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# The Relationship Between Cloud Computing Factors and Cloud Computing Behavioral Intention of First-Year University Students

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This is to certify that the doctoral dissertation by

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has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
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Walden University
2026

Abstract

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Intention of First-Year University Students

by

Gabriel Albino

MA, The Open University, UK, 2010

BS, Agostinho Neto University, 2007

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

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Abstract

In an era where vast amounts of data are generated daily, the ability to manage information through cloud computing has become critical; however, asymmetries in using this technology persist, particularly in developing countries. Academic managers often lack information about the factors influencing cloud computing usage. The purpose of this quantitative correlational cross-sectional study was to examine the relationship between cloud computing factors, including effort expectancy (EE), performance expectancy (PE), social influence (SI), and facilitating conditions (FC), and the first-year university students' cloud computing behavioral intention (CCBI) in the developing country of Angola. A structured questionnaire was administered to a random sample of 195 first-year university students. The unified theory of acceptance and use of technology (UTAUT) was used to create a research model, incorporating EE, PE, SI, and FC as predictor variables of CCBI. The results of the multiple linear regression model were statistically significant, $F(4, 190) = 24.05$, $p < .001$, explaining 33.6% of the variance in CCBI. Individually, EE, PE, and SI emerged as significant positive predictors of CCBI, whereas FC demonstrated a weaker, more indirect influence. Understanding this relationship could help academic managers design targeted policies and frameworks to enhance cloud computing usage in educational settings where the technology is still emerging in the current digitized world. The implications for positive social change include the potential for university leaders and policymakers to reinforce the UTAUT's relevance in guiding their technology implementation strategies in diverse educational environments, thereby improving the quality of life for individuals and communities.

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## Dedication

I dedicate this work to all my family, who patiently supported me throughout my study.

Acknowledgments

I am indebted to several individuals who directly or indirectly supported me in having this dissertation accomplished. First, I thank my professors at Walden; they gave me seminal management and methodological knowledge to understand the requirements of various aspects of the degree, to the extent that I have successfully completed this dissertation. Second, I thank my family, especially my younger children, who missed me in the evenings when I was engaged with my studies. To my spouse, I would have no words to describe the patience she had to take care of me when I was exhausted. Finally, but not least, I owe a debt of gratitude to my all-mighty God, who gave me the health and strength to face my studies from the coursework, prospectus, research proposal, to the dissertation stage.

Table of Contents

List of Tables

List of Figures

# Chapter 1: Introduction to the Study

The overarching topic of the present study is cloud computing. Cloud computing is a delivery of information technology resources over the internet, allowing users to access services such as computing power, storage, and databases from a cloud provider (Shahbaz & Zahid, 2022; Thavi et al., 2021). Cloud computing can be private, public, or hybrid, and can serve various societal strata (Karamujic, 2025; Verma et al., 2022). Technology produces unprecedented volumes of data, which make the use of traditional system of managing information incompatible (Gopal et al., 2024; Shahbaz & Zahid, 2022), and cloud computing can be a solution. Cloud computing serves several purposes, including information systems management.

Cloud computing also presents challenges such as complexity, performance expectations, and security. Consequently, various studies have been conducted to explore and examine factors relating to its usage and adoption (Aliyu et al., 2024; Kabra et al., 2023; Song, 2022). However, research in developing countries is scarce (Abdallah et al., 2024), and usage rates vary across regions (Karamujic, 2025; Tripathy et al., 2023; Tudor et al., 2025).

The purpose of the present quantitative study was to examine the relationship between existing cloud computing factors, such as effort expectancy and performance expectancy (Matar et al., 2020; Venkatesh et al., 2003), and the first-year university students’ intention to use cloud computing in Angola. My goal for this examination was to support academic managers in creating policies and frameworks for encouraging cloud computing usage and promoting positive social change; not only may students be able to collaborate at the academic level but may also collaborate with family and friends. This chapter includes the background, problem statement, purpose, research question, hypotheses, theoretical foundation, nature, definitions, assumptions, scope, delimitations, and limitations of the study. The chapter ends with a discussion of the significance of the study for theory, practice, and positive social change, including a summary and transition to the next chapter.

## Background of the Study

Information management has become a concern in recent years, requiring interventions and research to understand the supporting mechanisms. Sequeira et al. (2024) contended that higher education institutions experience the challenge of managing a considerable amount of data in the current technological era. These researchers proposed the development of a business intelligence system to meet the requirements and specificities of higher education institutions. Bin (2024) undertook a similar intervention in higher education and developed a system based on cloud computing to enhance the practicality and efficiency of college students taking vocational programs. These interventions demonstrate that researchers have acknowledged the challenges of information management and have started to create mechanisms for supporting higher education institutions in the current digital era.

