence on BI to use, accept, and adopt SaaS cloud computing services and applications by the university students in their academic work.*

Perceived usefulness (PU)

Perceived usefulness (PU) is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance” (Davis, 1989, p. 320). In other words, when there is a higher perceived usefulness of an innovative technology, such as SaaS cloud computing services, there is also a higher possibility that users will be quickly driven towards the actual adoption or acceptance of SaaS cloud computing innovation technology. In the context of cloud computing, Park and Kim (2014, p. 378) define PU as, “the degree to which users believe that using mobile cloud services improves their job performance and predicts that it will have similar positive effects on attitude toward and intention to use mobile cloud services.” Drawing on the previous definitions, this study defines PU as the degree in which university students believe that SaaS cloud computing services’ usage, acceptance, or adoption improve and enhance their performance in academic achievements and are perceived to be better usable, understandable, and reliably accessible compared with the conventional methods – e.g., storing/uploading/sharing different data in a local computer or inside a local server – that would eventually lead to positive effects on attitude and the usage, acceptance, or adoption of SaaS cloud computing services and applications.

PU has emerged as one of the significant and dominant factors influencing and determining the adoption of cloud-based applications and services owing to outstanding and exceptional characteristics inherited (Sharma et al., 2016). These features include, but not limited to, the low cost, accessibility, variety of IT resources, flexibility, reliability, and pay-as-you-use paradigm regardless of location, time, or device, as long as one has means of connectivity to the cloud. Owing to these perceived useful features, one’s job is assumed to be more efficient, and productivity would likely increase. The rationale behind the inclusion of the PU → AUSaaS relationship in the current research rests on the students’ perception on the usefulness of using, accepting, or adopting SaaS services and applications – e.g., exchange and sharing files using social media applications, Dropbox, Google Drive, Microsoft OneDrive, etc. that leverage the conventional IT methods – in their academic life inside or outside the university campus, which would eventually improve their academic work and increase their performance and academic productivity. In this case, it is more likely that this positive perception of usefulness would be reflected in their usage, acceptance, or adoption SaaS services.

Based on the review of previous works in the existing literature, it can be observed that a majority of research on technology adoption and acceptance models and their extensions focus on the relationship PU→BI (Besbes et al., 2016; Dong et al., 2017; Huang, 2016; Venkatesh & Davis, 2000) and less attention is given to PU → actual behavior. However, there is a limited number of previous works which identified that PU has been validated and included in models with a causal linkage from PU to the actual use, acceptance, or adoption of technology. Consequently, based on the above arguments and the dearth of studies in the relationship PU → AUSaaS, the following is hypothesized:

H5-1. *PU is believed to have a direct, strong, positive, and statistically significant relationship with AUSaaS.*

In addition, reviewing the previous works in the literature, a consensus in academia that PU is a strong influencer of ATT can be identified. This notion is supported by a large body of research (Baturay et al., 2017; Besbes et al., 2016; Huang, 2016; Ma et al., 2016). Furthermore, this relationship confirmed its theoretical foundation by TAM in studying the individual’s behavior (Davis et al., 1989) and DTPB (Taylor & Todd, 1995). For example, Davis (1989) emphasized the pronounced and stronger effect of PU on ATT compared with that of perceived ease of use. Davis explained further that adopting an application in a system is at the utmost priority accomplished by its usefulness (i.e., the function it performs for them) and then by how easy or hard to get the system to perform these functions (i.e., the ease of use). To put things together, the researchers assume the strong support of the relationship PU →ATT empirically and theoretically that the situation holds for this relationship in the context of the current study and expect to find an important effect of PU in driving respondents’ ATT to accept, use, or adopt SaaS Cloud computing services and applications. To further explain, when the students feel that SaaS services and applications are useful in their daily academic tasks, it will be more likely to influence their attitude to use it, as this will create a positive perception

in that it will reflect in their performance and productivity in their academic achievements. Hence, the following is hypothesized:

H5-2. PU is believed to have a direct, positive, and statistically significant relationship with ATT of respondents to use, accept, or adopt SaaS cloud computing.

Perceived ease of use (PEU)

Perceived ease of use (PEU) has its theoretical foundation in theories such as TAM (Davis et al., 1989) and DTPB (Taylor & Todd, 1995). It is defined as, “the degree to which a person believes that using a particular system would be free of effort” (Davis, 1989, p. 320). In particular, Davis added, “This follows from the definition of ‘ease’: freedom from difficulty or great effort”. In other words, Davis is pointing to the feelings of being free from worries, difficulties, or effort to achieve the perceived performance when using the innovative system. More precisely, the more easily that the technology or innovation is perceived, the more likely is this technology influencing the ATT. Drawing on the above, the study defines PEU as the degree in which the SaaS cloud computing services’ adoption, acceptance, or usage is believed to be easy and free from worries, difficulties, or effort to achieve the perceived performance by the individuals (i.e., students) and is readily understandable. Further, the relationship PEU → ATT has gained empirical support in the literature by various works in different contexts (Dong et al., 2017; Huang, 2016; Richad et al., 2019; Smith, 2008), in which the results reveal a positive and significant relationship with ATT.

In addition, drawing upon TAM, PEU appeared to be a significant influencer and has a direct effect on PU because the easier the technology to use, the more useful the individual would perceive its use (Venkatesh, 2000). Moreover, the findings affirm the association between PEU and PU by the study of Venkatesh (2000). This finding is further supported with a large body of literature (Arpaci, 2016; Dong et al., 2017; Huang, 2016; Richad et al., 2019). However, other findings are not aligned with abovementioned results. Agarwal and Karahanna (2000), for example, found an inconsistent result in their study that demonstrates that PEU is not associated with PU. Another study by Smith (2008) revealed similar findings in the nonsignificant statistical effect of PEU on PU in finding the products while searching on the web sites. Agarwal and Karahanna (2000) referred to the search and not the purchase of goods on the web sites that led to the reduction of the impact of PEU on PU. Based on these inconsistencies in previous works the researchers articulate to investigate this relationship in the context of the current study and explore this relationship in the area of SaaS cloud computing. Moreover, when a technology is perceived difficult to be understood, used, or accessed, it is unlikely to be used, accepted, or adopted, as a negative perception is created. In contrast, when it is easy, accessible, and understandable, it would likely increase the students’ acceptance and productivity in their tasks and assignments in academic life. Consequently, this creates a positive perception on them of its usefulness. Therefore, the following is hypothesized:

H6-1. PEU has a direct and positive influence on ATT to use, accept, or adopt SaaS cloud computing services and applications by the university students in their academic work.

H6-2. PEU has a direct and positive influence on PU to use, accept, or adopt SaaS cloud computing services and applications by the university students in their academic work.

In summary, after developing the hypotheses, the researchers propose the conceptual framework with the relations postulated in the study (refer to Figure 1). All constructs are represented in reflective mode, where arrows pointing from latent constructs to the items (or indicators).

METHODOLOGY

THE POPULATION AND SAMPLE

The population of the study is the student in the higher education sector of public and private universities. The sample frame is the students in degree level at public universities in Malaysia, and

finally, the sample is the students drawn from three public universities in the northern part of Malaysia. The researchers took into account the variety of the respondents to be from different schools and geographical locations. Having this variety in mind would presumably cover different groups of the community with different cultures, perceptions, and ethnicity. In principle, the selection of the sample focused on university communities represented by students, as these communities – with a mixture of different races, cultures, languages, and beliefs – offer respondents from different areas in Malaysia. These cultural differences are more likely to influence the perceptions, attitudes, and behaviors of the individuals (Hofstede, 1984). In this way, the differences in culture creates differences in the way that an individual thinks and acts and, accordingly, affects behaviors that are socially acceptable or not (Sang et al., 2015). Therefore, the respondents from universities offer an appropriate mix that can be expected to provide a clear clue of the phenomena investigated because different cultures provide different perceptions, opinions, and attitudes towards a behavior (i.e., adopting and using SaaS cloud computing services). In other words, the opinions gained from this study would likely provide a wider view of different perceptions from different social and ethnic groups regarding the acceptance and adoption factors. This would, in turn, help SaaS vendors, higher education authorities, and universities to focus on the main factors affecting the adoption and acceptance of SaaS services and applications.

MEASUREMENTS SURVEY INSTRUMENT

A survey instrument was used in a quantitative research approach to explore and evaluate the relationships in the model postulated. The respondents (i.e., the unit of sampling) of the study are students from three public north Malaysian universities (sample frame). A structured questionnaire with two parts was designed. The first part was the demographics that are pertinent to age, gender, and race, and the second part (see the Appendix) covered the different beliefs of the respondents with the constructs related to the current study. For simplicity in understanding the questions, pictures of SaaS cloud computing services were added in the survey. These pictures facilitated the comprehension of the services in a visualized way and made answering the survey enjoyable.

