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Exploring Factors Influencing Gen Z's Acceptance and Adoption of AI and Cloud-Based Applications and Tools in Academic Attainment

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Abstract

Generation Z faces diverse challenges in education amidst the swift evolution of technology. This study investigates the factors shaping Generation Z's acceptance and adoption of AI and Cloud-based applications in Oman's higher education sector. Despite limited attention to this area in Oman and the Gulf Cooperative Council countries (GCC), this research addresses the gap by employing the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, recognized for its effectiveness in understanding technology adoption. Through a quantitative approach, Generation Z students in Omani higher education institutions were surveyed, and SmartPLS was utilized for analysis. Results indicate a significant positive relationship between all UTAUT antecedent factors, with Performance Expectancy being non-significant. This study offers novel insights into global understandings of Generation Z's learning trends with AI and Cloud-based applications in higher education, aiming to enhance pedagogical approaches. Notably, it pioneers such efforts within the GCC context. Recommendations for similar research in other GCC countries are provided to enrich regional perspectives. Limitations and future directions are addressed, emphasizing the importance of comprehending Generation Z's interaction with technology to advance educational practices in the digital age.

Keywords:

Performance Expectancy; Artificial Intelligence (AI); Cloud-based Apps; Effort Expectancy; Facilitating Conditions; Generation Z; Oman Vision 2040; PLS-SEM; Social Influence; UTAUT.

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1- Introduction

The relationship between AI and cloud computing is symbiotic, with each enhancing the other to elevate the pedagogical process to new heights. Cloud computing provides the infrastructure and resources needed to support the vast computational requirements of AI applications. AI, in turn, leverages the scalability, accessibility, and storage capabilities of cloud computing to process large volumes of data efficiently. Through cloud-computing big data, AI applications can analyze and derive insights from massive datasets collected from various sources, including educational platforms, student interactions, and learning materials. This comprehensive pool of educational knowledge serves as a valuable resource for both students and educators. Students benefit from personalized learning experiences and adaptive

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feedback tailored to their individual needs, while educators gain access to valuable insights that inform their teaching strategies and interventions. Together, AI and cloud computing empower the educational ecosystem, facilitating a seamless transition towards innovative and effective teaching and learning practices.

The integration of technology into education has revolutionized both teaching and learning paradigms. Notably, Artificial Intelligence (AI) and Cloud-based applications have emerged as pivotal technological advancements, offering myriad benefits to the education sector [1]. These benefits encompass enhanced collaboration, expanded resource access, and increased flexibility. Today, emerging nations have made significant investments in the adoption of cloud-edge technology across various fields and economies [2], especially institutions of higher education, which are increasingly recognizing the value of advanced technologies such as cloud-based learning tools. Wu & Plakhtii [3] advocate for a comprehensive exploration of cloud-based learning services to identify optimal educational solutions. They emphasize the advantages of cloud-based e-learning applications, highlighting streamlined content processing, efficient educational process organization, robust knowledge monitoring tools, and improved security measures. Additionally, Wang et al. [4] underscore the dearth of research on usability factors predictive of the continued use of cloud e-learning applications. These studies emphasize the pivotal role of cloud-based e-learning tools in the pedagogical landscape, underscoring the need for further investigation into cloud-based applications and tools amidst digital transformation and the advent of a new era of learning. Furthermore, it is highlighted that future research endeavors would greatly benefit from collecting a more comprehensive dataset in order to enhance the credibility and robustness of scientific findings [2].

In recent times, there has been a surge in the adoption of technology, particularly artificial intelligence (AI), aimed at revolutionizing the learning journey to make it more immersive, efficient, and fruitful. AI-driven tools, such as language learning platforms, chatbots, and voice recognition systems, hold promise for enriching the educational landscape by amplifying both teaching and learning endeavors [5]. By leveraging these innovative solutions, students can experience heightened engagement, efficiency, and efficacy, thus fostering greater enthusiasm and dedication towards their educational pursuits.

Interestingly, there is mounting evidence suggesting that AI tools can offer significant assistance to students learning, aiding in the enhancement of language proficiency, boosting student involvement, and delivering tailored feedback [5]. Recently, AI cloud-based applications and tools have garnered significant attention for their transformative potential, especially in education [6, 7]. Their adoption in higher education institutions is driven by the desire to refine teaching methodologies, enhance learning experiences, and streamline administrative processes. Moreover, these technologies promise to provide ubiquitous access to educational resources, enabling students to engage with learning materials anytime, anywhere, and from any device with internet access [8]. Consequently, scholars and educators are increasingly aware of the urgent need to conduct comprehensive investigations into the impact of these technologies and their implications for education [1]. Cooper [9] indicated that the discussion around AI usage in educational settings is still relatively new and is in its infancy to be explored thoroughly [10]. Additionally, as emphasized by Ali et al. [11], AI tools have intervened in the educational sector, necessitating new research to evaluate the feasibility and viability of AI platforms to inform various pedagogical methods of instruction. Despite the extensive literature on AI tools in education, which predominantly examines the perspectives of academic instructors, scientists, and researchers, there exists a notable gap in research regarding students' perceptions of incorporating AI tools like ChatGPT into higher education settings [10]. Given the novelty of AI tools, there is a limited understanding of students' willingness to adopt them, highlighting the need for empirical studies to explore students' attitudes and viewpoints regarding the influence and implications of AI in educational contexts.

Building upon previous research, it is evident that although AI holds promising potential in education, its integration into instructional settings lags behind other sectors like business [12]. This gap can be attributed to the oversight of teachers' roles in incorporating AI-based tools into educational practices [13]. Furthermore, there is little research on ChatGPT and other generative AI tools that could enhance the pedagogical process by using these innovative tools ethically to foster critical students’ critical thinking [14]. Therefore, there is an urgent need for further investigation to explore effective strategies for integrating AI into educational environments, with a particular focus on both educators' and students' perspectives [12]. More importantly, it is critical to emphasize that some previous works in literature shed light on the usage of AI tools in education and academia, focusing on various aspects such as ChatGPT's application in the general pedagogical process [15], AI usage in medical education [16], and teachers' knowledge to pedagogically and ethically use AI-based tools [17]. However, there is a gap in understanding students' perceptions across different cultures and educational settings in higher education institutions. This emphasizes the need for further empirical research to explore how students from diverse backgrounds perceive and interact with AI tools in educational environments. Moreover, Celik [12] suggests that leveraging AI to enhance learning performance could potentially lead to a reduction in dropout rates, emphasizing the importance of bridging the gap between AI's potential and its implementation in education. Hence, exploring perceptions on the acceptance and adoption of AI tools among students at higher education institutions is essential to better understand and build the full picture of the primary stakeholders, the students and educators, and to better advocate educational practices with state-of-the art technologies along with fine tailoring curriculum that meets HEI objectives and students objectives as well.

Relying on the review of previous works, the researchers could conclude that despite the potential advantages of AI cloud-based applications and the risk of using such AI cloud-based tools among higher education institutions, empirical research on factors influencing their adoption within the pedagogical process remains limited, especially among Generation Z students, who are the leaders of the coming decades. Also, to the best of the researcher's knowledge, the breadth and depth of studies covering Gen Z perceptions of using and adopting AI cloud-based tools in Gulf Cooperative Council (GCC) countries in general and specifically in Oman are lacking, especially after the pandemic as those tools emerged as facilitators and game-changers worldwide.

This study addresses the aforementioned gap by employing the UTAUT [18] framework to explore determinants shaping the adoption of AI cloud-based applications among Generation Z students in Omani higher education institutions. It was mentioned in Hiran & Dadhich [2] that further studies should examine how various theories of innovation, such as the technology acceptance model (TAM) and the transfer of technology model (ToT) Model. For instance, they can explore how these mid-range theories impact the technical, operational, and organizational aspects of AI-enabled models. Hence, the main objective of the current research is to enhance understanding of the factors driving the acceptance and adoption of AI and Cloud-based applications in the pedagogical landscape. By illuminating the perspectives and behaviors of Generation Z students towards these technologies, educators and policymakers can gain valuable insights to inform the design and implementation of educational initiatives in Oman's higher education sector.

The significance of this research lies in its potential to enhance our understanding of the factors driving the adoption of AI and Cloud-based applications in the pedagogical landscape. By shedding light on the perspectives and behaviors of Generation Z students towards these technologies, educators and policymakers can glean valuable insights to inform the design and implementation of educational initiatives in Oman's higher education sector. Moreover, this study is expected to contribute to the broader discourse on technology acceptance by examining Generation Z's perceptions of online learning facilitated by AI and Cloud-based applications and tools, thus enriching the existing body of knowledge in this field.

2- Literature Review

2-1- Background on Generation Z

2-1-1- The Rationale for Recruiting Generation Z University Students

The study focused on recruiting Generation Z students as respondents for several reasons, drawing on the rationale provided by Taufiq-Hail et al. [8]. Firstly, bachelor's degree students, who typically constitute Generation Z during data collection, represent the largest segment of the university population and tend to possess greater technological proficiency than their counterparts at the master's or doctoral level. Additionally, due to their relatively young age, these students often exhibit heightened enthusiasm for exploring novel technologies and are keen to evaluate their merits and drawbacks. Furthermore, these students are known for their active engagement on campus, boundless energy, and keen interest in technological advancements across various devices, services, and applications. These inherent traits make university students well-suited candidates for investigating the acceptance and adoption of e-learning facilitated by AI and Cloud-based applications and tools, as their perspectives are likely to offer valuable insights into usage patterns and preferences within this demographic.