Whereas considerable interventions have been undertaken to alleviate the challenges of information management, technology usage is often resisted. In the Ethiopian educational context, Hiran and Dadhich (2024) discussed that students and faculty members tend to resist change from traditional methods of information management to using cloud-based technologies. In a related study, in the Indian educational context, Wairiya et al. (2022) discussed that the emergence of mobile cloud technology creates opportunities for teachers to enhance students' learning, but teachers and students tend to resist the adoption of such technology. Many other studies have included the discussion of technology resistance in educational contexts, such as Yadegaridehkordi et al. (2020) in Malaysian universities, Matar et al. (2020) in Jordan universities, and Aruleba et al. (2022) at an institution of higher education in South Africa. Resistance concerns have motivated researchers to conduct studies to understand mechanisms supporting the usage of information systems, including cloud computing.

Cloud computing research is asymmetrical across the globe and requires considerable attention in developing countries. In their study examining the adoption of cloud computing in higher education institutions in Yemen, Alghushami et al. (2020) noted that cloud computing was comprehensively researched, but the most focus was placed on developed countries. In a related study, Hiran and Dadhich (2024) underscored the numerous advantages of cloud computing, such as information dissemination and work facilitation in organizations but stated that cloud computing research was mostly conducted in industrialized nations. Researchers, such as Shahbaz and Zahid (2022) in Pakistan and Thanh et al. (2020) in Vietnam, expressed similar reservations. These concerns indicate strong arguments for the need to conduct research in developing countries, including Angola, to understand factors relating to cloud computing usage.

The discussion of the asymmetries in investigating cloud computing has highlighted the scarcity of research in education, mainly in institutions of higher education. Abdallah et al. (2024) underscored the relevance of mobile learning applications in institutions of higher education and lamented that the widespread adoption of such technology within university institutions remained scant in developing countries. Al-Hajri et al. (2021) acknowledged the flourishing of higher education institutions regarding the usage of cloud computing but stated that there was still a serious shortage of cloud computing literature in the Arab regions. Similarly, Alghushami et al. (2020) stressed that very little was known regarding factors influencing cloud computing usage in less developed countries, mainly in Yemen. An even more interesting piece of evidence regarding the scarcity of cloud computing research in higher education was pointed out by Hiran and Dadhich (2024). These researchers stated that only 32% of universities in Africa had implemented cloud computing by 2022. Again, the evidence provided in the previous studies indicates a need to maximize research on cloud computing usage in developing countries, including Angola, mainly in higher education institutions.

## Problem Statement

The underlying issue for searching the literature in the present study was that higher education institutions experience a challenge with information management and require sophisticated virtual storage and collaborative devices (Clissa et al., 2023; Yunlong & Jie, 2024). In a survey, Silverglate and Jarvis (2022) found that 45% of the participants expressed concerns about information management. Sillence et al. (2023) analyzed the negative consequence of digital information accumulation and found that data overload was among the problems students experienced. In turn, digital data overload caused productivity loss, anxiety, and being overwhelmed. This problem may become even more pronounced for first-year university students who enter a new educational system, requiring them to manage large amounts of data. The social problem is that first-year university students in developing countries, specifically in Angola, are not supported with policies and frameworks of factors, such as effort expectancy, performance expectancy, social influence, and facilitating conditions (Matar et al., 2020; Venkatesh et al., 2003) related to cloud computing behavioral intention.

Although researchers have investigated this issue, the topic has not been explored in this way: Abdallah et al. (2024) indicated that cloud computing adoption within developing country universities was limited and proposed a model that could be tested in different developing countries, focusing on constructs such as social influence and facilitating conditions. Whereas some research has been undertaken in developing countries (Hiran & Dadhich, 2024; Khayer et al., 2021), no studies have examined the relationship between cloud computing factors (e.g.: effort expectancy and performance expectancy) and cloud computing behavioral intention of first-year university students in Angola. Thus, the present study addressed such a gap by extending the unified theory of acceptance and use of technology (UTAUT) to support academic managers in higher education institutions in Angola in creating policies and frameworks of cloud computing factors for encouraging first-year university students to use cloud computing. The specific research problem that was addressed through this study is that academic managers in developing countries, specifically in Angola, lack information concerning cloud computing factors, including effort expectancy, performance expectancy, social influence, and facilitating conditions, related to cloud computing behavioral intention of first-year university students, preventing them from developing policies and frameworks to support efficient data management and collaboration.

## Purpose of the Study

The purpose of this quantitative correlational study was to examine the relationship between cloud computing factors, including effort expectancy, performance expectancy, social influence, and facilitating conditions, and the first-year university students' intention to use cloud computing (cloud computing behavioral intention) in a developing country, specifically in Angola. The result indicated which of the cloud computing factors academic managers in higher education can utilize to create policies and frameworks for encouraging first-year students' intention to use cloud computing.

## Research Question and Hypotheses

The present study included the following research question:

Research Question (RQ): What is the relationship between cloud computing factors and the first-year university students' cloud computing behavioral intentions in Angola?

Null hypothesis ($H_0$): There are no relationships between cloud computing factors and the first-year university students' cloud computing behavioral intention in Angola.

Alternative hypothesis ($H_1$): There are relationships between cloud computing factors and the first-year university students' cloud computing behavioral intention in Angola.