The items were borrowed from the well-established and published former works and based on different models or theories. Also, the instrument adapted, their construct validity and internal consistency and reliability (i.e., Cronbach's alpha and construct validity based on Hair et al. (2017)) were tested, validated, and proven its scales. The items were scored using a five-point Likert scale (Likert, 1932), where 1 = strongly disagree to 5 = strongly agree. Modifications were made to suit the context of the study. Afterwards, the questionnaire instrument was sent to a group of experts to confirm its content validity, i.e., the suitability, the meanings of the questions reflecting what is intended by the researchers, and the simplicity in understanding the questions without difficulty or misinterpretation. The group of experts are professionals in the field of questionnaire development and empirical studies that focus on the interaction between technology and innovation. On the other hand, they possess expertise in studies that focus on human behavior such as acceptance, adoption, and usage of innovative systems in different fields. Based on their recommendation amendments were made. SmartPLS 3.2.7 (Ringle et al., 2015) partial least squares structural equation modeling (PLS-SEM) software was used as a main analytical tool to analyze the validity of the items used and to assesses the hypotheses of the current study. SPSS version 21 was used to analyze the respondents' demographic profile.

SAMPLE SIZE AND SAMPLING PROCEDURE

In practice, it is not logical to select each member of the targeted population; therefore, the need for a sample in the targeted population is crucial. The sample is defined as, “a subgroup of the target population that the researcher plans to study for generalizing about the target population” (Creswell, 2012, p. 142). A sample is a representative of the whole population under investigation and is a subset of the population. In other words, “It comprises some members selected from it (i.e., some not all elements of the population)” (Sekaran, 2003, p. 266). For these reasons, the researchers studied

the sample to draw a conclusion that could be generalized to the whole population under study (Sekaran, 2003). The sample frame or targeted population is selected to be the students from the public universities in the northern Malaysia.

More importantly, the selection of the north part of Malaysia for sampling is based on the following notions. Firstly, Malaysia represents Asia with all its varieties of different cultures (i.e., Chinese, Indian, and Malay), languages, beliefs, and it is considered truly Asia (Ndubisi, 2012). Secondly, Malaysia is a multi-ethnic and multi-cultural country that can present many of the cultures in Asia (Thien et al., 2014). More importantly, the culture values have an influence on how the people think and behave when it comes to the introduction of an innovative new technology such as SaaS services (Choi et al., 2014). Thirdly, Thien et al. (2014) demonstrated the three dominant ethnic groups in Malaysia that consist of Malay, Chinese, and Indians in which they have distinguished cultures, languages, beliefs, religions, and values. These unique differences influence the perceptions of these groups and assure the importance of this variety of differences that are based on Hofstede's cultural values (Thien et al., 2014). This view is also in line with Cohen's (2007) in which he pointed out the role of culture in influencing a specific behavior and commitment within the same country. Fourthly, in Malaysia the students enrolled in any university have to come from different districts and areas of Malaysia. The government implements a specific strategy to mix the students from different ethnic groups and geographical areas (i.e., different districts) aimed to impose the harmony in Malaysian society that includes universities. More importantly, universities are the source of imparting the knowledge and technological skills for the community it resides in and are a microcosm that encompasses diversity of cultures and social groups (Sabi et al., 2016). Therefore, when studying the acceptance, usage, or adoption of SaaS services inside the universities, we are actually studying the whole community that is representative of the society of the Malaysian context.

In principle, sampling is divided into two types; namely, probability sampling and non-probability sampling. The probability sampling is the most rigorous way of sampling in quantitative research as the sample is representative of the population under study and therefore can be generalized (Creswell, 2012). Further, probability sampling can be defined with four types; namely, simple random sampling, systematic sampling, cluster sampling, and stratified sampling (Creswell, 2012). In fact, the study conducted a complex multistage cluster sampling, then stratified proportionate sampling and, finally, on its last stage for testing respondents, the random sampling was conducted.

To explain more, firstly, the cluster sampling in its concept aims to divide the large population into groups with diverse characteristics within groups and common characteristics among these groups (Sekaran, 2003). The definition of cluster sampling is referring to "Groups or chunks of elements that, ideally, would have heterogeneity among the members within each group (and) are chosen for study in cluster sampling" (Sekaran, 2003, p. 274). In this study, the researchers assume that heterogeneity resides within the different three parts of the Malaysian Peninsula based on geographical location (i.e., the first condition), and homogeneity that exists among the groups of the cluster as the respondents are students studying at the universities (i.e., the second condition). Moreover, the cluster sampling can be either single stage (Sekaran, 2003) or multiple stage (Creswell, 2012; Sekaran, 2003). In principle, in this current research, the researcher adopts the multi-stage probability sampling that is given by Sekaran (2003, p. 275) as in the following example, "if we were to do a national survey of the average monthly bank deposits, cluster sampling would first be used to select the urban, semi-urban, and rural geographical locations for study. At the next stage, particular areas in each of these locations would be chosen. At the third stage, banks within each area would be chosen". The study follows the example explained and three stage cluster sampling strategy is implemented in the higher level of sampling: (1) Malaysian Peninsula is divided into three geographical locations (i.e., Northern, Middle, and Southern part); (2) then selecting the Northern part of the Malaysian Peninsula as a second step; (3) after that, this cluster is divided into smaller clusters (i.e., universities); and finally (4) the students are sampled.

Secondly, the second sampling step is employed by utilizing stratified sampling. Stratified sampling is a probability sampling in which the population is stratified or divided into chunks or stratum (i.e., single of strata) based on specific characteristic. Sekaran (2003, p. 256) asserts in this sampling “each important segment of the population is better represented, and more valuable and differentiated information is obtained with respect to each group.” Sekaran also explains that it suits different scenarios to be used and the population can be stratified according to the size of company, geographical area (region), gender, age, department, function, or a combination of these elements. An example of the stratification is given by studying the consumer preferences for a specific product, where market segments, gender, age, geographical area are possible stratum where differences or heterogeneity do exist (Sekaran, 2003). In the same vein, if we study the perceptions of the students pertaining the SaaS adoption, acceptance, or usage, it is plausible to divide the university into different schools or stratum (i.e., this is congruent with the previous example of market segment and function that represent different schools of the university). Furthermore, there are two conditions in this regard: the homogeneity within the group, and heterogeneity among groups (Sekaran, 2003). To explain, the universities were divided into different groups or strata, where each school is regarded as one stratum and heterogeneity among different schools is conspicuous as they offer different fields of study as explained earlier. On the other hand, homogeneity within each stratum or school is obvious as the unit of sampling is the student studying at the same school of the same university. Accordingly, the selection of the stratified sampling is the second stage of sampling, after clustering phase (i.e., three clusters of Malaysian Peninsula → selection of Northern part as one cluster). To summarize the sampling procedures – and based on the foregoing argumentation – in this study, the population is divided into three geographical clusters and one cluster is chosen, i.e., northern part of Malaysian Peninsula. After that, the universities (i.e., the strata in the selected cluster) with different schools were chosen with stratified sampling based on the size and field of study. Finally, in its last stage for testing respondents (i.e., the student), the random sampling is conducted to collect responses as recommended by the literature (Sekaran, 2003).

Pertaining the identification of the sample size, there are number of methods, such as the rule of 10 where the maximum number of indicators in formative or reflective construct or the maximum number of structural paths towards a specific construct in the model are multiplied by 10 (Hair et al., 2017). Also, rules provided by Cohen’s statistical power analysis and the G*Power statistical power analyses software package are other methods to identify the minimum sample size (Hair et al., 2017). However, based on the recommendations of Hair et al. (2017), the G*Power statistical power analyses program was utilized. Hence, for an effect size of 0.15 (medium), an alpha error probability of 0.05, and a statistical power of 0.80, the minimum sample size required found to be 98. However, a larger sample size provides a better statistical power and expands our insights of the phenomenon under study. Therefore, the researchers articulated to collect as many responses as possible within different resources available. After collecting the responses, the total valid number of responses was 289, out of 450 distributed questionnaires, which achieved 0.99 statistical power.

FINDINGS AND DISCUSSIONS

DATA SCREENING AND COMMON METHOD BIAS ANALYSIS

The total number of questionnaires distributed was 450. The collected number of questionnaires was 378 responses. The screening phase started after the collection of the responses. The procedure conducted to eliminate the unfilled and uncompleted responses, the ones with similar response’s patterns or stylistic and nondifferentiated manner, and finally the outlier’s analysis and removal of these responses were conducted. Consequently, the valid number of responses of the current study obtained was 289 with response rate of 64.22%.

Pertaining to common method bias (CMB), it is widely agreed in academia that the measurement method error is the cause of the common method variance bias and not the constructs per se that

were measured by these items (Podsakoff et al., 2003). In principle, method bias has a critical effect on items' validity and reliability as well as the covariation between constructs (Mackenzie & Podsakoff, 2012). To evaluate the common method bias variance, the researchers performed Harman's one-factor test, which is the most widely used technique in academia (Podsakoff et al., 2003). This technique is performed by loading all the items into an exploratory factor analysis (EFA). The unrotated component principal factor analysis with one fixed factor to extract was used. Then the varimax was used to simplify the factor structure for each data set (Podsakoff et al., 1984).

If a single factor emerged from this analysis or one factor found to account for the majority of the covariance of all items included in the analysis (Podsakoff et al., 2003), then common method variance does exist. Hence, it is presumed problematic and threatens the validity of the conclusion of the relationships among items or indicators of the measurement used. In other words, measurement errors are the main source of method biases (Podsakoff et al., 1984). Consequently, common method bias (CMB) was investigated before proceeding to the analysis of the model.