2-1-2- Generations' Cohort Taxonomy and Generation Z

A generation is conventionally understood as a cohort of individuals born within a specific timeframe, although the precise duration of each generation varies. Scholarly literature indicates a range of 15 to 18 years, with discrepancies of three to four years between different sources [19]. Within the educational context, researchers have identified four primary generational cohorts. For instance, Mahmoud et al. [20] present a comprehensive classification, delineating Generation X (1965–1981), Generation Y (1982–1999), and Generation Z (2000–2012). This study focuses specifically on Generation Z students in higher education institutions within the Omani context.

The literature review reveals various terms used to refer to this generational cohort. For example, Generation Z, also known as centennials or post-millennials, encompasses individuals born between 1995 and 2012. Le et al. [21] define Generation Z as the first cohort with widespread access to digital communication, while Djafarova & Foots [22] similarly delineate Generation Z as those born from 1995 to 2010. Additionally, Elshami et al. [23] categorized Generation Z as individuals born after 1997.

According to Thangavel et al. [24], Generation Z includes those born between 1996 and 2010, with a significant portion currently in high school, college, or the workforce. This generation is also referred to by various names, including Post-Millennials, Generation Next, and Centennials [24–27]. These authors emphasize Generation Z's association with digital technology and social media and their status as the younger siblings of Millennials and children of Generation X.

Additionally, Srisathan et al. [28] classify Generation Z as individuals born between 1997 and 2009. Despite slight variations in their exact boundaries, these generational definitions collectively support the notion that Generation Z encompasses individuals born from the late 1990s through the late 2012s. Based on the review of existing literature, this study considers Generation Z individuals born between 1997 and 2012, aligning with prevailing research on their demographic characteristics and technological affinity.

2-1-3- Merits of Generation Z

Generation Z represents a distinctive cohort with characteristic that set them apart from previous generations. Notably, their unparalleled familiarity and comfort with technology and social media stand out as defining features. Termed "digital natives," Generation Z individuals have grown up immersed in the internet, smartphones, and social platforms, profoundly shaping their behaviors and preferences. This tech-savvy generation adeptly navigates various digital platforms for communication, entertainment, and learning [29, 30].

Moreover, Generation Z is marked by its social consciousness, technological adeptness, and penchant for innovation. They maintain constant connectivity through smartphones, tablets, and the Internet of Things, displaying a preference for written over oral communication and possessing access to vast information [25]. Unlike Baby Boomers and Millennials, Generation Z's affinity for digital tools and expectations for technology integration in education is notably higher [28]. This understanding of Generation Z's traits guides the selection of respondents in this study, focusing specifically on university students. These individuals are often described as multimodal learners due to their independent learning skills, allowing them to thrive with digital resources [23].

Furthermore, Generation Z exhibits a strong commitment to diversity, inclusion, and social justice. They actively advocate for equality and justice and are more likely to embrace diversity and inclusivity in their social and professional environments. Additionally, their entrepreneurial spirit, independence, and self-reliance distinguish them, as they are motivated to forge their paths and often engage in freelance work and entrepreneurship, leveraging the gig economy to shape their careers [22].

In summary, Generation Z possesses a unique blend of traits, including technological proficiency, social consciousness, and entrepreneurial drive, setting them apart as an innovative and impactful generation. These characteristics underscore the importance of exploring their perspectives on adopting AI and Cloud-based applications and tools in higher education, given their potential to shape the future of learning.

2-2- Oman 2024 Vision in Enhancing Education and Adoption of Emerging Technologies

Oman Vision 2040 aims to transform the country into a knowledge-based society that thrives on innovation and entrepreneurship. Education is a crucial component of this vision, and the government of Oman has been investing heavily in this sector to achieve the desired outcome. The vision emphasizes the importance of providing high-quality education to all citizens and promoting lifelong learning. To achieve this, the government has initiated several programs and projects, including the establishment of new universities and colleges, modernization of existing educational institutions, and the promotion of e-learning tools and technologies.

The focus is not only on traditional education but also on technical and vocational education to equip citizens with the skills and knowledge required to compete in the global economy and technological advancement. The vision recognizes the need to keep pace with technological advancements and stresses the importance of innovation in education. The ultimate goal is to prepare Oman's youth to become the leaders and entrepreneurs of the future, capable of contributing to the country's socio-economic growth and development.

2-3- Generation Z and Education Alignment with Oman 2040 Vision

The use of technology in education has significantly transformed the way students learn and educators teach. The integration of technology into education has revolutionized both teaching and learning paradigms. Among the forefront of technological advancements are Artificial Intelligence (AI) Cloud-based applications, which offer a myriad of benefits to the education sector, including enhanced collaboration, expanded access to resources, and increased flexibility.

Generation Z students, who were born after 1996 and have grown up with technology, are considered to be the primary users of Cloud-based applications. In Oman, the government has placed a strong emphasis on the development of the higher education sector to meet the demands of the country's growing economy. The Ministry of Higher Education has implemented several initiatives, such as the National Strategy for Higher Education 2040, to enhance the quality of higher education in the country. In line with these initiatives, many universities in Oman have taken the initiative to incorporate AI and Cloud-based applications in the pedagogical process to enhance the learning experience of students. However, despite the potential benefits of cloud-based applications, there is still limited empirical research on the factors influencing the adoption of Cloud-based applications in the pedagogical process, particularly among Generation Z students in Oman.

2-4- UTAUT as An Underpinning Theory for Understanding the Acceptance and Adoption of AI and Cloud-Based E-Learning Tools

In the era of information and knowledge age, the acceptance and adoption of e-learning that utilize AI and Cloud-based applications and tools (e_CloudAC) have become increasingly important to cope with recent challenges in the field of education. E-learning AI and Cloud-based applications and tools provide access to educational materials and resources anytime, anywhere, and on any device, making learning more flexible and convenient for students and educators. According to the Unified Theory of Acceptance and Use of Technology (UTAUT), the acceptance and adoption of technologies- such as cloud-based e-learning applications and tools- are influenced by several key factors, including performance expectancy, effort expectancy, social influence, and facilitating conditions. Studies have shown that UTAUT is a useful framework for understanding the factors that influence the acceptance and adoption of technology in higher education and e-learning contexts.

In their study, Wang et al. [31] aimed to establish a comprehensive technology acceptance framework for cloud-based e-learning and identify factors that predict the intention to use it. In another study, Abbad [32] utilized UTAUT to analyze the factors that determine the acceptance and usage of Moodle, an e-learning system at a public university in Jordan. While in Vietnam, a group of researchers using the extended UTAUT model investigated the factors affecting the acceptance and adoption of e-learning based on cloud computing among accounting students [33]. Other studies, such as the work of Kumar & Sharma [34], argue that cloud computing technology-based platforms can support traditional learning methods by offering convenience, flexibility, and higher learning outcomes for students, while Koh and Kan [35] found that students who frequently used learning management systems for content learning and discussion desired to engage in student-centered e-learning activities. These studies have proven the suitability of using UTAUT as the underpinning theory of the current research.

3- Hypotheses Development

3-1- Accepting and Adopting AI and Cloud-Based Applications and Tools (e_CloudAC)

The Unified Theory of Acceptance and Use of Technology (UTAUT) defines acceptance and adoption as the willingness of an individual to use and integrate a particular technology into their daily activities [18]. Acceptance pertains to the willingness of users to embrace new technologies, whereas adoption denotes the actual utilization and integration of these technologies within the educational context. In the scope of this study, the acceptance and adoption of AI and Cloud-based applications and tools refer to the extent to which Generation Z students are inclined to use and integrate AI and Cloud-based applications and tools in their educational endeavors. This aspect is increasingly crucial for educational institutions striving to enhance their teaching and learning processes.

According to the Unified Theory of Acceptance and Use of Technology (UTAUT), the acceptance and adoption of technology hinge upon four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs are pivotal in shaping users' attitudes and behaviors toward technology adoption. Various studies have underscored the significance of acceptance and adoption of e-learning AI and Cloud-based applications and tools in the educational realm. For instance, Wang et al. [31] sought to establish an integrated technology acceptance framework and identified factors predictive of Cloud e-learning adoption. The study identified determinants such as IS success, learning object criteria, technology acceptance, motivations, social cognitive factors, and expectancy values.

Similarly, Nguyen et al. [33] conducted a study aimed at identifying factors influencing the behavioral intention of accounting students to utilize e-learning based on cloud computing in Vietnam. Employing the extended UTAUT model, the study revealed that performance expectancy exerted the strongest influence, followed by effort expectancy, price value, facilitating conditions, hedonic motivation, and social influence. Additionally, the study highlighted that habits directly impacted the application of e-learning, while hedonic motivation and facilitating conditions significantly influenced the use of e-learning based on cloud computing. Therefore, educational institutions must provide training, support, and awareness of their benefits to foster the acceptance and adoption of e-learning AI and Cloud-based applications and tools. Addressing any concerns or challenges and cultivating a positive attitude toward technology adoption is essential. This can be achieved by involving both students and teachers in the process and addressing their needs and concerns. The ultimate aim is to deliver an enhanced learning experience that caters to the requirements of all stakeholders involved in the educational process.