Finding a response to this research question was essential because first-year university students start a new academic journey, which may be more challenging regarding information management and collaboration than that of high school (Akhtar & Akhtar, 2025; Venezia & Jaeger, 2013; Xavier & Meneses, 2022). At a university level, students are engaged in more extensive writing assignments and collaboration with peers and professors. Additionally, most of them start job commitments, and face-to-face collaboration may be challenging. Therefore, socializing them in cloud computing usage from the entrance level may ensure they are prepared to cope efficiently with the burden of information management and collaboration.

Analyzing this main alternative hypothesis leads to more specific alternative hypotheses, which are presented next based on the key constructs: effort expectancy, performance expectancy, social influence, and facilitating conditions. Many researchers found that effort expectancy has a direct influence on behavioral intention (Abdallah et al., 2024; Alfalah, 2023; Aliyu et al., 2024; Khayer et al., 2021). On the other hand, a few other researchers identified that effort expectancy exhibits no direct effect on behavioral intention (Al-Okaily et al., 2023; Alotumi, 2022; Masadeh et al., 2024; Matar et al., 2020). These discrepant findings suggest that some or all effects of effort expectancy on behavioral intention may be realized through mediation, and this hypothesis is yet to be examined.

Like effort expectancy, performance expectancy received considerable attention among researchers, and its effect on behavioral intention was found positive (Abdallah et al., 2024; Aliyu et al., 2024; Masadeh et al., 2024; Matar et al., 2020). However, a study indicated that performance expectancy has no direct effect on behavioral intention (Alotumi, 2022). Because the majority of the studies portrayed a direct positive result, performance expectancy is hypothesized to have a direct positive effect on behavioral intention in the present study.

Effort expectancy and performance expectancy have a linkage with perceived ease of use and perceived usefulness, respectively, and considering the four constructs is essential in stating hypotheses. Indeed, effort expectancy and performance expectancy were partly derived from perceived ease of use and perceived usefulness in the technology acceptance model (Taherdoost et al., 2024; Venkatesh et al., 2003). Because the influence of perceived ease of use on information technology usage is mediated by perceived usefulness (Dwivedi et al., 2019; Lin & Yu, 2023), a hypothesis is formulated in the present study that the effect of effort expectancy on behavioral intention is partially or fully mediated by performance expectancy.

*Alternative hypothesis* ($H_{1.1}$): Effort expectancy is positively related to cloud computing behavioral intention.

*Alternative hypothesis* ($H_{1.2}$)*:* Effort expectancy is positively related to performance expectancy.

*Alternative hypothesis* ($H_{1.3}$): Performance expectancy is positively related to cloud computing behavioral intention.

The influence of facilitating conditions on behavioral intention has been widely identified in the literature (Abdallah et al., 2024; Aliyu et al., 2024; Kabra et al., 2023; Wandira et al., 2024), but such an effect is known to be indirect. When they validated the

UTAUT, Venkatesh et al. (2003) found that the effect of facilitating conditions on behavioral intention was mediated by effort expectancy, and more recent studies have revealed similar results (Athambawa et al., 2023; Haneefa, 2023). Therefore, the following alternative hypotheses are formulated:

*Alternative hypothesis ($H_{1.4}$)*: Facilitating conditions are positively related to effort expectancy.

*Alternative hypothesis ($H_{1.5}$)*: Facilitating conditions have no effect on cloud computing behavioral intention when effort expectancy is present.

Social influence has also been examined comprehensively, and its influence on behavioral intention has been established (Abdallah et al., 2024; Yadegaridehkordi et al., 2020; Zacharis & Nikolopoulou, 2022). Despite such establishment, other researchers found that social influence does not have a direct influence on behavioral intention (Alotumi, 2022; Matar et al., 2020). In a recent study, Chen et al. (2021) found that social influence affected continuous intention indirectly via performance expectancy. Therefore, the influence of social influence on cloud computing behavioral intention is hypothesized to be partially or fully mediated by performance expectancy in the present study.

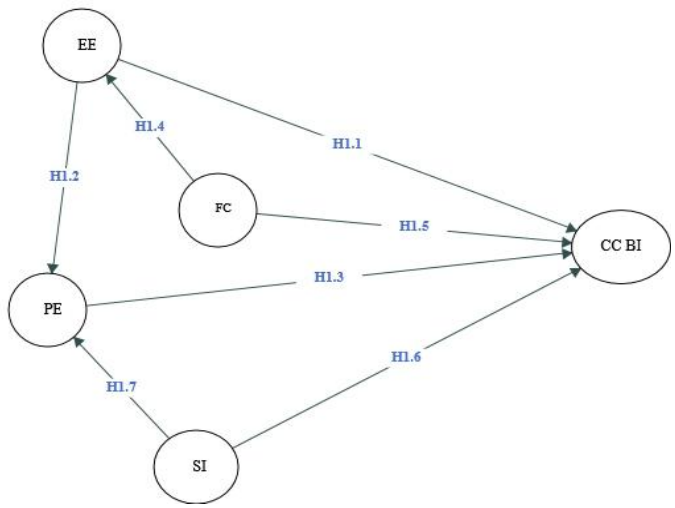
*Alternative hypothesis ($H_{1.6}$)*: Social influence is positively related to cloud computing behavioral intention.