Fortunately, the analysis conducted revealed more than one factor and no factor explains the substantial amount of the covariance of the variables entered. The largest value obtained from the first variable was 48%, which is less than the suggested threshold. Therefore, no general (or single) factor that represents all or the majority of the variables (i.e., items) was found. That is to say, no single factor emerged to fit all dataset.

Notwithstanding ruling out the possibility of CMB by using such analysis is not the optimal solution as argued by Podsakoff et al. (2003), it offers some post hoc evidence and a clue for its absence (Karlaluoto et al., 2002). Besides, there was not a single source for data collection in the current study – i.e., data gathered from different sources, e.g. respondents of different educational level, ages, races, and different schools – and that further diminish the probability for CMB as noted by Mattila and Enz (2002). After conducting the above initial procedures, the investigation revealed no issues of common method bias; so, the researchers proceeded with the analysis in the following subsections.

DESCRIPTIVE STATISTICS

When analyzing the demographics, the results show a majority of females (72.3%) over males (27.7%). Furthermore, by referring to the group distribution on Table 1, the results show that Group 1 (18-26) consisted of 95.5% of the respondents, followed by Group 2 (27-35) with 2.8%, and Group 3 (36-44) with 1.7%. As the demographics data show, the majority of the respondents are female (which reflect the actual population of the Malaysian society), and the dominant age is in Group 1 (i.e., 18-26), where the young generation's perception of the current study is obtained. Different races were identified with different ethnicities, showing that 60.6% were Malay, 26% Chinese, 10.7% Indians, and 2.8% the other ethnicities. These statistics reflect the actual society in Malaysia. Interestingly, with the clear diversity of the respondents, this would likely provide more views of the different races and highlight the aspects related to the adoption, usage, and acceptance of the SaaS cloud computing area of research. Table 1 summarizes the results.

Table 1. Demographic profile descriptive analysis

Category	Frequency	Mean	Std. Deviation	Percentage
<i>Gender</i>		1.72	0.448	
Female	209			72.3%
Male	80			27.7%
<i>Age group</i>		1.06	0.305	
Group 1: 18-26	276			95.5%
Group 2: 27-35	8			2.8%
Group 3: 36-44	5			1.7%

Category	Frequency	Mean	Std. Deviation	Percentage
<i>Ethnic group</i>		1.71	0.305	
Malay	175			60.6%
Chinese	75			26%
Indian	31			10.7%
Others	8			2.8%

MEASUREMENT MODEL ASSESSMENT

First and most importantly, the assessment of the measurement model should be performed before proceeding to examine the hypotheses of the model. If no issues arise in the measurement model assessment, then proceeding with the analysis is warranted. The procedure included evaluation of three steps, namely: (1) the convergent validity; (2) the internal consistency and reliability; and finally (3) the discriminant validity. Meeting these three steps makes it possible to proceed to the structural model analysis (i.e., the hypotheses testing).

The first step in the measurement model assessment is to check the convergent validity, which includes the assessment of the average variance explained (AVE) and the loadings of the items (indicators). The loadings should be within the range of the threshold, 0.7 or above, as well as AVE for all constructs should be 0.5 or above as indicated by Hair et al. (2017). It is worth mentioning that loadings between 0.4 and 0.7 are considered for deletion only if their deletion results in an increase in composite reliability (CR) and AVE as stressed by Hair et al. (2017). By referring to Table 2 results, it is clear that there are no issues of the convergent validity, as all indicators have loadings range of 0.7-0.9 and exceeds the recommended threshold of 0.7. After that, AVE is examined against the threshold of 0.5. Results show that AVE values range between 0.5-0.8 for all constructs, which meets the requirements. Additionally, rho A range is 0.7-0.9, which is within the threshold of the recommended value 0.7 (Latan et al., 2018). By meeting the thresholds of AVE and items' loadings, the convergent validity is established (Hair et al., 2017). The second step in the measurement evaluation process is to test the internal consistency and reliability, where CR can be in the range of 0.6 to 0.7 in exploratory research, as is the case of the current study (Hair et al., 2017), and Cronbach's alpha is preferably to be above 0.7. The results of CR are in congruent with the critical values where the values range (0.8-0.9) exceeds the threshold. After that, the Cronbach's alpha is checked against the threshold. Table 2 shows that the obtained values range (0.7-0.9) is falling within the recommended cut-off values. By meeting the two criteria, the internal consistency and reliability for the constructs are established as indicated by the literature (Hair et al., 2017). It is worth mentioning that CR is the upper limit of the reliability and Cronbach's alpha is the lower limit of reliability and reporting both is essential based on the recommendations of Hair et al. (2017).

Table 2. Internal consistency, reliability, and convergent validity

Latent Variable	Items	Loadings $> = 0.7$	ρ_{ho_A} $> = 0.7$	Ave $> = 0.5$	Cr $> = 0.7$	Cronbach's α 0.6-0.9
AUSaaS	AUSaaS1	0.7	0.7	0.5	0.8	0.7
	AUSaaS2	0.7				
	AUSaaS3	0.8				
	AUSaaS4	0.7				
BI	BI1	0.9	0.9	0.8	0.9	0.9
	BI2	0.9				
	BI3	0.9				
	BI4	0.9				

Latent Variable	Items	Loadings > = 0.7	<i>rbo_A</i> > = 0.7	Ave > = 0.5	Cr > = 0.7	Cronbach's α 0.6-0.9
ATT	ATT1	0.9	0.9	0.7	0.9	0.9
	ATT2	0.8				
	ATT3	0.9				
	ATT4	0.9				
SN	SN1	0.9	0.9	0.8	0.9	0.9
	SN2	0.9				
	SN3	0.9				
	SN4	0.9				
PBC	PBC1	0.9	0.9	0.7	0.9	0.9
	PBC 2	0.9				
	PBC 3	0.9				
	PBC 4	0.8				
PEU	PEU1	0.8	0.9	0.8	0.9	0.9
	PEU2	0.9				
	PEU3	0.9				
	PEU4	0.9				
PU	PU1	0.8	0.9	0.7	0.9	0.9
	PU2	0.9				
	PU3	0.9				
	PU4	0.9				

The third step in the analysis of the measurement model is to check the discriminant validity of the constructs. Following these considerations, the discriminant validity is assessed in a three-step approach by investigating the different coherent and complete analysis of: (1) Fornell and Larker's (1981) criterion; (2) cross-loadings, and (3) HTMT_{inference} (Heterotrait-Monotrait ratio of correlation). To explain further, the Fornell-Larker criterion is investigated in which the diagonal values should be larger than all off-diagonal values (i.e., the diagonal values are the values of the square root of AVE). As can be seen in Table 3, the loadings in bold are the correlations of each construct with itself, which should be higher than any values with other constructs to achieve the discriminant validity. This criterion is met, and no violations found. Following that, the cross-loadings assessment is performed. The rule of thumb is that the loadings of each item with its respective latent construct should be higher than other loadings with other constructs in order to reflect its appropriateness to reflect its own construct; if they are other than that, its inclusion with the respective construct may need to be reconsidered (Chin, 1998). As seen in Table 3, the results show no violations for this measure. Hence, the Fornell-Larker criterion is checked, and no violations appear to be applicable in this step. Finally, HTMT_{inference} is assessed to further augment our analysis of the discriminant validity, as it is a new and coherent approach to assess the discriminant validity, especially when considering the drawbacks of the Fornell-Larker criterion and the cross-loadings as indicated in the literature (Henseler et al., 2015). Therefore, if HTMT_{inference} does not have a value of 1 in its lower and higher boundaries of the confidence interval (i.e., for 95% bias-corrected and accelerated bootstrapping procedure, 2.5% and 97.5% are the boundaries) for all combinations of the constructs (Hair et al., 2017), then the HTMT_{inference} is significantly different than 1. Looking at Table 4, the value range is 0.41–0.91, which is less than the value of 1. Thus, this result speaks in favor of discriminant validity of the two constructs, where the two constructs are distinct.

Table 3. Discriminant validity with Fornell-Larker criterion analysis

Construct	ATT	AUSaaS	BI	PBC	PEU	PU	SN
ATT	0.86						
AUSaaS	0.60	0.72					
BI	0.78	0.64	0.89				
PBC	0.56	0.52	0.59	0.84			
PEU	0.67	0.55	0.67	0.66	0.87		
PU	0.72	0.58	0.69	0.63	0.75	0.85	
SN	0.49	0.55	0.5	0.62	0.52	0.53	0.89

Note. Values at the diagonal represent squared root of AVE; however, the other values represent the correlations of the constructs.