3-2- Behavior Intention (BI) → Accepting and Adopting of e-Learning Cloud-Based Applications and Tools (e_CloudAC)

Behavioral intention (BI) refers to individuals' readiness or plan to use e-learning AI and Cloud-based applications and tools in the educational process [36]. It is a key construct in the Technology Acceptance Model (TAM) [37] and its variants, such as UTAUT, and has been shown to directly influence the actual use of information systems, including e-learning systems [38].

Understanding and predicting behavioral intention are critical in assessing the effectiveness of e-learning AI and Cloud-based applications and tools in Omani higher education institutions. Recent research by Zhang et al. [39] identified several determinants influencing college students' adoption of e-learning systems, including system quality (SQ), social influence (SI), and facilitating conditions (FC), which significantly impacted behavioral intention (BI). However, no significant association was found between information quality (IQ) and BI, and there was no significant positive association between FC and BI with use behavior (UB).

Other studies have consistently demonstrated a strong positive association between BI and the actual use of e-learning systems. For example, the recent study of Strzelecki [10] and Romero-Rodríguez et al. [40] revealed the significant and positive relationship between BI and students' acceptance of ChatGPT in higher education. Besides, Alharbi & Drew [41] found a significant positive relationship between BI and the actual use of learning management systems (LMS) among academics in a Saudi Arabian university. Similarly, Al-Rahmi et al. [42] identified behavioral intention as a significant predictor of knowledge-sharing behavior in e-learning systems.

While some studies have reported no significant relationship between BI and the actual use of e-learning systems [39], the majority of research findings support a positive and significant relationship. Based on these results, the following hypothesis is posited:

H1. *BI positively and significantly impacts accepting and adopting e-learning AI and Cloud-based applications and tools (e_CloudAC) in the learning journey of Generation Z*

3-3- Social Influence (SI) → Behavior Intention (BI)

Social influence (SI) is defined by Venkatesh et al. [18] as "the degree to which an individual perceives that important others believe he or she should use the new system" (p. 455). It encompasses the influence of significant individuals, such as family members, friends, and colleagues, on an individual's decision to adopt or use a particular technology or system. In the context of this study, SI pertains to the impact of others' beliefs, opinions, and expectations on Generation Z students' inclination to utilize AI Cloud-based applications and tools in their learning endeavors.

The widespread adoption of cloud-based tools and applications in higher education institutions globally has garnered significant attention in recent years. These technologies have demonstrated their ability to enhance the learning experience and improve educational quality across various domains [43-45]. However, successful adoption hinges on various factors, with social influence being a prominent determinant.

Numerous prior studies have highlighted the pivotal role of social influence in shaping the acceptance and behavioral intention to use e-learning technologies, including AI and Cloud-based applications and tools [22, 29, 34, 35] as well as the use of online innovative technologies that are cloud-based online services [46]. For instance, Chang et al. [47] investigated the impact of users' performance expectancy, effort expectancy, social influence, and facilitating conditions on the usage of online agricultural statistics learning systems. Their study, employing satisfaction surveys and the UTAUT model, revealed a positive influence of social influence and facilitating conditions on students' usage behavior towards the e-learning platform, particularly in the agricultural community.

Similarly, a recent study Utami et al. [48] examined educators' attitudes toward cloud-based learning technology, which is widely employed to facilitate the educational process in Indonesia. The research utilized the Technology Acceptance Model (TAM) variables, namely perceived usefulness (PU) and perceived ease of use (PEOU), augmented by perceived risk (PR) and social influence (SI). The findings indicated a notable correlation among factors influencing technology utilization, with the exception of PU and PEOU.

In addition, Tarhini et al. [49] found that social influence significantly influenced behavioral intentions to use e-learning systems. Additionally, Khechine et al. [50] demonstrated a significant relationship between social influence and the behavioral intention to use learning management systems in education. However, contrary findings were reported by Yakubu & Dasuki [51], who found that social influence did not significantly impact the behavioral intention to use e-learning applications.

Recognizing the significance of social influence, UTAUT incorporates a social component in its model. While the Technology Acceptance Model (TAM) [37] initially overlooked social influence, UTAUT emphasizes the importance of integrating the opinions of friends and relatives of actual users into the model. Based on these arguments, the researchers hypothesize the following relationship:

H2. *SI possesses a positive and significant impact on Generation Z's intention to accept and adopt e-learning AI and Cloud-based applications and tools (e_CloudAC) in the learning curve of Generation Z.*

3-4- Facilitating Conditions (FC)→ Behavior Intention (BI) and Accepting and Adopting E-Learning AI and Cloud-Based Applications and Tools e_CloudAC

Facilitating conditions refers to the perception of the availability of organizational and technical infrastructure to support the use of e-learning systems [18]. It encompasses users' beliefs regarding their ability to access necessary resources and receive adequate support to utilize cloud-based e-learning tools and programs effectively within the university setting.

Several studies have underscored the significant role of facilitating conditions in influencing the behavior and intention to use e-learning technologies and innovative technologies [28, 41–43, 51, 52]. For example, Yakubu & Dasuki [51] found that facilitating conditions significantly impacted users' behavior in adopting technology. Similarly, Abushakra & Nikbin [53] revealed a positive association between facilitating conditions and the intention to use Internet of Things (IoT) technology. Moreover, Zhang et al. [39] identified facilitating conditions as a critical determinant influencing college students' adoption of e-learning systems, with a significant positive impact on behavior intention. Also, the majority of studies identified similar findings with regard to the relationship between FC and BI in the use of innovative technologies [54].

On the other hand, FC has contradicting results in the literature. Some research reveals a positive and significant relationship between FC and actual behavior [29, 37], while other works show no significant association between FC and the use of cloud-based e-learning systems [39]. Also, some studies revealed no significant relationship between FC and BI using mobile banking [55].

Given that e-learning systems rely on adequate technological infrastructure and resources, facilitating conditions are essential for enhancing users' confidence and ability to adapt and utilize cloud-based tools and applications effectively. Therefore, institutions must provide the necessary support and resources to facilitate the successful adoption of AI cloud-based e-learning systems.

Based on the literature review, the researchers hypothesize the following in the context of e-learning Cloud-based system use behavior:

H3_1. *FC would positively and significantly influence Generation Z's intention to accept and adopt e-learning AI and Cloud-based applications and tools (e_CloudAC).*

H3_2. *FC would positively and significantly influence Generation Z's behavior in accepting and adopting e-learning AI and Cloud-based applications and tools (e_CloudAC).*

3-5- Performance Expectancy (PE) → Behavior Intention (BI)

Performance Expectancy (PE) is a construct that refers to the degree to which individuals believe that using a particular system or technology will improve their job performance or make a task easier to perform [18]. In the context of AI cloud-based applications, PE relates to the belief of Generation Z students that using these tools would enhance their academic performance or make the learning process more efficient and easier to perform.

In numerous studies, performance expectancy has been highlighted as a significant factor shaping behavioral intention to use e-learning systems [21, 35, 40, 46]. These studies consistently demonstrate the importance of performance expectancy in influencing individuals' intentions to use e-learning systems. For instance, in recent work [40] Performance expectancy was found to have a significant positive influence on the behavioral intention to use ChatGPT. Similarly, recent work has proven the positive and significant relationship between performance expectancy BI to use ChatGPT in higher education by students [10]. Additionally, in other research areas [47, 56, 57], the results support the positive and significant relationship between PE and BI.

Additionally, Venkatesh et al. [18] proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies performance expectancy as the highest predictor of user behavioral intention. This suggests that individuals are more inclined to adopt and use new technologies if they perceive them as beneficial. Therefore, this construct is added to the proposed model of the current research to investigate its influence on BI to use AI Cloud-based applications and tools based on the stance of Generation Z students in Oman. On the other hand, PE is not statistically significant with behavior intention.

Considering this body of literature, it is reasonable to expect that students who perceive cloud-based tools and applications as beneficial for their academic tasks will exhibit a positive attitude towards using and adopting these technologies. Thus, the researchers propose the following hypothesis:

H4. *PE would positively and significantly influence Generation Z's intention to accept and adopt e-learning AI and Cloud-based applications and tools (e_CloudAC).*

3-6- The Effort Expectancy (EE) → Customer Behavior Intention (BI)

The effort expectancy (EE) is defined as "the degree of ease associated with the use of a system" [37]. In the context of the current study, it refers to the Generation Z students' perception of the ease and convenience associated with using a system or technology and how this perception influences their intention to use and adopt e-learning AI and Cloud-based applications and tools in the educational context.

Several studies have supported the positive relationship between effort expectancy and behavioral intention to use e-learning systems. For instance, a study has found that EE has a direct positive impact on the BI to use ChatGPT by students in higher education institutions [10]. Similarly, Al-Mamary [58] found that effort expectancy significantly predicted students' intention to use a learning management system in higher education in Saudi Arabia. Similarly, a study by Huang et al. [59] investigated the factors that influence students' intention to use e-learning systems in the context of higher education in Taiwan. The results showed that effort expectancy was a significant predictor of intention to use e-learning systems. However, some recent studies have reported contradictory findings, suggesting that effort expectancy may not always have a significant impact on behavioral intention [30, 60-62]. Despite these conflicting results, the majority of the literature provides strong evidence for the positive and significant relationship between effort expectancy and behavioral intention to use e-learning systems in various educational contexts.