*Alternative hypothesis ($H_{1.7}$)*: Social influence is positively related to performance expectancy.

The hypothesized relationships are graphically represented in Figure 1, and the constructs are abbreviated as effort expectancy (EE), performance expectancy (PE), facilitating conditions (FC), social influence (SI), and cloud computing behavioral intention (CCBI).

**Figure 1**

*The Research Framework Used in the Present Study*




## Theoretical Foundation

The foundation of the present study was Venkatesh et al.'s (2003) UTAUT. This theory stipulates that EE, PE, SI, FC, and behavioral intention are antecedents of the usage behavior of an information system, with behavioral intention mediating the influence of EE, PE, and SI on usage behavior (Venkatesh et al., 2003). The UTAUT further includes the moderating effects of gender, age, experience, and voluntariness of use in the relationship between variables: Gender moderates the relationships between EE and behavioral intention, PE and behavioral intention, and SI and behavioral intention; age moderates the relationship between EE and behavioral intention, PE and behavioral intention, SI and behavioral intention, and FC and usage behavior; experience moderates the relationships between EE and behavioral intention, SI and behavioral intention, and FC and usage behavior. Finally, voluntariness moderates the relationship between SI and behavioral intention. For simplicity, and given the short-scale nature of the present study, the examination consisted of only five constructs, in which case EE, PE, SI, and FC were the predictors of behavioral intention, in light of the research model by Matar et al. (2020).

The logical connections between the research framework and the nature of the present study include Venkatesh et al.'s (2003) UTAUT because this theory has been extensively examined in higher education (Abdallah et al., 2024; Alfalah, 2023; Al-Hajri et al., 2021; Arpaci et al., 2023). Furthermore, the UTAUT is robust because it resulted from a synthesis of eight theories or models (explanation in the next chapter), explaining technology adoption. Venkatesh et al. (2012) reported that, on users' intention to consume information technology, the UTAUT explained 70% of the variance. Consequently, the UTAUT is promising in detecting the relationship between cloud computing factors and first-year university students' cloud computing behavioral intention (CCBI) in the Angolan context.

The UTAUT has been recently extended to include habit, hedonic motivation, and price value in the context of user-consumer (Tamilmani et al., 2021; Venkatesh et al., 2012). This extension suggests that the theory is current and more robust than its initial development, capturing more factors of the adoption of technological information systems. However, given its short-scale nature and in a new context of information systems usage, the present study included only the initial key concepts of the UTAUT in the form that Matar et al. (2020) utilized them, that is, consisting of EE, PE, FC, SI, and behavioral intention.

Several other theories and models exist that could be the foundation for the present study, but the UTAUT is so encompassing that can tap the constructs in other theories or models. One example is the technology acceptance model initially conceptualized by Davis (1989) and later extended by Venkatesh and Davis (2000). This model contains the antecedents of behavioral intention, a construct that is relevant to the present study. Another example is the innovation diffusion theory (Rogers, 1983), which consists of a cyclical process of “invention, innovation, diffusion and adoption or usage” (Oyuga et al., 2023, p. 157). However, all such theories were synthesized into the UTAUT (Venkatesh et al., 2003) and integrating them back into the synthesized theory could appear redundant. For instance, perceived ease of use and perceived usefulness in the technology acceptance model correspond to EE and PE in the UTAUT, respectively (Venkatesh et al., 2003). Similarly, results demonstrability in the innovation diffusion theory could be linked to PE in the UTAUT. Consequently, the UTAUT is such a comprehensive theory that can support in understanding the relationship between existing cloud computing factors and the first-year university students’ CCBI in the Angolan context.

The theories from which the UTAUT was synthesized continue to evolve, and new dimensions are added, as is the example of the modified technology acceptance model by Shahbaz and Zahid (2022). This continuous development of the theories suggests that the UTAUT can still be extended using its original theories. However, the present study is short scale and using an integrated research model could make the research complex, requiring additional effort and time to examine constructs in a particular context. Because an integrated model can lead to a more robust result than one based on a single research approach (Javed et al., 2024), only using the UTAUT in the present study is an important limitation.

## Nature of the Study

The present study consisted of a quantitative correlational research design, aligning with my epistemological and ontological perspectives. According to Burkholder and Burbank (2020), as well as Bryman (2016), epistemology is the belief in how knowledge can be best generated. Some scientists believe that generating knowledge is achieved through a deductive approach (objectivity), whereas others contend that an inductive approach is a better pursuit (subjectivity). In yet another perspective, some scientists contend that combining deductive and inductive reasoning is a way forward to generating sound knowledge (technicality) (Bryman, 2016). Objective epistemology was the underlying perspective in the present study.