Table 4. Discriminant validity with HTMT_{inference} results

Path	Path Coefficients	CI at 2.50%	CI at 97.50%
AUSaaS -> ATT	0.77	0.65	0.86
BI -> ATT	0.87	0.81	0.91
BI -> AUSaaS	0.81	0.71	0.89
PBC -> ATT	0.64	0.51	0.75
PBC -> AUSaaS	0.68	0.52	0.80
PBC -> BI	0.66	0.54	0.76
PEU -> ATT	0.75	0.65	0.83
PEU -> AUSaaS	0.69	0.56	0.81
PEU -> BI	0.74	0.64	0.82
PEU -> PBC	0.76	0.66	0.83
PU -> ATT	0.82	0.74	0.89
PU -> AUSaaS	0.75	0.64	0.85
PU -> BI	0.77	0.67	0.85
PU -> PBC	0.72	0.62	0.81
PU -> PEU	0.85	0.76	0.91
SN -> ATT	0.55	0.41	0.67
SN -> AUSaaS	0.68	0.56	0.78
SN -> BI	0.54	0.42	0.66
SN -> PBC	0.70	0.58	0.80
SN -> PEU	0.58	0.46	0.69
SN -> PU	0.59	0.47	0.70

Note. Values of confidence interval (CI) do not cross the zero value in its range; thus, achieving the discriminant validity of the criterion HTMT_{inference}.

Based on the above findings in the three steps, the measurement model has established its internal consistency reliability, convergent validity, and discriminant validity. Hence, evaluating the structural model in the next section is warranted and justified. As a visualized summary of the measurement model assessment, Figure 1 provides insights of the findings.

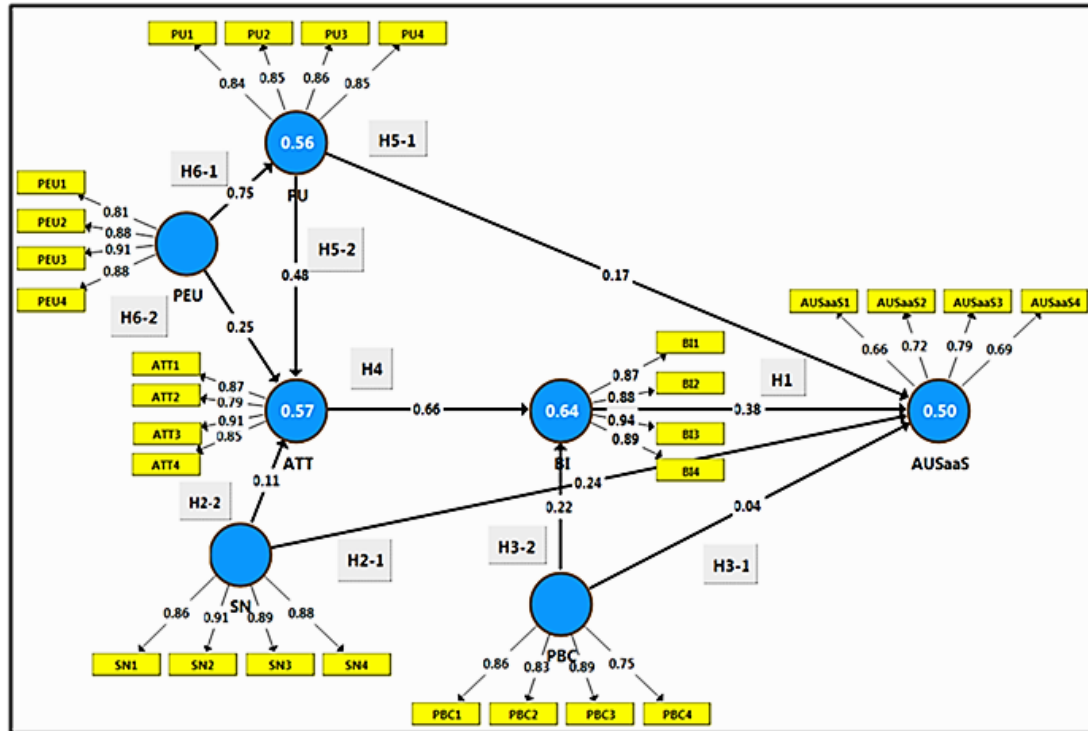


Figure 1. Measurement model assessment

STRUCTURAL MODEL EVALUATION AND HYPOTHESES TESTING

The evaluation of the structural model is examined by using bootstrapping, with settings that include the bias-corrected and accelerated options in the Smart PLS 3.2.7 program (Ringle et al., 2015) and a 5000 resample. To start with the assessment process of the hypotheses, checking the collinearity issues is a prerequisite before departing to the structural model analysis as emphasized by Hair et al. (2017). Therefore, each set of predictor variables is checked against collinearity issues with their dependent variable. To do that, the variance inflation factor (VIF) is the sign of collinearity and is checked to find out if $VIF > 5$. In case VIF revealed to be higher than 5, collinearity issue arises and to overcome this issue the possibilities are: (1) to remove the constructs, (2) to merge them, or (3) to create high-order construct (Hair et al., 2017). By referring to Table 5, the results revealed and confirm that no value of more than 5 exists in VIF. The values range (1.46-2.42) < 5 affirms that the model does not have any critical collinearity issues. Following that, the determination coefficient R^2 is checked for each endogenous construct and the effect size f^2 of every driver construct (or predictor) on its endogenous construct is analyzed.

Table 5. Collinearity issues analysis testing of VIF

Latent Variables	ATT	AUSAAS	BI	PBC	PEU	PU	SN
ATT			1.46				
AUSAAS							
BI		2.07					
PBC		2.13	1.46				
PEU	2.41						
PU	2.42	2.26				1	
SN	1.46	1.74					

Note. Values do not violate the criterion of variance inflation factor ($VIF > 5$).

Before probing into the analysis of R^2 , it is noteworthy to understand that R^2 is the variance explained by the exogenous constructs of the endogenous constructs and thereby is considered a measure of the model's predictive accuracy (i.e., in-sample prediction) (Sarstedt et al., 2014). The acceptable values for R^2 can be described as weak (0.19), moderate (0.33), or substantial (0.67 or above) (Chin, 1998). Also, there is a related measure to R^2 that is the effect size f^2 . To explain, the effect size f^2 is a measure used to test the impact of an exogenous construct on an endogenous construct when it is in the model or omitted. This value is evaluated to test the change of R^2 in both cases. The thresholds of f^2 are small (0.02), medium (0.15), or large effect sizes (0.35) (Chin, 1998).

By scrutinizing the values in Table 6, it is clear that the results demonstrate moderate to highly moderate values of R^2 in all dependent constructs (or exogenous construct) that range from 0.50 to 0.64. The final outcome of this model – i.e., AUSaaS – has an explained variance of $R^2 = 0.50$ by the driver constructs BI, PU, SN and PBC, which is considered a promising value in this exploratory study. Additionally, the explained variance of ATT by PU, PEU, and SN is highly moderate ($R^2 = 0.57$) and affirms its predictive accuracy in the model. This value suggests that the inclusion of these variables with the postulated relationship in exploring the salient factors for using and adopting SaaS cloud computing among university students is validated. Furthermore, the explained variance of PU ($R^2 = 0.56$) is contributed by PEU, which not surprising in the field of the current study and is congruent with other research in innovative technologies. Interestingly, BI has shown the highest pronounced variance ($R^2 = 0.64$) that is explained by ATT and PBC. In addition, the effect size f^2 analysis reveals that PEU has a very large effect size ($f^2 = 1.28$) on PU. This reflects the strong effect of PEU on PU which is supported theoretically by TAM. Furthermore, ATT exerted the highest effect size on BI ($f^2 = 0.82$, large effect), followed by PBC ($f^2 = 0.09$, small effect). This means the influence of ATT on BI is dominant. In addition, the effect size on AUSaaS by BI is the highest ($f^2 = 0.14$, medium effect), whereas SN, PU, and PBC exert a small to no effect sizes ($f^2 = 0.07$ and $f^2 = 0.03$ with small effect, and $f^2 = 0.002$ with no effect size, respectively). This result draws the conclusion of the dominant role of BI on AUSaaS more than any other constructs. Further, the effect of SN shows its strength over PBC and PU on AUSaaS. This means the social norms should not be neglected in explaining the adoption of AUSaaS. Moreover, PU emerged as a new player in explaining the acceptance, adoption, and usage of SaaS services and applications that should be given attention in acceptance SaaS cloud computing acceptance studies. Also, there is a strong evidence that PBC has no effect on AUSaaS, which contradicts with its inclusion in TPB theory. Finally, the effect size on PU by PEU is obviously high ($f^2 = 1.28$). This relationship is supported empirically by this model in the context of SaaS cloud computing adoption model. Also, it indicates that including the relationship PEU towards PU is justified in the model suggested by this study.

Table 6. Coefficients of determination R^2 and effect size f^2

Latent Constructs	ATT	AUSAAS	BI	PU
Coefficient of Determination R^2	0.57	0.50	0.64	0.56
Effect Size f^2	ATT		0.82	
	BI	0.14		
	PBC	0.002	0.09	
	PEU	0.06		1.28
	PU	0.22	0.03	
	SN	0.02	0.07	

After the initial checking of collinearity and coefficient of determination, the next step is to evaluate the significance and strengths of the relationships of the model. As seen in Table 7, the results reveal that BI has the highest effect on AUSaaS, with a positive pronounced value of $\beta = 0.38$, which is significant ($p < 0.05$, $t = 5.81$), followed by SN with a positive $\beta = 0.24$ path coefficient and the

corresponding significant values ($p < 0.05$, $t = 4.23$), and finally PU with a weak correlation ($\beta = 0.17$) but significant effect on AUSaaS ($p < 0.05$, $t = 2.62$).