Considering the existing research, it is reasonable to hypothesize that students who perceive e-learning AI and Cloud-based applications and tools as easy to use and convenient are more likely to have a positive intention to accept and adopt these technologies. Therefore, the following hypothesis is proposed (Figure 1):

H5. *Effort expectancy (EE) positively and significantly influences the intention of Generation Z student to accept and adopt e-learning AI and Cloud-based applications and tools (e_CloudAC) in their educational journey.*

3-7- The Conceptual Framework of the Study

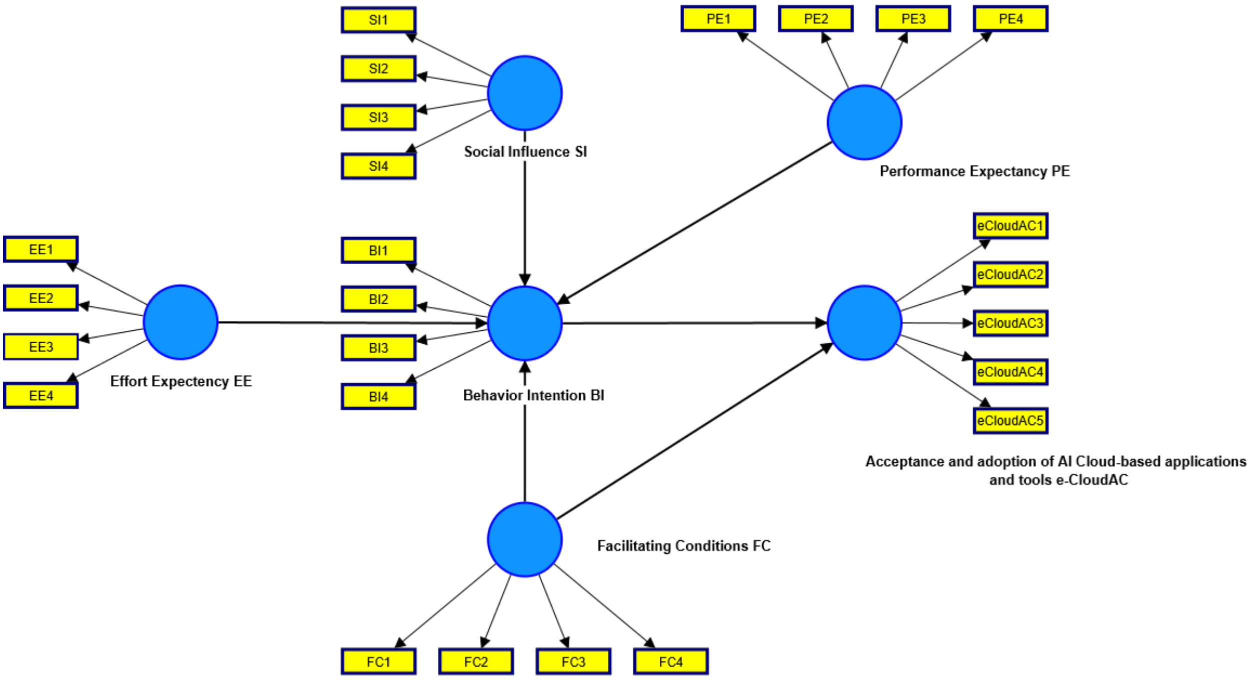

Figure 1. Conceptual Framework

4- Research Methodology

This study aims to investigate the factors influencing the adoption of AI and Cloud-based applications among Generation Z students in Oman's higher education sector, utilizing the UTAUT framework. The research will be conducted in selected higher educational institutions across Oman, targeting Generation Z students who have experience in utilizing AI and Cloud-based applications in the pedagogical process. It will employ a quantitative research approach using convenience non-probability sampling for data collection and a survey questionnaire.

The questionnaire, crafted using Google Forms, encompassed sections that introduced the study's objectives and extended invitations for participation. Furthermore, respondents were supplied with the author's contact details to provide feedback or recommendations, thereby fostering an open channel for communication. Moreover, participants were assured of the voluntary nature of their involvement, with the option to withdraw from the survey at any point. Ethical considerations were meticulously addressed throughout the data collection process, with paramount emphasis placed on safeguarding participant privacy and ensuring anonymity. To uphold this commitment, measures such as deactivating the email option in the online survey were implemented to bolster anonymity and enhance participant confidentiality. The demographic section of the questionnaire comprised inquiries regarding gender, age, academic degree, and institution type. The constructs under investigation were divided into two sections: Section 1 encompasses demographic data, and Section 2 contains the independent variables (Social Influence (SI), Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Behavioral Intention (BI)), alongside the dependent variable of the study (e_CloudAC).

This exploratory study collected a modest number of responses (469 responses), effectively manageable by SmartPLS 4.0, which offers a good level of statistical power. To determine the minimum recommended sample sizes, G Power Analysis was used according to the recommendations and guidelines of Sarstedt et al.'s [63]. Employing the G*power software analytical tool [64] resulted in a minimum sample size of 138, factoring in a power level of 0.95, an alpha error probability of 0.05, and a medium effect size of 0.15 [63]. Refer to Figure 2 for G*power output.

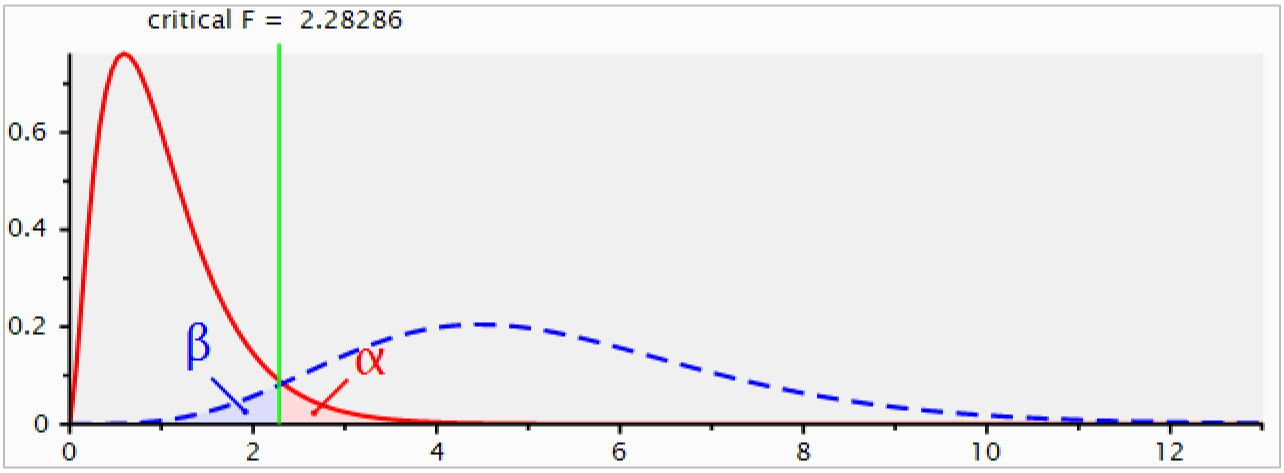

Figure 2. G*Power Sample size output

SmartPLS, a nonparametric method, mitigates concerns related to normalcy and data distribution issues [55, 56], is robust against missing data, and accommodates various scales. The significance of PLS-SEM lies in its capacity to simultaneously compare models oriented towards explanation and prediction [57, 58]. Our research, which is both exploratory and prediction-oriented, benefits from PLS-SEM's dual focus on these aspects of model evaluation. This aligns perfectly with the nature of our study, where we aim to comprehend emerging and complex relationships and predict latent constructs within our conceptual framework. It's worth noting that while PLS-SEM inherently possesses the ability for prediction-oriented assessments, it has primarily been applied in explanation-oriented studies due to the lack of suitable prediction-oriented tools [65-68]. In our case, PLS-SEM emerges as a suitable choice given the exploratory nature of our research, enabling us to extract valuable insights into relationships between latent variables and facilitating subsequent model refinement.

Employing a two-step approach, the Partial Least Squares Structural Equation Modeling (PLS-SEM) procedures commence with measurement evaluation, followed by structural evaluation of the hypotheses [63]. When evaluating the measurement model theory, certain factors must be considered. Firstly, the internal consistency reliability of latent constructs should be 0.7 (although 0.6 or 0.7 are acceptable for exploratory research), according to Sarstedt et al. [63]. Secondly, indicator reliability should have outside loadings of 0.708 or less. Thirdly, the average variance extracted (AVE) of the construct's measurements should be equal or less than 0.5. Finally, in terms of discriminant validity, the indicator's outer loadings should be higher than all other loadings with other constructs, according to Sarstedt et al. [63] and Sarstedt et al. [69]. Additionally, the square root of the AVE for each construct should be greater than its highest correlation with other constructs, which is known as the Fornell-Larker criterion [70].

The flowchart of the research methodology that was used to achieve the study's aims is shown in Figure 3.