Ontology refers to belief about reality and being (Babbie, 2017; Burkholder & Burbank, 2020). Some researchers posit that reality exists independently of individuals so that there is one reality for everyone (objectivity) (Burkholder & Burbank, 2020). In contrast, some researchers argue that reality is socially constructed, so that truth is dependent on individuals' interpretations (subjectivity) (Maxwell, 2013; Ravitch & Carl, 2021). Yet another ontological perspective is that truth can be both dependent on and independent of a researcher in such a way that the researcher can gain more holistic knowledge when considering dual perspectives (technical or holistic) (Bryman, 2016). The basis of the present study was an objective ontological perspective.

Whereas objective epistemological and ontological perspectives underpinned the study, the underlying assumption was that each research design can lead to sound knowledge generation. Using a quantitative research design was the result of the research question in consideration: examining the relationship between cloud computing factors (e.g.: EE and PE) and first-year university students' CCBI in Angola. This research question aligns perfectly with variance theory (Maxwell, 2013; Ravitch & Carl, 2021), requiring a quantitative research design to test hypotheses.

The research model of the present study consisted of four predictor variables and one outcome variable, depicted in Figure 1, using the items from the UTAUT (Venkatesh et al., 2003), mainly as in the study by Matar et al. (2020). More specifically, EE, PE, SI, and FC predicted CCBI. Research indicates that such predictor variables have direct and indirect influences on behavioral intention (Alotumi, 2022; Masadeh et al., 2024); therefore, the research model included direct and mediation analyses.

Participants consisted of an initial random sample of 85 first-year university students, based on a G*Power analysis (Buchner et al., 2024; Memon et al., 2020), and letter extended to 195 to improve statistical power and ensure more reliable estimates of effect size (sample estimation explained in Chapter 3). The research instrument was a structured questionnaire, based on a 5-point Likert scale (1-Strongly Disagree to 5-Strongly Agree), and validation included content and reliability, using alpha (α) and composite reliability equal to or greater than .7 (Abdallah et al., 2024; Hair et al., 2022;

Matar et al., 2020). The performance of a regression analysis to understand the relationship between relevant cloud computing factors and CCBI (Field, 2024; Warner, 2021) shed light on the dimensions that can support academic managers in higher education institutions in developing countries, specifically in Angola, in creating policies and frameworks for using cloud computing.

## Definitions

The definition of the four predictor variables and the outcome variable follow. The definitions include *cloud computing* because this term can elicit different interpretations.

*Behavioral intention*: the intention to use a system (Athambawa et al., 2023). A user has the behavioral intention to do something if they plan or predict they will do such a thing. Behavioral intention is a psychological condition that ignites the usage of an information system or the performance of an activity (Al-Okaily et al., 2023).

*Cloud computing*: service provided over the internet (Shahbaz & Zahid, 2022; Thanh et al., 2020). Cloud computing services can be public, private, or hybrid. Most public cloud computing services, such as Google Drive, OneDrive, and DropBox, are free (Ghaffari & Lagzian, 2018; Verma et al., 2022).

*EE*: the perception that using a system is free of difficulties (Athambawa et al., 2023; Holzmann et al., 2020). EE is similar to perceived ease of use, in which a user anticipates that employing a system will require minimal efforts (Verma et al., 2022).

*FC*: the perception that support exists for using or learning to use a system (Abdallah et al., 2024). Internet availability and the existence of materials instructing on how to use cloud computing are examples of FC. FC can also refer to knowledge availability to use a system (Matar et al., 2020).

*PE*: the perception that using a system will result in performance gains (Alfalah, 2023; Venkatesh et al., 2003). PE is an extrinsic motivation element, which leads an individual to believe that using a system will result in superior achievements on the job or studies (Matar et al., 2020).

*SI*: the perception that important others consider using a system an essential pursuit (Abdallah et al., 2024; Thanh et al., 2020). Specifically, SI is a motivator for using a system, and this motivator is based on the influence of others who can provide a reward (Al-Okaily et al., 2023; Venkatesh et al., 2003). In a university context, SI can be a result of students perceiving that professors believe that using an information system augments academic success.

## Assumptions

An excellent point from which to start is the definition of an assumption provided by Crawford et al. (2020). According to these authors, an assumption is a taken-for-granted condition serving as the backbone of a study's meaningfulness. An assumption has three attributes: a. showing criticality to a study, b. containing a basis on which the assumption is stated, and c. relating to a procedure that a researcher cannot fully control. On the basis of these attributes, I discuss two assumptions for the present study. First, cloud computing users must have access to a computer or smartphone. This assumption is critical because possessing a computer or smartphone is still a problem in developing countries (Sharp, 2022; Vassilakopoulou & Hustad, 2023). Further, ensuring full possession of such digital devices is the Government's or Ministry of Education's responsibility to create proper policies and interventions. The attribute cannot be controlled in the study.

Second, participants in the present study must understand the meaning of cloud computing. Cloud computing is a technical term and is a new technology (Abdallah et al., 2024; Thavi et al., 2021). Research participants in a developing country may not respond to the survey questionnaire appropriately if they do not understand the meaning of what they are asked to predict or envisage (Bryman, 2016). Whereas efforts can be made to reveal the meaning in the research process, the school is responsible fully for making such a meaning available to students in the first place. Therefore, the assumption that participants in the study must understand the meaning of cloud computing is critical and is related to a procedure to be only partially controlled in the process of the research.