To further augment the analysis, the 95% confidence interval is analyzed. While inspecting the 95% confidence interval (CI) with bias-corrected and accelerated (BCa) settings, the results show a strong and significant effect of BI on AUSaaS. That is, both boundaries of CI, the lower 2.5% and the upper 97.5% boundaries, do not include zero (Table 7). Similarly, CI values corroborate the results obtained for the significant and positive role of SN and PU on AUSaaS. Therefore, **H1**, **H2-1**, and **H5-1** are supported. On the other hand, PBC exerts a very weak correlation ($\beta = 0.04$) with AUSaaS and a nonsignificant value ($p = 0.55$, $t = 0.59$). Additionally, CI with BCa further confirms this result, given that zero exists in its range [-0.10 – 0.17]. Consequently, **H3-1** is supported.

To further proceed with hypotheses analyses, as seen in Table 7, the results reveal that ATT exerts a pronounced value of $\beta = 0.66$, being the highest positive correlation with a significant statistic with BI ($p < 0.05$, $t = 16.91$), followed by PBC, with a relatively weak ($\beta = 0.22$) correlation with BI but a positive and significant relationship ($p < 0.05$, $t = 5.06$). While inspecting the 95% confidence interval (CI), the results show the significant effect of ATT and PBC on BI, as no zero value is found in either of the intervals. Hence, **H3-2** and **H4** are empirically supported in the model postulated. Besides, the ATT effect on the BI dependent construct emerged as the dominant construct that exposed more influence on it than other driver construct (PBC). This gives an indication of the significant and dominant role of attitudinal behavior on the intention to adopt/accept the SaaS services that translates the technological elements (i.e., PU and PEU) into behavior that impacts one's intention to adopt the SaaS services and applications.

Table 7. Path coefficients and hypotheses testing

Path (Mean/SD)	Path Coefficients	<i>t</i>	<i>p</i>	CI 2.50%	CI 97.50%
TT -> BI (0.66/0.4)	0.66	16.91	0.00***	0.58	0.73
BI -> AUSaaS (0.38/0.07)	0.38	5.81	0.00***	0.25	0.50
PBC -> AUSaaS (0.05/0.07)	0.04	0.59	0.55	-0.10	0.17
PBC -> BI (0.22/0.04)	0.22	5.06	0.00***	0.14	0.30
PEU -> ATT (0.25/0.07)	0.25	3.86	0.00***	0.12	0.38
PEU -> PU (0.75/0.04)	0.75	18.53	0.00***	0.66	0.82
PU -> ATT (0.48/0.06)	0.48	7.43	0.00***	0.34	0.59
PU -> AUSaaS (0.17/0.07)	0.17	2.62	0.01**	0.05	0.30
SN -> ATT (0.11/0.05)	0.11	2.08	0.04**	0.01	0.21
SN -> AUSaaS (0.24/0.06)	0.24	4.23	0.00***	0.13	0.35

Note. ** $p < 0.05$; *** $p < 0.001$

Following that, the effects of PU and PEU on ATT are analyzed. As seen in Table 7, the results highlight the significant and positive correlations of both latent constructs (i.e., PU and PEU) towards ATT with a pronounced $\beta = 0.48$ and the corresponding statistics ($p < 0.05$, $t = 7.43$, and CI = [0.34-0.59]), and $\beta = 0.25$ with the corresponding statistics ($p < 0.05$, $t = 3.86$, and CI = [0.12-0.38]), respectively. Therefore, the results affirm the support of the two hypotheses **H5-2** and **H6-2** in the current research. The final assessment in this section is given for the last hypothesis **H6-1**. Looking at the results in Table 7, PEU is found to exert a high correlation with PU with a pronounced $\beta = 0.75$ and significant related statistics ($p < 0.05$, $t = 18.53$, and CI = [0.66-0.82]). Therefore, hypothesis **H6-1** is supported. Additionally, the results confirm the role of PEU on PU in the context of the study and goes in line with TAM theory relationships. That explains the inclusion of these relationships in the proposed model to help the research in revealing the salient factors that explains the adoption of SaaS services (refer to Figure 2 for structural model analysis summary).

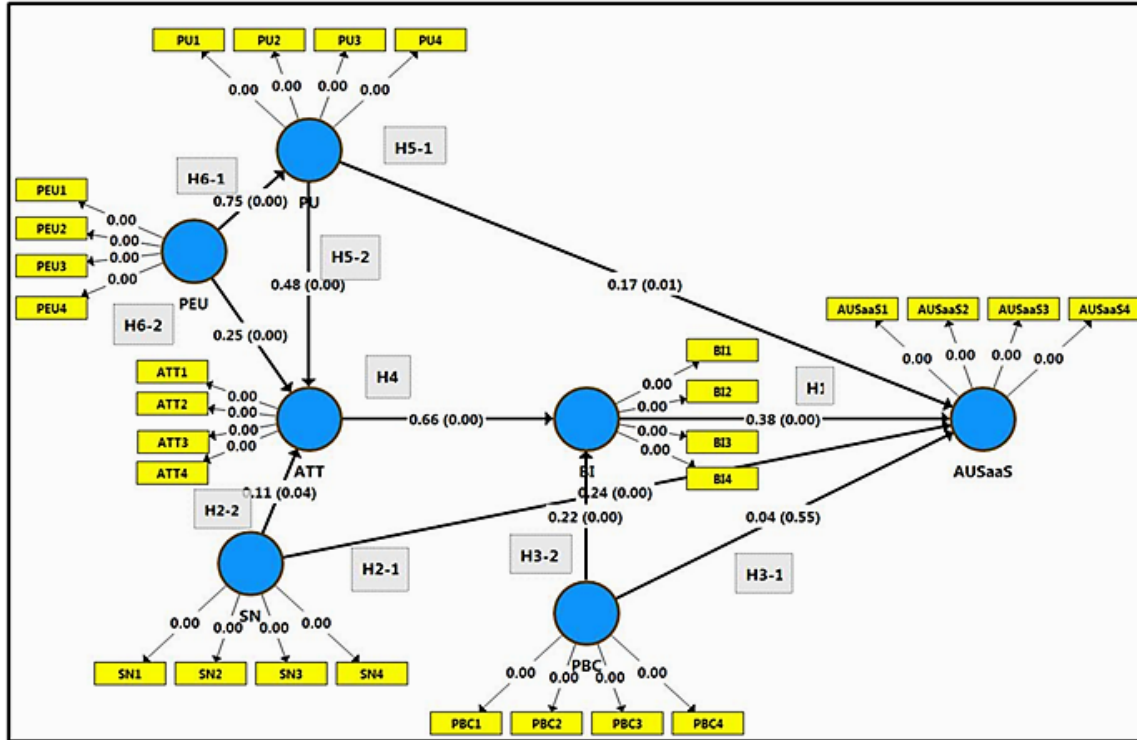


Figure 2. Structural model assessment and hypothesis paths highlighted by H number

The final step in our analysis takes into consideration the analysis of predictive relevance (Q^2) of the model, where values less than 1 and higher than 0 are considered acceptable (Hair et al., 2014); hence, the model shows its predictive relevance (Latan et al., 2018). Additionally, the effect size q^2 is obtained to further support the results of Q^2 and can be described as having small ($q^2 = 0.02$), medium ($q^2 = 0.15$), or large ($q^2 = 0.35$) effects. To proceed with the analysis, Table 8 explicates the results obtained and shows that all the endogenous constructs have values considerably above zero (i.e., values in the range 0.24-0.48 for cross-validated redundancy). Moreover, the effect size q^2 for the relationships $PEU \rightarrow ATT$ is considered small ($q^2 = 0.033$); for $PU \rightarrow ATT$ is almost medium ($q^2 = 0.11$); and for $SN \rightarrow ATT$ is almost small ($q^2 = 0.013$). In addition, the effect size q^2 for the relationships $BI \rightarrow AUSaaS$ is small ($q^2 = 0.05$), and for $SN \rightarrow AUSaaS$ is a small effect ($q^2 = 0.03$), whereas PU and $PBC \rightarrow AUSaaS$ have the smallest effect size ($q^2 = 0.01$). Furthermore, no effect size found in the relationship $SN \rightarrow BI$ ($q^2 = 0.00$), whereas $BI \rightarrow AUSaaS$ has a small effect size ($q^2 = 0.08$) as well as $SN \rightarrow AUSaaS$ (0.03). To summarize, the model has proven its predictive relevance and its appropriateness for the field of study, SaaS cloud computing usage, acceptance, and adoption.