4-1-Analyses and Discussions of Results

4-1-1- Demographic Analyses

The descriptive analysis of the Generation Z students' profile offers valuable insights into the composition of the study's sample population. In terms of gender distribution, the results show a relatively balanced representation, with 45.6% of Generation Z students identifying as male and 54.4% as female. This balanced gender ratio ensures a comprehensive perspective in the study, encompassing both male and female viewpoints. A significant majority of Generation Z students (80.8%) fall within the age range of 1997-2004, indicating that the sample predominantly comprises individuals in their late teens to early twenties. This age distribution aligns with the characteristics commonly attributed to Generation Z, ensuring relevance and alignment with the study's objectives.

Regarding educational background, Generation Z respondents exhibit diversity, with 38.4% holding a diploma and 61.6% possessing a bachelor's degree. This variance in academic qualifications enriches the study by incorporating a wide range of perspectives and experiences. Furthermore, a notable majority of Generation Z students (63.3%) are affiliated with private institutions, while 36.7% belong to public institutions. This distribution ensures a heterogeneous mix of experiences from private and public educational settings, thereby enhancing the robustness and generalizability of the study's findings.

Overall, the descriptive analysis provides a comprehensive overview of the demographic profile of Generation Z students, highlighting key characteristics and ensuring the representation of diverse perspectives within the study. The detailed figures of the descriptive analyses are presented in the Table 1.

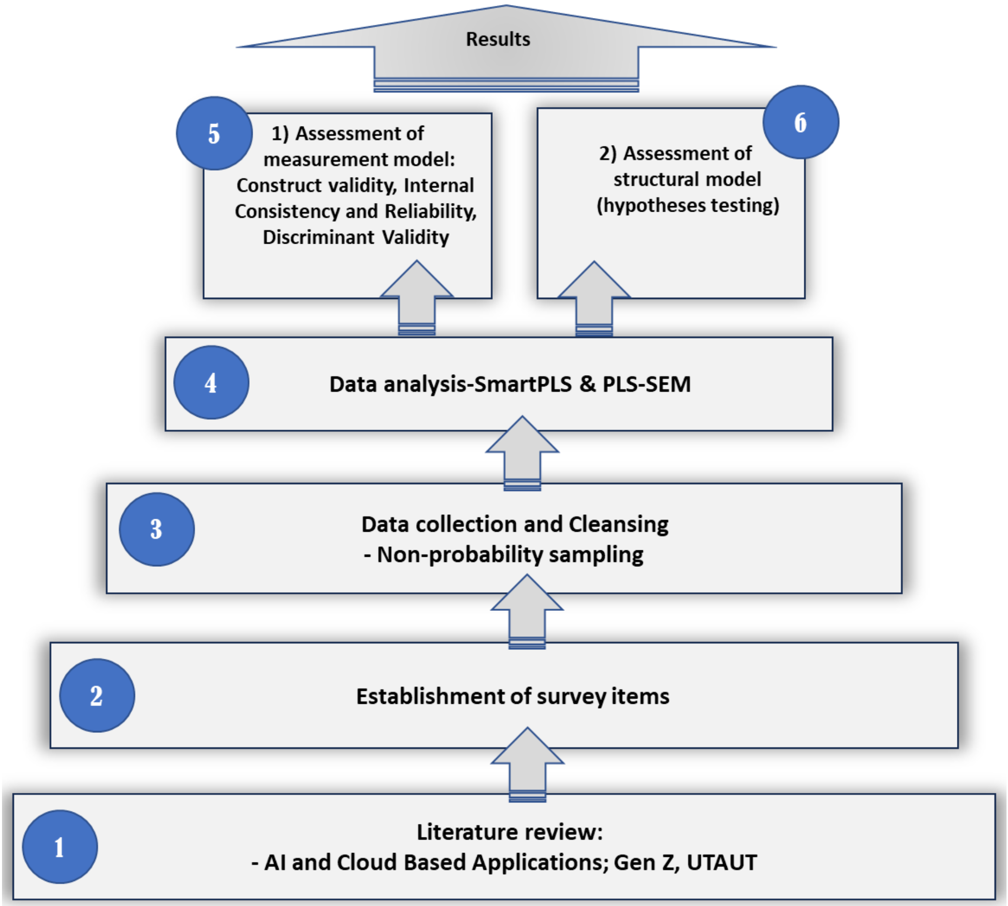

Figure 3. Overall Research Methodology Flowchart

Table 1. Respondents' demographics of experience and academic degree

Attribute	Std. Deviation	Mean	Frequency	Percent%
Gender				
1. Male	0.499	1.54	214	45.6%
2. Female			255	54.4%
Total			***469***	***100%***
Age				
1. Was born 1997-2004	0.5647	1.239	379	80.8%
2. Was born 2005-2009			78	16.6%
3. Was born 2010-2012			12	2.5%
Total			***469***	***100%***
Academic Degree				
1. Diploma	1.64	1.64	180	38.4%
2. Bachelor's Degree			289	61.6%
Total			***469***	***100%***
Institution type				
1. Private	0.482	1.37	297	63.3%
2. Public			172	36.7%
Total			***469***	***100%***

4-2- Model Measurement Evaluation

The measurement model underwent a comprehensive evaluation, encompassing convergent validity, outer loadings, internal consistency, and discriminant validity. Convergent validity, assessed through Average Variance Extracted (AVE) with a threshold of 0.5 or higher [63], met the criterion with values ranging from 0.51 to 0.80 (Table 2). Outer loadings of items were examined, surpassing the recommended threshold of 0.6 [71], thus confirming structural convergence validity.

Internal consistency and reliability were scrutinized using Composite Reliability (CR) and Cronbach's alpha. All latent variables exceeded the CR cut-off of 0.7, and Cronbach's alpha values surpassed the recommended range of 0.60 to 0.70. Consequently, both convergent validity and internal consistency/reliability were established. In summary, the measurement model demonstrates robustness in these aspects, as shown in Table 2.

Table 2. Internal consistency and reliability and convergent validity

Latent construct	Items	Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavior Intention BI	BI1	0.76	0.79	0.79	0.86	0.61
	BI2	0.77				
	BI3	0.78				
	BI4	0.81				
Effort Expectancy EE	EE1	0.79	0.70	0.70	0.83	0.62
	EE2	0.79				
	EE4	0.79				
Facilitating Conditions FC	FC1	0.74	0.70	0.70	0.82	0.53
	FC2	0.74				
	FC3	0.73				
	FC4	0.70				
Performance Expectancy	PE1	0.90	0.92	0.92	0.94	0.80
	PE2	0.90				
	PE3	0.89				
	PE4	0.89				
Social Influence SI	SI1	0.74	0.69	0.70	0.81	0.52
	SI2	0.79				
	SI3	0.62				
	SI4	0.71				
e-CloudAC	eCloudAC1	0.68	0.76	0.77	0.84	0.51
	eCloudAC2	0.70				
	eCloudAC3	0.74				
	eCloudAC4	0.75				
	eCloudAC5	0.71				

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

As a final step in the measurement model evaluation, the discriminant validity criterion is assessed (Figure 4). Two main steps are undertaken for this analysis. Firstly, the Fornell and Larker criterion [70] is checked, where the square root of AVE in the diagonal should be greater than all off-diagonal values. As shown in Table 3, this measure is fulfilled.

Table 3. Discriminant validity with Fornell-Larker criterion analysis

Latent construct	1	2	3	4	5	6
1. Acceptance and adoption of AI Cloud-based applications_ and tools e-CloudAC	**0.72**					
2. Behaviour Intention BI	0.64	**0.78**				
3. Effort Expectancy EE	0.49	0.44	**0.79**			
4. Facilitating Conditions FC	0.52	0.49	0.55	**0.73**		
5. Performance Expectancy	-0.05	-0.08	-0.10	-0.12	**0.89**	
6. Social Influence SI	0.56	0.62	0.52	0.59	-0.12	**0.72**

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

Secondly, the cross-loading values of each item with its respective construct must correlate higher than with other constructs to achieve discriminant validity. As seen in Table 4, the results are congruent with the aforementioned criterion.

Table 4. Discriminant validity with cross-loading analysis

	e-CloudAC	Behavior Intention BI	Effort Expectancy EE	Facilitating Conditions FC	Performance Expectancy PE	Social Influence SI
BI1	0.47	0.76	0.33	0.40	-0.05	0.47
BI2	0.49	0.77	0.39	0.41	-0.09	0.50
BI3	0.48	0.78	0.28	0.36	-0.03	0.45
BI4	0.56	0.81	0.36	0.37	-0.09	0.52
EE1	0.36	0.34	0.79	0.40	-0.11	0.37
EE2	0.40	0.35	0.79	0.47	-0.08	0.44
EE4	0.40	0.35	0.79	0.44	-0.06	0.42
FC1	0.38	0.33	0.46	0.74	-0.10	0.42
FC2	0.41	0.34	0.38	0.74	-0.08	0.45
FC3	0.38	0.37	0.39	0.73	-0.08	0.46
FC4	0.35	0.38	0.39	0.70	-0.07	0.40
PE1	-0.06	-0.09	-0.10	-0.11	0.90	-0.08
PE2	-0.05	-0.08	-0.09	-0.09	0.90	-0.14
PE3	-0.02	-0.07	-0.10	-0.11	0.89	-0.08
PE4	-0.03	-0.07	-0.08	-0.11	0.89	-0.13
SI1	0.45	0.48	0.42	0.48	-0.10	0.74
SI2	0.45	0.49	0.47	0.44	-0.07	0.79
SI3	0.32	0.37	0.27	0.36	-0.06	0.62
SI4	0.38	0.42	0.31	0.42	-0.11	0.71
eCloudAC1	0.68	0.41	0.29	0.39	-0.06	0.40
eCloudAC2	0.70	0.44	0.32	0.35	-0.06	0.39
eCloudAC3	0.74	0.50	0.40	0.41	-0.03	0.49
eCloudAC4	0.75	0.46	0.37	0.38	0.02	0.39

Discriminant validity analysis of the two tests above supports the assessment of all components of the estimated model. The results of all analyses performed so far warrant the evaluation of the hypotheses testing in the next section.