In a quantitative study, assumptions can also be considered from the perspective of the statical test to be used and the characteristics of the data to be generated. Such assumptions differ from the ones described by Crawford et al. (2020). According to Field (2024), statistical assumptions represent a condition ensuring that what a researcher is attempting to perform functions as expected. When using parametric test procedures, such as multiple linear regression and one- or two-way analysis variance, researchers assume that data are normally distributed, exhibit linearity, and do not depict multicollinearity, to mention a few (Field, 2024; Warner, 2021). Researchers can control these assumptions by checking several statistics such as Cook's distance and

Mahalanobis distance (Field, 2024). Therefore, in the present study, a discussion of such assumptions is part of the methodology chapter, mainly in the data analysis plan.

## Scope and Delimitations

The focus of the present study was on examining the relationship between cloud computing factors (EE, PE, SI, and FC) and the first-year university students' CCBI in developing countries, specifically in Angola. The purpose was to identify cloud computing factors that academic managers in higher education institutions could utilize to encourage cloud computing usage, and the research model included a regression analysis (Field, 2024; Walden University, 2018; Warner, 2021). The research site was Angola, and this scope is essential because, being a developing country, Angola is one of the countries still at the early stage of technology usage (Kolade, 2025; Tripathy et al., 2023). Other countries could be part of a larger-scale study, but the present study was short scale and included only one developing country to yield some insights into how the existing cloud computing factors may relate to CCBI.

Within Africa, Angola is still a large space, and more delicate specifications are necessary regarding participants, time, and location (Crawford et al., 2020). Participants were first-year university students. This population was essential because students commence a new academic journey, which may be more challenging than high school education (Kocsis & Molnár, 2024; Marshall et al., 2017; Waterhouse & Samra, 2025). Scoping the study to this level of higher education was essential to ensure that students gain access to tools to succeed in managing information throughout their academic journey and probably beyond. In addition, several sectors exist in Angola, but the focus of the present study was specifically on higher education institutions, and generalizability can be limited to these sectors.

## Limitations

The present study consisted of a quantitative correlational research design within a cross-sectional time horizon, but this research design imposes limitations. One important limitation is that such a design cannot help establishing causality (Bryman, 2016; Saunders et al., 2023; Tharenou et al., 2007). This type of design supports observing or collecting data from cases at only one point in time (Bryman, 2016), obtaining a portion of data rather than acquiring historical data that could help establish systematic observation (Bryman, 2016; Saunders et al., 2023). Consequently, the research design in the present study can highlight associations or correlations but cannot definitively indicate that one variable causes a change in another. Addressing this limitation in the present study entailed plotting variables in such a way that the direction of the relationship is discernible (Bryman, 2016), that is, expecting that behavioral intention causes relevant cloud computing factors is unlikely. Further, regression analysis was the measure for addressing such a limitation in a process referred to as “statical control” (Warner, 2021, p. 64), that is, examining one variable while controlling for the other.

Another limitation of quantitative design in a cross-sectional time horizon is the presence of cohort effects. Cohort effects can occur when differences between participants or groups are not attributed to the variables being examined but rather to characteristics unique to individuals or groups themselves, such as cultural background, age, or life experiences (Liang, 2024; Yang & Yu, 2024). This limitation pertains to demographic variables and minimizing it in the present study consisted of exploring age, gender, possession of a smartphone, and possession of a laptop computer.

## Significance of the Study

Cloud computing is a contemporary practice of managing information in the current digital era, in which unprecedented volumes of data are produced daily. The on-premises devices are no longer compatible with the current massive data production, and cloud computing is one of the identified solutions (Taufiq-Hai et al., 2021). In contrast, cloud computing investigation in developing countries is limited (Abdallah et al., 2024; Al-Hajri et al., 2021; Hiran & Dadhich, 2024; Khayer et al., 2021). Although some studies have been conducted, efforts in the Angolan context are scant. As a result, the present study was conducted in the Angolan context, mainly in a higher education institution, to generate insights into the cloud computing factors relating to CCBI of first-year university students. The study contributed to theory, practice, and positive social change, as detailed in the next sections.

### Significance to Theory

The present study extended the UTAUT by examining the relationship between cloud computing factors (e.g.: EE and PE) and CCBI of first-year university students in a developing country, specifically in Angola. The UTAUT has been extensively used in several contexts, such as South Korea (Song, 2022), Bangladesh (Khayer et al., 2021), Maylasia (Amron et al., 2021), and Palestine (Abdallah et al., 2024), but its employment in the Angolan context is scant. As Halkias and Neubert (2020) discussed, the process of applying a theory to a new setting is commonly known as theory extension. This extension entails adapting a pre-existing theory to an alternative environment to ascertain its validity or determine if modifications are necessary. More specifically, Dissanayake (2015) emphasized that theory extension is a significant method for generating original knowledge and enhancing current theories, a point that resonates with Tong and An (2023), as well as Leong et al., 2022) (2022). As a result, the use of the UTAUT in the Angolan context was an essential extension, which can indicate how the theory holds in a particular developing country context.