Table 8. Predictive relevance Q^2

Latent Variables	Predictive Relevance	Effect Size q^2	
	$Q^2 (=1-SSE/SSO)$	ATT	AUSaaS
ATT	0.39		0.05
AUSaaS	0.24		
BI	0.48		
PBC			0.01
PEU		0.033	
PU		0.11	0.01
SN		0.013	0.03

APPROXIMATE MODEL FIT ASSESSMENT

Originally, PLS-SEM is designed to have a prediction-oriented nature not a theory-testing nature. However, a growing call for extending its capabilities to include theory testing by developing model fit indices to judge a well-specified from an ill-specified model is sought by researchers; that is, how well the hypothesized model fits the empirical data. The goodness-of-fit (GoF) is one of the indices proposed (Tenenhaus et al., 2004; Tenenhaus et al., 2005) to validate PLS models. In other words, it is assumed to be applied for model selection or model validation, thereby the model with higher fit is better and valid ((Henseler & Sarstedt, 2013). However, this measure is refuted by Henseler and Sarstedt (2013) empirically and conceptually and their research shows that GoF does not represent goodness-of-fit criterion for PLS-SEM and cannot represent formative models (Hair et al., 2017). Also, their research shows that it is not a suitable measure for model validation as it is unable to separate the valid model from the invalid model and researchers would be misled if they interpret the higher GoF as an indicator of a better model. Besides, GoF does not penalize overparameterization efforts. Consequently, the absolute measure of fit, which is the standardized mean square residual (SRMR) between the observed and the model implied correlations, is an alternative recommended measure of fit (Hair et al., 2017). When its value is less than 0.10, or of 0.08 as a more conservative cut-off value, the model can be assumed of having a good fit. It is worthwhile to demonstrate that SRMR is not reported in numerous empirical studies in different disciplines in the academia and widely neglected in reporting it in PLS-SEM studies. This could be referred to the less interest of the measure by the majority of researchers or the results obtained do not support the results obtained. Another possibility could be referred to the extra analysis that might distort the results obtained. However, to augment the current study, the researchers articulate to include it as a rigorous measure to validate the model postulated in the area of SaaS cloud computing adoption and to be among the pioneers to include such advance analysis in the PLS-SEM area of research.

To obtain SRMR in SmartPLS 3.2.7, two values are calculated, i.e., the saturated value and the estimated value of SRMR. To explain more, in the saturated model, the correlation between all constructs is assessed and this model is the previous model assumed. On the other hand, the estimated model is dependent on the total effect scheme and considers the model structure. For the purpose of the assessment of the overall model, the SRMR in the estimated model is assessed and should be less than 0.08 to be acceptable. For the measurement assessment, the saturated model is assessed and should be less than 0.08 to be acceptable.

The root mean squared residual covariance matrix of the outer model residuals (RMS_{β}) is another criterion suggested by Lohmöller (1989) and advocated by a number of scholars (Hair et al., 2017; Henseler et al., 2014; Henseler et al., 2016) to measure the good fit in PLS-SEM models. RMS_{β} can distinguish a well-specified model from ill-specified model (Hair et al., 2017; Henseler et al., 2016). The suggested values of RMS_{β} lie between 0.12 and 0.14 (Henseler et al., 2014); however, the lower the value the better (i.e., below 0.12). To conclude, the SRMR and RMS_{β} are the approximate model fit criteria recently recommended measures that can be used to test the good fit in PLS-SEM models when theory testing is considered; however, more research is needed to unveil their measures' behavior across model constellations and a range of data (Hair et al., 2017).

As an extended analysis in the current research, the model fit analysis is assessed to find out SRMR and RMS_{β} as reporting them is lacking in the current empirical studies research. After running the analysis in SmartPLS software and performing the evaluation, the SRMS values obtained were in the recommended range. That is, RMS_{β} obtained is 0.13, which is less than the threshold of 0.14. Also, the values of SRMR obtained in the range 0.05- 0.06, which is less than the recommended threshold of 0.08; thus, our model achieves a good fit. In this case, the research revealed the good fit of the model postulated in the current study and further augments the previous results in the former sections. Hence, the model of the research is proven in its accuracy, relevance, and good fit. Table 9 illustrates the results obtained.

Table 9. Approximate model fit assessment

Assessment	SRMR (< 0.08)	RMS _{beta} (0.12-0.14)
<i>Overall model</i>		0.13
Approximate model fit (estimated)	0.06	
<i>Measurement model</i>		
Approximate model fit (saturated)	0.05	

DISCUSSION

The current study seeks to underpin the salient factors influencing the acceptance and adoption of SaaS cloud computing applications and services that are accessed, used, and practiced during the daily errands in students' academic lives at the university. The framework is based on TPB with its main constructs (i.e., attitudinal, normative, and control beliefs) and augmented by two critical constructs of TAM (i.e., perceived ease of use and perceived usefulness) that are relevant to the context of SaaS cloud computing and meet the purpose of the study.

The results present the direct determinants of ATT, BI, and the final outcome of the study, which is the acceptance and adoption of SaaS cloud computing services and applications. The findings are discussed in detail below.

Behavior intention (BI)

While investigating the role of BI of the respondents on accepting and adopting SaaS cloud computing services and applications, the results shed more light on the crucial role of BI in shaping the behavior of the students and in forming future plans to continue using, accepting, and adopting this innovative technology. Not surprising, the findings are in concert with former works in the field of innovative technologies and the adoption process of innovative services or applications (Alalwan et al., 2017; Dong et al., 2017). In addition, the findings are aligned with different theories that affirm the role of BI in the actual behavior such as: TRA, TAM, and TPB. However, the findings contribute to the area of SaaS services acceptance and adoption as there is a dearth of studies cover the topic under investigation. Additionally, the findings contend the importance of including BI in the model suggested to unveil the salient factors of SaaS acceptance at the universities.

Subjective norms (SN)

Regarding subjective norms, SN revealed to have a positive and significant relationship with ATT on using, accepting, and adopting SaaS applications and services. This finding indicates that the students by being in groups create a sense of belonging to that group and that, in turn, creates a reciprocal relationship with others to exchange ideas, concerns, benefits, skills, and knowledge of the best practices to improve their academic performance. Hence, this sense of belonging motivates them to use SaaS services when they realize its importance to their academic achievements. Not surprisingly, the findings are congruent with the limited previous works regarding the positive and significant relationship with ATT (Al-Swidi et al., 2014; Arpaci, 2016; Hamari & Koivisto, 2013; Huang, 2016; Pedersen, 2005; Taufiq-Hail et al., 2017a). However, the results shadow its importance in the context of the study and contributes to its importance.

Additionally, SN emerged as an important predictor of AUSaaS with a significant effect, which showed that the surrounding social relationships have an influence on the decision of students to accept, use, or adopt an innovative technology such as SaaS cloud computing. Although there is a dearth of works pertaining to this relationship, the findings are aligned with the empirical results revealed by the work of Alzahrani et al. (2017), where SN exerts a significant and positive attitude towards the actual behavior (i.e., actual usage of games). In addition, the sense of belonging to groups, especially in group assignments inside classes or joining groups of the same race outside the classes

with companions and colleagues, motivates the students to practice new innovations that can be reflected on their academic achievements. This happens, in particular, when they perceive that significant others are gaining attention and being successful in their academic work when using new services that are SaaS based applications.

To summarise, it is noteworthy to highlight the effect of significant others in influencing and changing the attitude and behavior of others within the social environment especially in collectivistic society such as Malaysia. That is, the students apt to group inside university campuses based on their needs to perform some classwork, group assignments or according to cultural or belief inclination. Hence, the role of SN is crucial to change one's attitude and behavior to adopt SaaS cloud-based technology.

Perceived behavior control (PBC)

The PBC is not significantly correlated with AUSaaS and contradicts with the findings of other previous works that revealed a positive and statistically significant relationship between the two constructs (Alzahrani et al., 2017; Cheung & To, 2016; S. Jain et al., 2017). The result obtained suggests that the students may currently do not have a strong trust of their capabilities and skills to directly use new and innovative technology. They are more or less apt to think of the future usage, practice, acceptance, or adoption of this technology than to directly tackle the difficulties with a new technology (i.e., the actual use behavior). This also might shed light on the fact that students at this age and at the degree level have less knowledge and experience in life, generally, and in encountering new challenges that led to less confidence on their capabilities and self-esteem. Consequently, they are more unlikely to directly practice the behavior under study, although inner feeling for future usage or acceptance is created.

Conversely, the results attained show a strong and positive linkage between perceived behavior control and the behavior intention. This can be interpreted as the students weighing their skills and considering them to be sufficient and strong enough to practice new innovative ideas, such as those provided by different SaaS services; and this creates a sense of self-esteem and confidence to plan future practices, such as continuing to use, accept, or adopt SaaS services and applications. In addition, the sense of confidence is converted to a psychological and emotional positive motivator to think and plan for the future usage of SaaS. These findings are attested to by previous works (Chang et al., 2016; Cheung & To, 2016; Yeap et al., 2016) and are in accord with them. However, in the context of the study, this is regarded as another contribution that warrant attention in future studies on SaaS services or alike.