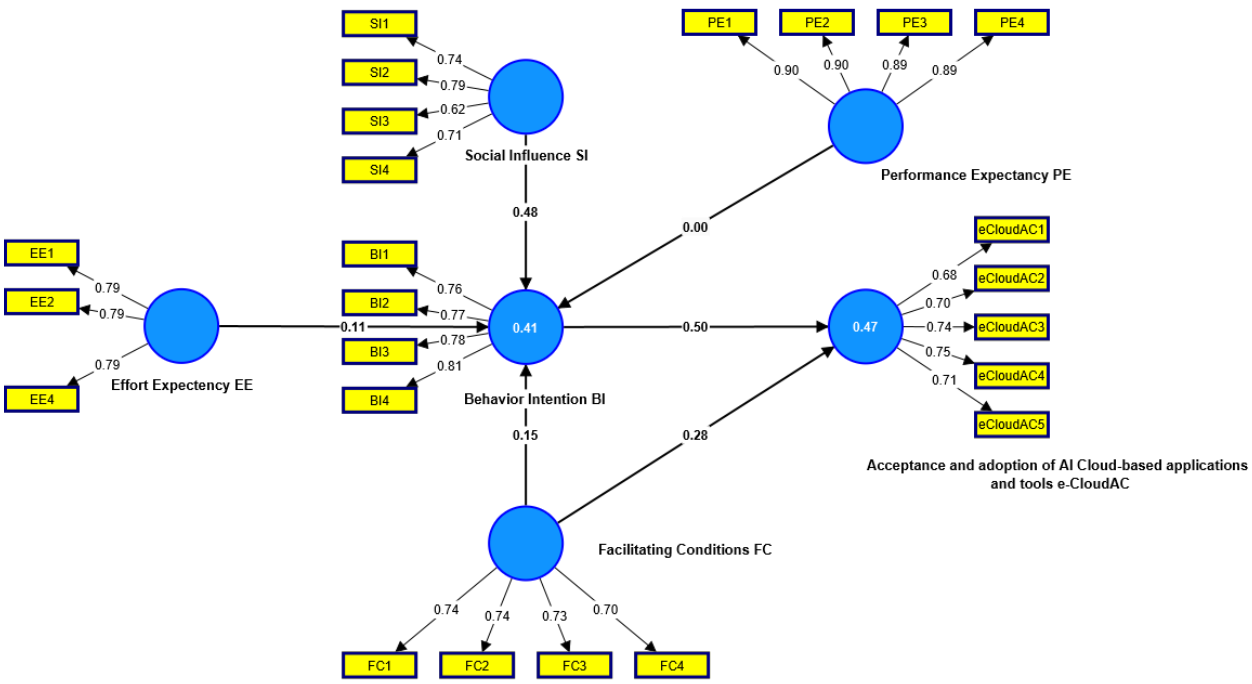

Figure 4. illustrates the results of the measurement model analyses

4-3- Hypotheses Testing via Structural Model Evaluation

Before proceeding with structural evaluation, collinearity was assessed to ensure compliance. The results indicated that all constructs had Variance Inflation Factor (VIF) values below 5, confirming the absence of collinearity issues (see Table 5).

Table 5. Collinearity issues evaluation with VIF analysis

Latent Variable	1	2	3	4	5	6
1. e-CloudAC						
2. BI	1.31					
3. EE		1.57				
4. FC	1.31	1.77				
5.PE		1.02				

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

4-3-1- The Coefficient of Determination (R^2) Analysis

The coefficient of determination (R^2) or out-of-sample prediction measures the proportion of variance in the dependent variable that is predictable from the independent variables in a regression model. In our study, the R^2 values for Behavioral Intention (BI) and the acceptance and adoption of AI Cloud-based applications and tools (e-CloudAC) are 0.41 and 0.47, respectively. According to Chin [71], R^2 values can be categorized as considerable (0.67), moderate (0.33), or weak (0.19). Our findings indicate a moderate level of explanatory power for both BI and e-CloudAC, suggesting that the independent variables collectively account for a substantial portion of the variance observed in the dependent variables.

Furthermore, to assess the magnitude of the relationship between the independent and dependent variables, the effect size (f^2) is calculated. Effect sizes quantify the strength of the relationship between variables and are categorized as small (0.01), medium (0.09), or large (0.25), according to Kenny [72]. In our study, the effect size for BI on e-CloudAC is ($f^2 = 0.36$), indicating a large effect size and suggesting a strong relationship between behavioral intention and the acceptance and adoption of AI Cloud-based applications and tools. This finding underscores the significant influence of behavioral intention on the willingness of Generation Z students to adopt innovative educational technologies.

On the other hand, the effect size of Effort Expectancy (EE) and Performance Expectancy (PE) on BI is ($f^2 = 0.01$) and ($f^2 = 0.00$), respectively, indicating a small effect size of EE and no effect of PE on BI; therefore, PE does not significantly contribute to e-CloudAC. Facilitating Conditions (FC) and Social Influence (SI) exhibit varying degrees of influence on e-CloudAC. FC effect size ($f^2 = 0.02$) exerts on BI and ($f^2 = 0.11$) on e-CloudAC, respectively, indicating small and moderate effect sizes. On the other hand, SI shows an effect size ($f^2 = 0.23$) on BI, as well as an indication and strong relationship with BI. These findings highlight the importance of considering multiple factors, including behavioral intention, facilitating conditions, and social influence, when examining the adoption of AI Cloud-based technologies among Generation Z students in higher education institutions. Refer to Table 6 for more details.

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

Latent Constructs	Behavior Intention BI	Acceptance and adoption of AI Cloud-based applications and tools e-CloudAC
Coefficient of Determination R^2	0.41	0.47
Effect size f^2 of antecedent and driving constructs		
e-CloudAC		
BI		0.36
EE	0.01	
FC	0.02	0.11
PE	0.00	
SI	0.23	

Examining the outcomes in Table 7 reveals insightful results regarding the impact of various factors on users' behavioral intentions and the subsequent acceptance and adoption of e-learning AI and Cloud-based applications and tools. In the following subsections, a detailed explanation and interpretation of the relationship between the postulated in the current research.

Table 7. Path coefficient and hypotheses testing

Path	Path Coefficients Beta	Sample Mean	STDEV	t values	p values	LL CI 2.5%	UL CI 97.5%	Hypotheses Remarks
BI → e-CloudAC	0.50	0.50	0.05	10.53	*0.00	0.42	0.58	Supported
EE → BI	0.11	0.11	0.05	2.10	*0.02	0.02	0.19	Supported
FC → e-CloudAC	0.28	0.28	0.04	6.29	**0.00	0.20	0.35	Supported
FC → BI	0.15	0.15	0.05	2.68	**0.00	0.06	0.23	Supported
PE → BI	0.00	0.00	0.04	0.00	0.50	-0.05	0.08	Not Supported
SI → BI	0.48	0.48	0.05	9.59	**0.00	0.39	0.55	Supported

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

4-3-2- Behavioral Intention (BI) → Acceptance and Adoption of e-Learning AI and Cloud-Based Applications and Tools (e-CloudAC)

The results obtained from Table 7 provide valuable insights into the relationship between various factors and the behavioral intentions of Generation Z students in Omani higher education institutions regarding the acceptance and adoption of e-learning AI and Cloud-based applications and tools. Specifically, the analysis indicates a statistically significant relationship between behavioral intention (BI) and the acceptance and adoption of e-learning AI and Cloud-based applications and tools (e-CloudAC) among Generation Z students ($\beta = 0.50$, $p \leq 0.05$, $t = 10.54$), with confidence intervals [0.41-0.60]. This significant finding validates Hypothesis H1, suggesting that the behavioral intentions of Generation Z students play a crucial role in shaping their willingness to adopt and integrate AI cloud-based applications and tools into their educational experiences.

In the context of Oman's 2040 vision for educational advancement and innovation, this result underscores the importance of prioritizing the alignment of educational strategies with the preferences and intentions of Generation Z students. As digital natives, Generation Z students are inherently accustomed to technology-rich environments and exhibit distinct preferences and behaviors regarding adopting innovative educational technologies. Therefore, understanding and addressing their behavioral intentions is paramount to fostering a culture of technological innovation and digital transformation in Omani higher education institutions.

Moreover, the consistency of these findings with prior research [29, 30] provides additional support for the validity and reliability of the results. By corroborating the outcomes of previous studies, this finding reinforces the notion that Generation Z students' behavioral intentions are indeed influential in driving their acceptance and adoption of AI cloud-based applications and tools in the educational context.