The extension of the UTAUT in the present study was in the form utilized by Matar et al. (2020) in a university context in Jordan. This author found that whereas PE and FC were antecedents of behavioral intention, EE and SI had no effect on behavioral intention. The theory, therefore, did not fully hold in the Jordanian university. The examination of the relationship between the relevant cloud computing factors and CCBI in the present study indicated how the theory holds in the Angolan university contexts. Mainly, the research model revealed which cloud computing factors academic managers can utilize to create a framework for incentivizing cloud computing usage among first-year university students.

**Significance to Practice**

The practice of cloud computing in the Angolan context is limited. Angola is a developing country, and this context is known to be lagging in technology usages, including cloud computing (Alfalah, 2023; Masadeh et al., 2024). Although some studies on cloud computing have been conducted in developing countries (Abdallah et al., 2024;

Hiran & Dadhich, 2024; Yadegaridehkordi et al., 2020), no research has been identified in the Angolan context to date. The present study generated knowledge to contribute to the practice of cloud computing in the Angola context, and probably beyond. Specifically, the research provided university officials and policymakers with insights into the information required to assist students in becoming efficient information systems managers in the current digitized world. Academic managers and IT professionals in the research setting may understand relevant factors relating to CCBI and create a framework to support students in maximizing their capabilities to manage information and collaborate with peers and professors more efficiently.

Cloud service providers may also benefit from the findings from the present study. By recognizing the constructs leading to CCBI and mitigating possible constraints, cloud service providers can augment their offerings, elevate consumer satisfaction, and expand their market share (Stieninger et al., 2022; Taufiq-Hai et al., 2021). Cloud services are free to a certain extent and can involve costs when the free plan is exhausted. For example, Google Drive currently offers 15 gigabytes of free storage, and users exceeding this storage capacity incur costs. Cloud service providers may attract more users with a paid plan among university students if these students' capabilities are enabled by enhancing factors leading to usage.

## Significance to Social Change

The outcome of the present study may provide support for enhancing positive social change. Cloud computing demonstrates versatility by allowing anyone with the internet access to use such an information system (Shahbaz & Zahid, 2022; Thanh et al., 2020). This possibility leads to good societal transformation because students obtain a digital tool for their study and future workplace. In addition, students may use a technological information system in their homes and communities. Indeed, cloud computing is now regarded as a part of people's daily lives (Sharma et al., 2020; Yunlong & Jie, 2024). Students can soon learn how to use cloud computing to collaborate with one another, their professors, family, and friends. They can form communities of practice and participate in other social activities relevant to their community. The outcome of this study links to Yob and Brewer’s (2018) argument about the common good, which constitutes an essential parallelism to a positive social change. The outcome also resonates with Reupert (2023), who contends that research contributing to positive social change helps improve the life quality and wellbeing of communities and individuals. Students may have their burden of information management reduced and be provided with a tool to interact with others in any environments.

## Summary and Transition

This chapter has included the rationale and initial implementation for the present study. Further, it has consisted of a background of the study, highlighting the concern with information management in the current digital era. The chapter has entailed an analysis of the interventions to the concerns regarding information management, as well as considering that cloud computing is still resisted, requiring continuous research in different contexts. The social and specific research problems have been central to the problem statement, linking to the purpose of the study, which is to examine the relationship between relevant cloud computing factors and first-year university students' CCBI in the Angolan context.

This chapter has also described the research question and related hypotheses, including the theoretical foundation. It has explained the operationalization of constructs and preliminary information to the methodology section by discussing the nature of the study. The sections on definitions, assumptions, scope and delimitation, and limitations has followed to provide information that can help readers focus when reading the present dissertation. The final section has discussed the significance of the study for theory, practice, and positive social changes. The next chapter substantiates the rationale and initial implementation by examining, analyzing, and discussing existing knowledge to establish the foundation for the study.

# Chapter 2: Literature Review

Students in higher education institutions face problems with information management. Sillence et al. (2023) examined the adverse effects of digital information accumulation and identified data overload as one of the challenges students faced. Sillence et al. discovered that the overload resulting from digital data reduced productivity, heightened anxiety, and caused the feelings of being overwhelmed. Several other studies have expressed concerns regarding the need to support students with information management in higher education institutions, mainly in developing countries (Abdallah et al., 2024; Hiran & Dadhich, 2024; Khayer et al., 2021), but efforts in the Angolan context are scarce. Academic managers in this context lack information regarding factors they can use to create a framework for encouraging cloud computing usage.

The purpose of the present study was to examine the relationship between cloud computing factors (e.g., EE and PE) and first-year university students' CCBI in developing countries, specifically in Angola. This chapter proceeds as follows. First, I present the literature search strategy and describe the theoretical foundation. Then, I perform an exhaustive review of the extant literature and end the chapter with a summary and conclusions of essential themes emerging from the literature.