Attitude (ATT)

The reported results presented in the findings section reveal a positive and significant relationship of ATT towards BI. This goes in concert with previous works especially those related to ICT (Peng et al., 2012) and innovative technologies (Arpaci, 2016; Gao & Huang, 2019; Salahshour Rad et al., 2019; Taufiq-Hail et al., 2017b). It is worthwhile to note the positive advantages of SaaS cloud computing perceived by the students in accomplishing their academic tasks. These perceived advantages create a positivity that is reflected by their attitude that most likely would shape their intention towards the adoption and acceptance of this technology. In other words, the advantages of SaaS cloud computing online services outweigh the conventional methods. In the conventional methods of using IT resources, the drawbacks can be summarized as: (1) the access of computer resources are limited to inside office and during office times; (2) the storing or accessing data via USB stick, which is apt to malfunction; and (3) the limited sharing capabilities inside premises/campus. However, the advantages of SaaS services and applications include: (1) around the clock access to applications, storage, and other SaaS cloud computing services; (2) freedom accessibility regardless of location, time, or device; (3) variety of free application and services that are updated/offered all the year around; and (4) freedom of worries in crashing the systems/applications as the services offered are

maintained by the SaaS providers themselves. Hence, these tangible benefits of SaaS services presumed by the students in their academic life would likely affect their ATT and, therefore, influence their intention to perform the behavior in question. In addition, the three constructs of PEU, PU, and SN appear to have jointly appropriate correlation toward predicting ATT, as they explain 57% of the variance of ATT, which is considered substantial in this explorative study. This means that the inclusion of the three constructs from two different theories enhanced our understanding of the salient factors affecting the adoption of SaaS services. Also, it means that the relationship SN towards ATT is collectively with PU and PEU direct the attitude of students towards the acceptance and adoption of SaaS services.

Perceived usefulness (PU) and perceived ease of use (PEU)

Based on the aforementioned findings, where PU and PEU appear to have a positive and significant relationship with ATT, PU appeared to have a more influential effect on ATT than PEU, despite the direct stronger effect of PEU on PU toward ATT. This, in essence, can provide a clue that the primary driver of the students' attitude towards accepting and using SaaS services and applications is PU. This can be interpreted as the degree of intellectual capabilities that one possesses to perceive the usefulness of different SaaS applications and services leads to the attitude of using these services as a result of prior cognition and belief that these services would be beneficial to enhance one's job performance. Also, it can be said that when the user of SaaS services perceives these services as better to use, understand, and reliably access compared with the conventional methods – such as storing, uploading and sharing different data in a local computer or inside a local server – this would most likely urge them to use and adopt these services and applications to enhance their performance in tasks assigned to them.

In other words, when a person is a novice at any technological or practical undertaking, they are more likely to be reluctant and hesitant in practicing the intended behavior, and they become more concerned about its usefulness. On the other hand, when they are familiar with it and gain the confidence of the appropriateness and usefulness of the cloud services and applications, they become more aware of its usefulness in achieving their tasks. In the same vein, this cognition leads students to use and adopt these innovative technologies to perform well in their academic achievements.

Additionally, the effect of PEU on PU appears to be very strong with an extremely high correlation; hence, this provides more insights of the connectedness between PEU and PU. These different findings are in accordance with previous studies; namely, in the relationships of $PU \rightarrow ATT$ (Besbes et al., 2016; Gao & Huang, 2019; Ma et al., 2016; Taylor & Todd, 1995), $PEU \rightarrow ATT$ (Huang, 2017; Richad et al., 2019), and $PEU \rightarrow PU$ (Besbes et al., 2016; Islam & Sheikh, 2019). However, including this relationship has proven its role in the context of SaaS cloud computing context.

Moreover, the role of $PU \rightarrow AUSaaS$ is proven to gain significance in the current research. This finding is in line with the findings of previous research conducted on university students in Pakistan (Ali et al., 2018). This result can be interpreted as the students highly perceive the practical benefits of SaaS cloud services in their academic works and achievements, where they can gain immediate access to many resources from the university library or directly from the internet, store their data online, share their results and findings with other colleagues, and meet the requirements in academic classes by uploading their assignments through portals. Also, the usefulness is perceived by the university students in saving numerous time and efforts to register for the semester, view their results and pay fees online. Thus, time, effort, money, and academic productivity are the core perceived benefits when applying SaaS cloud services and applications in the academic life of university student. That is to say, the perceived usefulness has a direct impact and explains why the students adopt SaaS services.

IMPLICATIONS, LIMITATIONS, AND FUTURE DIRECTIONS

Methodological and theoretical implications

This research provides an understanding of the factors influencing the acceptance and usage of SaaS cloud computing applications and services from the perspective of university students with an adequate skill set and knowledge. The current research offers methodological, theoretical and practical implications that envisage a contribution to the body of literature and the audience of SaaS cloud computing represented by the government educational sector, SaaS service providers, as well as technology managers and decision makers.

Pertaining the methodological aspect, the study followed the thorough, rigorous, and cohesive analysis and survey design that is scarcely followed in the academic studies as it constitutes lengthy research reporting that is avoidable in such empirical surveys. These methods include: (1) the comprehensive literature review to refine the most expected factors to influence the adoption; (2) the selection of factors from two theories to utilize the strength of the two theories; (3) the postulation of new relationships; (4) the data screening and analysis phase that employed common method bias, rigorous measurement and structural analysis; and (5) the analysis of approximate model fit assessment that lacks in majority of empirical studies in IS/IT employing PLS-SEM analyses. The procedures used justify meeting one sub-objective of the study in leading a comprehensive analysis on the research.

On the theoretical side, the framework suggested is formed by the integration of two well-known theories, i.e., TAM and TBP, with modifications of some relationships that exist in TPB and TAM. That is, firstly, the direct relationship between SN and the BI is changed to be between SN and AUSaaS, where few research papers exist to explore the effect of SN on the actual behavior. Secondly, the relationship between SN and ATT is scarcely investigated in academia pertinent to SaaS cloud computing acceptance and adoption as well as other innovative technology or behavior adoption studies. Thirdly, the direct link between PU and ATT is investigated in breadth in many previous works; however, the current study focuses on the exploration of its direct influence on the actual behavior, which is not present in the actual TAM model. All the new relationships have empirically proven their appropriateness and inclusion in the model suggested and exerted statistical significance.

Practical implications

On the practical side, the outcome of the present study provides empirical support for the appropriateness of the model to explore the salient factors influencing the adoption of SaaS cloud computing at the university campus. The results show that the different relationships explained 50% of the variance of dependent variable AUSaaS in the model postulated. This warrants meeting the main objective of the study to produce and validate the model. Also, it is envisaged that university rectors, government higher education sector's management, different private and public organizations, SaaS business providers, and software development firms would benefit from the outcome of the study to focus on the factors that showed significance in the relationships investigated. In addition, the aforementioned entities should pay adequate attention when providing SaaS services, developing software packages/services, or even developing a syllabus for students. This means that when providing or developing these services, attention should be steered towards these two factors, as the students are more relaxed in using SaaS services when they perceive its easiness and get acquainted with it. Consequently, PU becomes more influential in the acceptance and adoption process and the results prove this relationship with AUSaaS. Hence, another sub-objective of the study is met by exploring this relationship directly between PU and AUSaaS.

Pertinent to the influential factors in the current explorative study, the findings emerged that PEU and PU are key elements in predicting the attitude towards the acceptance process. This means that when providing or developing these services, attention should be steered towards these two factors, as the students are more relaxed in using SaaS services when they perceive its easiness, and when they

get acquainted with it. Therefore, its usefulness becomes more influential in the acceptance and adoption process.

As another sub-objective of the study, by exploring the direct relationship between PU and AUSaaS, PU emerged to be a significant influencer on the usage, acceptance, or adoption of SaaS cloud-based applications. The SaaS providers as well as university management should devote more efforts in developing, promoting, and updating new or existent packages and encourage university students to use them frequently as a result of their tangible benefits perceived. More importantly, as a practical contribution, the researchers highlight the benefit of using the university students as a testbed for new emerging and innovative technologies developed or updated as they are the building bricks of the future success in any community. By doing so and based on their eagerness to discover the new and innovative technologies, the results fall under a win-win relationship as the students would satisfy their desire to unveil the pros and cons of the new SaaS applications and services, on the one hand. On the other hand, the SaaS providers or the higher education institutes would get the feedback from the students to enhance new versions and overcome shortcomings of the services provided in future releases.

In light of the results obtained, SN also has proven its vital influence on ATT from one side, and on AUSaaS on the other side, which these two relationships are hardly studied in the academic research. By examining and validating these relationships, another sub-objective of the study is met. Additionally, it is worthwhile to pay considerable attention to the social factor in the attitude of the students and its impact on the adoption process. That is, if the decision makers at universities decide to implement these services, they should pay attention to the vital role of social influence. Furthermore, when the students are performing their tasks or assignments, they have a sense of being connected with colleagues, social groups, or even with the academic staff. This sense of connectedness is perceived virtually, which leads to the acceptance and usage and invokes the students' attitudes to use these innovative services or applications that emerge on social media with SaaS cloud-based technology. Hence, whenever a new application or service embarks on the cloud and the providers need it to be publicly accepted and used, this application or service would be more likely to be disseminated and going viral if it is perceived easy to use, useful, and meets the social connectivity demand of the current young generation.

Regarding PBC construct, the outcome of the study sheds light on its predictive influence on the intention to use and accept SaaS services. The direct relationship of PBC was not shown to be a significant factor, although it showed an indirect effect on the adoption process through BI. This can imply that the students first acquire the skills and knowledge in performing certain tasks that would initially incite their intention to use the SaaS based applications, and then this intention would be a future direction towards the acceptance of this technology. This result warrants that the decision makers at the university, for example, inculcate the professional skills of students and make them ready for the future work environment. Once they graduate, their skills and capabilities would be reflected in the job. In addition, when they reach the managerial level, they would make decisions to support and advocate the adoption of SaaS cloud computing services and application. Consequently, a sense of loyalty is created and cultivated and this, in turn, would increase the adoption rate dramatically by the enthusiastic and technologically savvy generation. By getting the aforementioned insights, another sub-objective of the study is met.