Overall, these insights emphasize the imperative for educational institutions and policymakers to proactively consider and address the behavioral intentions of Generation Z students when formulating strategies to promote the use of AI cloud-based technologies in higher education. By fostering positive attitudes and intentions among Generation Z students, institutions can enhance their readiness to embrace and effectively utilize these innovative technologies, thereby enriching their learning experiences and outcomes in Omani higher education institutions in alignment with the objectives outlined in Oman's 2040 vision for educational excellence and innovation.

4-3-3- Social Influence (SI) → Behavioral Intentions (BI)

The analysis of the relationship between Social Influence (SI) and Behavioral Intention (BI) among Generation Z students in Omani higher education institutions reveals statistical significance ($\beta = 0.48$, $p \leq 0.05$, $t = 9.59$), providing support for Hypothesis H2. This indicates that social norms exert a significant influence on students' behavioral intentions, particularly in their acceptance and adoption of AI cloud-based applications and tools. These findings underscore the substantial role of social influence in shaping students' attitudes and intentions toward technology adoption within educational settings, aligning with the objectives outlined in Oman's 2040 vision for educational advancement and innovation.

This conclusion is consistent with previous research findings [37, 38, 63, 64], further highlighting the importance of social factors in driving technology adoption behaviors among students. The study's results emphasize the importance of fostering a supportive social environment that promotes the benefits and advantages of AI cloud-based applications and tools. Positive endorsements and encouragement from peers, educators, and family members can enhance students' willingness to accept and adopt these technologies, thus facilitating their integration into the educational journey.

Conversely, negative perceptions or resistance from social circles may hinder students' adoption of AI cloud-based applications and tools, emphasizing the need for strategic interventions to address potential barriers and misconceptions. Educational institutions and policymakers in Oman can leverage social influence as a strategic lever to promote the acceptance and adoption of AI cloud-based applications and tools among Generation Z students.

This may involve implementing awareness campaigns, peer-to-peer learning initiatives, and community engagement programs that highlight the value and utility of these technologies in enhancing the learning experience and preparing students for the digital future. By understanding and harnessing the power of social norms, educational stakeholders can create a more digitally literate and technology-enabled learning environment, ultimately enhancing the educational outcomes and experiences of Generation Z students in Oman's higher education institutes in alignment with the objectives outlined in Oman's 2040 vision for educational excellence and innovation.

4-3-4- Facilitating Conditions (FC) → Behavioral Intentions (BI) and Acceptance and Accepting and adopting AI and Cloud-Based Applications and Tools (e_CloudAC) Relationships

The analysis of the relationship between Facilitating Conditions (FC) and users' behavioral intentions (BI), as well as their subsequent acceptance and adoption of e-learning AI and Cloud-based applications and tools (e-CloudAC), yields significant findings with important implications for the study, aligning with Oman's 2040 vision for educational advancement. Specifically, the results indicate that FC has a significant effect on both BI ($\beta = 0.15$, $p = 0.01$, $t = 2.74$) and e-CloudAC ($\beta = 0.28$, $p \leq 0.05$, $t = 6.11$), thus validating Hypotheses *H3_1* and *H3_2*, respectively.

These findings underscore the critical role of favorable conditions in influencing the behavioral intentions of Generation Z students and subsequently actualizing the adoption and acceptance of AI cloud-based applications and tools in the educational context. In the context of Oman's 2040 vision, which emphasizes the integration of advanced technologies into higher education, ensuring favorable conditions becomes paramount. When favorable conditions, such as adequate resources, technical support, and infrastructure, are present, Generation Z students are more inclined to develop positive behavioral intentions toward utilizing these technologies and are more likely to embrace them in their educational pursuits.

Moreover, the significance of FC in shaping behavioral intentions and driving actual adoption aligns with previous research findings. Studies conducted by Abushakra & Nikbin [53], Yakubu & Dasuki [51], and Zhang et al. [39] have all reported a positive and significant relationship between FC and BI. This consistency across studies further strengthens the validity and reliability of the current findings, suggesting that favorable conditions indeed play a crucial role in influencing users' intentions to adopt technology.

Furthermore, aligning the results with the work of Chang et al. and Strzelecki [29, 37] reinforces the notion that FC also exerts a significant and positive influence on the actual use and adoption of technologies. This implies that favorable conditions not only shape users' intentions but also contribute to the practical implementation and integration of AI cloud-based applications and tools into educational practices.

Overall, these results emphasize the importance of providing supportive and conducive conditions within educational institutions to facilitate the successful adoption and acceptance of AI cloud-based technologies among Generation Z students. By prioritizing the provision of favorable conditions, institutions can enhance students' willingness to engage with these technologies and optimize their educational experiences and outcomes in Omani higher education institutions, aligning with the objectives outlined in Oman's 2040 vision for educational excellence and innovation.

4-3-5- Performance Expectancy (PE) → Behavioral Intentions (BI) Relationship

The analysis of the relationship between Performance Expectancy (PE) and users' behavioral intentions (BI) regarding the adoption and acceptance of AI cloud-based applications and tools among Generation Z students in Omani higher education institutions yielded unexpected results. Contrary to expectations and hypotheses (H4), Performance Expectancy (PE) did not demonstrate a significant influence on BI ($\beta = 0.00$, $p = 1.00$, $t = 0.00$).

This unexpected finding suggests that Generation Z students' perceptions of the performance benefits associated with AI cloud-based applications and tools may not be a decisive factor in shaping their behavioral intentions towards adoption and acceptance. In other words, despite the potential advantages and perceived usefulness of these technologies, students' intentions to utilize them in their educational activities may not be significantly influenced by their expectations of performance outcomes.

This result is particularly intriguing in the context of Oman's 2040 vision for higher education, which emphasizes the importance of technological innovation and digital transformation in driving educational excellence and preparing students for the future workforce. While Performance Expectancy (PE) is typically considered a critical factor in users' intentions to adopt new technologies, its non-significant influence in this study suggests the presence of other influential factors that may outweigh perceived performance benefits in the decision-making process of Generation Z students.

This is consistent with previous scholarly reports [42, 65–67, 73-77]. For instance, Miraz et al. [78] similarly observed a non-significant relationship between facilitating conditions and the behavioral intention to use and adopt cryptocurrency in their study. Similarly, de Blanes Sebastián et al. [79] revealed a non-significant relationship between PE and BI in the context of users' intent in mobile payment systems. This parallel finding underscores the nuanced nature of technology adoption among contemporary users, where traditional determinants may not always hold.

The unexpected nature of this result highlights the need for further exploration into the complex interplay of factors influencing Generation Z students' acceptance and adoption of AI cloud-based technologies in Omani higher education institutions. By delving deeper into these underlying factors, educators and policymakers can gain valuable insights to inform strategies and initiatives to effectively integrate these technologies into educational practices aligned with Oman's vision for a knowledge-based economy and society.

4-3-6- Effort Expectancy (EE) → Behavioral Intentions (BI) Relationship

Analyzing the relationship between Effort Expectancy (EE) and users' behavioral intentions (BI) regarding the acceptance and adoption of AI cloud-based applications and tools among Generation Z students in Omani higher education institutions yielded significant results. Specifically, the path from Effort Expectancy (EE) to Behavioral Intention (BI) was found to be statistically significant ($\beta = 0.11$, $p = 0.04$, $t = 2.06$), thus providing support for Hypothesis 5 (see Figure 5).

This result underscores the importance of Generation Z students' perceived ease of use and interaction with AI cloud-based applications and tools in shaping their behavioral intentions. In the context of Oman's 2040 vision for higher education, which prioritizes technological advancement and innovation, it becomes imperative to ensure that emerging technologies, such as AI cloud-based applications and tools, are user-friendly and accessible to students.

In other words, when students perceive these technologies as easier to use and interact with, they are more inclined to exhibit positive intentions toward their acceptance and adoption in educational settings. This aligns with Oman's strategic goals of fostering a digitally proficient workforce and enhancing the quality of education through technological innovation.

The findings of the current study are consistent with previous research, as evidenced by similar results reported by [10, 58]. These studies also found a significant relationship between Effort Expectancy (EE) and Behavioral Intention (BI) in the context of technology adoption, further validating the robustness of the current findings.

Overall, the significant impact of Effort Expectancy (EE) on Behavioral Intention (BI) highlights the importance of designing AI cloud-based applications and tools that are intuitive, user-friendly, and aligned with Oman's vision for educational excellence in the digital age. By minimizing perceived effort and enhancing user experience, educators and developers can promote the successful acceptance and adoption of these technologies in Omani higher education institutions, thereby contributing to the realization of Oman's aspirations for a knowledge-based economy and society.

In sum, the results provide valuable insights into the complex interplay of behavioral intentions, social influences, facilitating conditions, performance expectations, and effort expectations in shaping users' decisions to accept and adopt e-learning cloud-based applications.