In summary, all the factors seem to have a vital influence on BI and AUSaaS to use, accept, or adopt SaaS innovative technology as revealed by their total effects in the results. Hence, these factors should be considered in drawing any future plans to build or provide this technology, while at the same time, the providers should build these networks to meet the expectations and perceived performance, availability, security, flexibility, manageability, affordability, scalability, accessibility, and durability with full technical support. More importantly, the strong intention towards accepting and using SaaS applications and services is clearly outstanding and encouraging the management of universities and higher education sectors' authorities to develop more applications, services for students, and

syllabi that are electronic-based and compatible with SaaS technology. Another worthy point is that the universities could form a community cloud university consortium to exchange research developments and facilities, exchange data, and form a space for students to exchange ideas. This, consequently, would help both the businesses (i.e., service providers) to obtain revenue and the universities to reduce the cost of upgrading their systems from time to time.

Managerial implications at universities and higher education sector

More importantly, the strong intention towards accepting and using SaaS applications and services is clearly outstanding and encouraging the management of universities and higher education sectors' authorities to develop more applications, services for students, and syllabi that are electronic-based and compatible with SaaS technology. Another worthy point is that the universities could form a community cloud university consortium to exchange research developments and facilities, exchange data, and form a space for students to exchange ideas. This, consequently, would help both the businesses (i.e., service providers) to obtain revenue and the universities to reduce the cost of upgrading their systems from time to time. Also, the outcome of the study shed the significant role of SN; therefore, it is advisable to utilize the social network to promote the applications of services developed in-house to students. Moreover, PU is another importing finding that shadows the importance of knowing the usefulness of SaaS products and applications. This finding infers to the role of promoting developed services and applications by highlighting their key benefits and how they could make significant improvements in the tasks or activities conducted. Lastly, the higher education institutes should emphasize the promotion of online SaaS cloud-based courses and blended education as they eliminate the intermittent of the education process during difficult times – such as Covid-19 pandemic, disasters, or natural catastrophic events – and reduce the cost for universities and students as well. SaaS cloud-based curriculum is getting its hype especially in the current pandemic of Covid-19; thus, the administration of universities should pay attentive attention toward shifting the pedagogical education towards the cloud.

LIMITATIONS AND FUTURE DIRECTIONS

Notwithstanding the insights of the results gained, limitations are present in the current study. First, the students at the bachelor level were recruited as respondents of the study, while not considering the master or doctoral students or even the lecturers. This is because this category of respondents is technology savvy and is the majority of university campus. Also, the bachelor's degree students, based on their young age, are frequently eager to explore things and find out their pros and cons. Additionally, the bachelor level students are active on the university campus, are energetic, and have a consuming passion for technological devices, services, and applications. Also, the sample frame in the current study focused on the public-sector universities in Malaysia; therefore, participants from private universities or other educational institutes are suggested in future work as they may reflect other perceptions.

In addition, the model proposed is a modification of TPB and TAM with a limited number of variables. However, it has proven its applicability and appropriateness empirically, suggesting that it can be extended in future works with other constructs such as trialability, compatibility, security, risk, privacy, and self-efficacy. In addition, the analysis of this research did not take the differences between ethnic groups, ages, genders, or fields of study into account due to paper length constraints, and these could be a recommended direction for future work.

CONCLUSION

Although cloud computing has gained popularity in the past decade, it is still not mature and many aspects that cover human behavior and interaction with cloud technologies still need to be probed. Meanwhile, cloud computing is expanding at a steady pace with the emergence of Internet of Things (IoT), Block Chain technology (BC), Artificial Intelligence (AI), and many forms of cloud computing

services. Therefore, it needs further investigation in all aspects that not only cover the technical, procedural, or legal aspects, but also the human factor, which is the vital element of the usage chain. This study aimed to investigate the influential effects of different constructs using an integrative model of TPB and TAM, where the model proposed proved its appropriateness and its predictive accuracy and predictive relevance. Also, the comprehensive analysis of approximate model fit has further confirmed the suitability of the model proposed in explaining the issue under study. Further, the results revealed that PEU is a vital predictor of PU and ATT. In addition, BI, PU, SN, and ATT are found to be the strongest contributors of AUSaaS, respectively. The study offers valuable findings, highlights relationships such as the direct link between PU and AUSaaS, and SN towards ATT. This brings new insights to the forefront of further research in different contexts. Moreover, the study presented methodological, theoretical, and practical implications. Lastly, in light of the results, these findings can facilitate decision makers at universities, government higher education sector authorities, and SaaS cloud computing providers to focus their attention on the vital factors that have emerged in the adoption process.

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APPENDIX

QUESTIONNAIRE ITEMS

1. Accepting and using SaaS cloud (AUSaaS)

Item No.	Description
AUSaaS1	1. I prefer online SaaS cloud computing services (e.g., store my data on a web storage such as Google Drive, calling friends using Tango or imo, using university portal, etc.) than using conventional methods (e.g., using USB drive or calling my friends using telephone).
AUSaaS2	2. I frequently use online SaaS cloud computing services for my academic studies (e.g., uploading my data/accessing e-mail, sharing my files, opening Pdf files online, uploading my assignments, etc.).
AUSaaS3	3. I believe that I could tell others the advantages of using SaaS cloud computing services in my academic study.

Item No.	Description
AUSaaS4	4. I would have no difficulty explaining why SaaS cloud computing services may or may not be beneficial.
Sources	(Renda dos Santos & Okazaki, 2016; Sharma et al., 2017; Taufiq-Hail & Ibrahim, 2018; Taylor & Todd, 1995)

2. Behavior intention (BI)

Item No.	Description
BI1	1. Intend to continue using SaaS cloud computing online services in my academic studies.
BI2	2. I will strongly recommend online services (e.g., accessing university library resources, uploading my assignments to the portal, registering for the semester, viewing my results) from SaaS cloud computing providers to others inside my university with colleagues or outside in my social network.
BI3	3. I plan to continue using SaaS cloud computing services frequently this term and onward.
BI4	4. Assuming that I have access to Internet, I intend to continue using SaaS cloud computing services.
Sources	(Huang, 2016; Renda dos Santos & Okazaki, 2016; Taylor & Todd, 1995)

3. Attitude (ATT)

Item No.	Description
ATT1	1. Using SaaS cloud Computing services is a good idea.
ATT2	2. Using SaaS cloud Computing services is a wise idea.
ATT3	3. I like the idea of using SaaS cloud computing services.
ATT4	4. Using SaaS cloud computing online services is beneficial to my academic studies/work.
Sources	(Huang, 2016; Renda dos Santos & Okazaki, 2016; Taylor & Todd, 1995)

4. Perceived ease of use (PEU)

Item No.	Description
PEU1	1. It would be easy for me to become skilled in using online SaaS cloud computing services (e.g., university portal, e-mail, Dropbox, Google Drive, Microsoft OneDrive, etc.).
PEU2	2. Learning to use online SaaS cloud computing services is easy for me (e.g., accessing university library resources, uploading my assignments to the portal, registering for the semester, viewing my results).
PEU3	3. I would find the online SaaS cloud computing services easy to use.
PEU4	4. Using SaaS cloud computing online services is clear & understandable.
Sources	(Davis, 1989; Huang, 2016; Renda dos Santos & Okazaki, 2016; Taylor & Todd, 1995)

5. Perceived usefulness (PU)

Item No.	Description
PU1	1. Using online SaaS cloud computing services (e.g., university portal, e-mail, Dropbox, Google Drive, Microsoft OneDrive, etc.) would facilitate achieving my duties in academic studies.
PU2	2. Using online SaaS cloud computing services would provide access to useful academic information.
PU3	3. Using online SaaS cloud computing services would save my time when working with electronic information (e.g., online reading, downloading articles, accessing university library resources, uploading my assignments to the portal, registering for the semester, viewing my results, etc.).
PU4	4. Using SaaS cloud computing online services increases my productivity by accessing my data anytime and anywhere.
Sources	(Davis, 1989; Huang, 2016; Renda dos Santos & Okazaki, 2016; Taylor & Todd, 1995)

6. Subjective norms (SN)

Item No.	Description
SN1	1. People who influence my behavior would think that I should use SaaS cloud computing services in my academic studies.
SN2	2. People who are important to me would think that I should use SaaS cloud computing services inside or outside the university.
SN3	3. People who are important to me would recommend using SaaS cloud computing online services to accomplish different university tasks efficiently and on time.
SN4	4. People who are important to me would find using SaaS cloud computing online services beneficial and practical.
Sources	(Huang, 2016; Renda dos Santos & Okazaki, 2016; Taylor & Todd, 1995)

7. Perceived behavior control (PBC)

Item No.	Description
PCB1	1. I would be able to use SaaS cloud computing services & applications.
PCB2	2. Using SaaS cloud computing services is entirely within my control and capability.
PCB3	3. I have the resources and the ability to make use of SaaS cloud computing facilities and services.
PCB4	4. I have the knowledge to use SaaS cloud computing services.
Sources	(Renda dos Santos & Okazaki, 2016; Taylor & Todd, 1995)

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