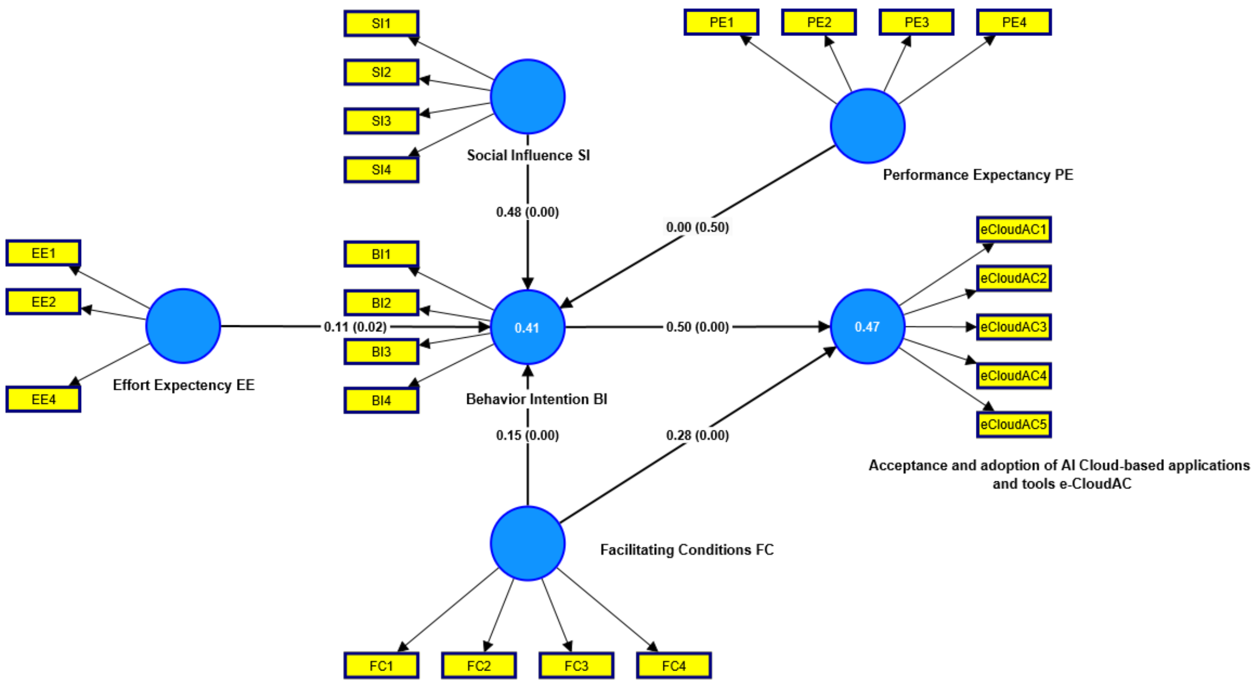

Figure 5. Hypotheses Analysis' Results

5- Contribution of the Study

Armed with insights into these influential factors, educational institutions in Oman stand poised to create environments that foster Generation Z's communication and adoption of cloud-based applications. Such initiatives promise to enrich the pedagogical process, offering students a more effective and engaging learning journey. In addition, cloud-based solutions provide adaptable content, interactive lessons, and real-time feedback, encouraging participation and autonomy in learning.

Educators and institutions can leverage these insights to tailor teaching methodologies and curricula, ensuring they resonate with and support Generation Z students effectively. Accomplishing this may necessitate providing educators with adequate training and resources to seamlessly integrate AI and Cloud-based applications into their teaching practices, along with infrastructural upgrades to facilitate smooth implementation. It is hoped that by using AI, cloud-based applications, and tools, educators can empower Generation Z to thrive in the digital age, unleash their creativity, and become lifelong learners armed with the skills and mentality to navigate an ever-changing environment. Furthermore, for Generation Z students, prioritizing user-friendly platforms that are intuitive and easy to navigate is paramount. Clear instructions and resources on effective application usage can significantly enhance their learning experience and foster collaborative and interactive environments where students can engage with peers and instructors.

Last but not least, AI and cloud-based applications provide Generation Z with crucial abilities for the future job, such as critical thinking, problem solving, and digital literacy. Hands-on experience with AI-powered tools, coding platforms, and virtual reality simulations prepares Generation Z for professions in emerging industries such as artificial intelligence, data science, and cybersecurity.

6- Conclusion

In unraveling the intricacies of Generation Z's engagement with AI and Cloud-based applications within Oman's higher education landscape, this study has unearthed valuable insights. By delving into factors like behavioral intention, effort expectancy, facilitating conditions, e-cloudAD, performance expectancy, and social influence, we have gained a deeper understanding of how these elements influence Generation Z's acceptance and adoption patterns of AI Cloud-based applications and tools in their learning journey.

Our findings underscore the pivotal role of users' behavioral intentions (BI) in driving the acceptance and adoption of cloud-based e-learning applications. Notably, social influence (SI) and the expectation of effort (EE) emerged as potent influencers of behavioral intentions, while facilitating conditions (FC) were found to impact both behavioral intentions (BI) and the activation of e-cloudAC for cloud-based e-learning application adoption. Surprisingly, performance expectancy (PE) did not significantly influence behavioral intentions (BI), suggesting that users' performance expectations may not be the primary driver of their intentions toward cloud-based e-learning applications.

While our study sheds light on critical insights, it is not without limitations. The sample size may affect the generalizability of our findings, and the specific context of our study could also be a limiting factor. Gender differences were not explored, and our data was confined to Oman, limiting its broader applicability. In the realm of future research, there are a wealth of avenues to explore. Researchers could delve deeper into the specific effects of different communication methods and seek to optimize the use of AI and Cloud-based applications for Generation Z students. Furthermore, exploring gender differences in the usage of these applications and conducting comparative studies across different GCC countries hold promise for enriching our understanding of Generation Z's interaction with technology in the educational sphere. By embracing AI and cloud-based apps, Oman can modernize its education system, improve learning results, and empower students and instructors to thrive in the digital age. To realize the full potential of these advances in Omani education, infrastructure constraints must be addressed, teacher training investments made, and fair access to technology ensured.

7- Declarations

7-1- Author Contributions

Conceptualization, T.H. and S.A.M.Y.; methodology, T.H. and S.A.M.Y.; software, S.A.M.Y., I.E., and A.R.; validation, A.R., S.A.M.Y., and T.H.; formal analysis, A.R., I.E., and T.H.; investigation, S.A.M.Y., T.H., and I.E.; resources, A.L. and T.H.; data curation, I.E., S.A.M.Y., and T.H.; writing—original draft preparation, T.H. and S.A.M.Y.; writing—review and editing, S.A.M.Y., T.H., and I.E.; visualization, I.E. and A.L.; supervision, A.L.; project administration; T.H., A.L., and I.E. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

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7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Prior to participating in this study, all participants provided informed consent. They were briefed on the study's objectives, procedures, and their rights as participants. Participation was voluntary, and individuals could withdraw from the study at any time without facing any consequences. All data collected were treated with strict confidentiality, and participant anonymity was maintained throughout the research process. Participants consented to the utilization of their data solely for research purposes. Additionally, to uphold confidentiality and ethical standards, no personally identifiable information, such as email addresses or telephone numbers, was collected as part of the survey.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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Appendix I

Appendix a. Research Questionnaire:

Table A. Survey Questionnaire items

Latent Variable	Item/indicator	Coding
Accepting and Adopting AI Cloud-based Applications and Tools (e_CloudAC)	I find AI cloud-based applications and tools preferable for my studies compared to traditional learning methods.	[80]
	I regularly incorporate AI cloud-based applications and tools into my study routine and academic attainment.	
	I am convinced of the advantages of AI cloud-based applications and tools over traditional methods, and I would recommend them to others.	
	I am confident in articulating the benefits of AI cloud-based applications and tools to others.	
Behavioural Intention (BI)	I have extensively utilized AI cloud-based applications and tools for my studies and academic attainment.	[71, 72]
	I am committed to using AI cloud-based applications and tools in my future studies.	
	I am ready to invest effort into utilizing AI cloud-based applications and tools for my studies.	
	I have plans to integrate AI cloud-based applications and tools into my upcoming study sessions.	
	I am inclined to incorporate AI cloud-based applications and tools into my study routine.	
Performance Expectancy (PE)	Using AI cloud-based applications and tools would make learning easier for me.	[81]
	I think that AI cloud-based applications and tools would improve my overall learning experience.	
	I would find AI cloud-based applications and tools useful in my studies.	
	Overall, I think that AI cloud-based applications and tools would be helpful for me in learning.	
Effort Expectancy (EE)	I am confident that using AI cloud-based applications and tools would be straightforward for me.	[77, 78]
	I believe that I can quickly develop proficiency in utilizing AI cloud-based applications and tools.	
	I perceive the use of AI cloud-based applications and tools to be user-friendly.	
	I anticipate minimal mental effort required when using AI cloud-based applications and tools.	
Social Influence (SI)	My family and friends endorse the use of AI cloud-based applications and tools for my studies.	[72, 79–81]
	I receive recommendations from instructors or peers who have successfully utilized AI cloud-based applications and tools.	
	I feel influenced by the widespread use of AI cloud-based applications and tools among my family, friends, instructors, or peers.	
	The opinions of others, including family, friends, instructors, or peers, significantly influence my decision to adopt AI cloud-based applications and tools.	
Facilitating Conditions (FC)	I have access to the necessary technological resources to effectively utilize AI cloud-based applications and tools.	[80, 81]
	The availability of technical support and assistance adequately supports my use of AI cloud-based applications and tools.	
	I find integrating the learning management system (LMS) with intelligent technologies such as AI cloud-based applications and tools easy to navigate.	
	The reliability of the internet connection in my area is sufficient to support the seamless use of AI cloud-based applications and tools.	