## Literature Search Strategy

The specific databases that I used were ProQuest, Science Direct, EBSCOhost, SAGE Journals Online, and Google Scholar. I used these databases because they returned a considerable number of papers when I entered some keywords of the study, such as *cloud computing* and *behavioral intention*, as I describe in detail in this section. According to Theile and Beall (2024), as well as Phillips and Barker (2021), databases relevant to a study's research question must be prioritized when searching the literature. The fact that the databases returned several research papers suggests that such data sources were relevant to the present study's research question.

The starting point for searching the literature was the Walden University online library search engine, mainly the advanced search facility. This facility contains delimiters regarding peer-reviewed materials, academic journals, and research published within a time frame, such as from 2020 to 2025, which are helpful in scoping the literature search (Phillips & Barker, 2021; Theile & Beall, 2024). Subsequently, I used Google Scholar for additional materials. Other free search engines exist (besides Google Scholar), such as Semantic Scholar, RefSeek, and Science.Gov (Paperpile, n.d.), but for the sake of research information quality, I retrieved all the papers using Walden University's online library search engine, with only a few from Google Scholar.

To initially set the inclusion and exclusion criteria, I followed the literature search process outlined by Theile and Beall (2024). I included studies if they investigated cloud computing, adopted correlational or experimental design, were quantitative, were conducted in a developing country, were published in the last 5 years (starting from 2020), were peer-reviewed, and were published in English. Establishing such criteria at the outset characterizes a systematic literature review, in which studies using similar populations and methods are synthesized to identify patterns and trends, as well as advance knowledge in a given domain (Hook et al., 2024; Theile & Beall, 2024).

Therefore, the literature review in the present study resulted in comprehensive preliminary insights into how relevant cloud computing factors might relate to first-year university students' CCBI in a developing country, specifically Angola, creating an initial foundation for supporting academic managers with the knowledge they need to encourage cloud computing usage.

A systematic literature review approach requires a team effort and may cause considerable limitations when used on an individual basis. Theile and Beall (2024) underscored the need for researchers to consider a team of at least two participants or collaborate with a librarian in the process. Similarly, Phillips and Barker (2021) suggested that a team of a minimum of three researchers should be considered for a systematic literature review. Phillips and Barker further indicated that fulfilling all the methodological requirements for a systematic literature review was impossible and suggested that the approach should be described as a review containing "systematic literature searches" (p. 350). In the present study, I leveraged this description to harness the robustness of the systematic literature review approach while conducting research on an individual basis. I made a subscription to receive regular alerts on cloud computing research in developing countries and captured as many relevant papers as possible during the literature review process.

After establishing the inclusion criteria, I initialized the process for searching articles. The first keywords I used were *cloud computing*, *education*, *developing countries,* and *behavioral intention*. Within the online library, I combined these keywords using the logical operator AND, and the search returned 45 records of which 20 appeared on the first page. Before refining the keywords for a second search, I scanned the titles of the articles retrieved to determine which ones to retain at this point in the process. Of the 20 articles appearing on the first page, I retained 16. Searching other pages resulted in five more articles, and the initial search overall returned an output of 21 relevant articles.

In the second search, I refined the keywords to include *cloud computing adoption*, *cloud computing usage*, *education* OR *higher education*, and *correlational* OR *Experimental*. To search with this refinement, I used logical and Boolean operators: *cloud computing adoption* AND *education* OR *higher education* AND *correlational* OR *Experimental*. This search returned only 12 records, of which only two were new. The other 10 had already appeared in the previous search.

Furthermore, I located more specific databases to continue searching and refining the keywords, such as *utilization, quantitative, data storage*, *data management*, *information sharing*, *predictor variables*, and *outcome variables*. I used these additional keywords together with *cloud* or *cloud computing* and retrieved as many quantitative articles as possible on the topic of cloud computing. The final stage of the article search consisted of the process referred to as *snowballing* (Theile & Beall, 2024; Zahedi et al., 2016). That is, I checked the reference lists of each relevant article to find the papers that were cited and that were relevant to the present study. The overall search resulted in 50 relevant articles, which I discuss thoroughly in the literature review section of this chapter.

## Theoretical Foundation

The foundation of the present study is the UTAUT by Venkatesh et al. (2003). This theory originated from the need to support researchers with a comprehensive research framework, incorporating knowledge from various research models of information systems adoption or usage (Kabra et al., 2023; Khayer et al., 2021; Song, 2022). As Venkatesh et al. (2003) commented, explaining users' adoption of new information systems is invariably considered as one of the established research fields, and various models have been developed. Researchers face the challenge of choosing from existing research models and eventually picking one they favor, disregarding the contributions from other theoretical models. The UTAUT was developed to comprehensively explain behavioral intention and usage, considering the contribution of various research models.

The UTAUT resulted from a synthesis of eight theories or models: the theory of reasoned action (Fishbein & Ajzen, 1975), the theory of planned behavior (Ajzen, 1985), the innovation diffusion theory ( Rogers, 1983), the model of personal computer utilization (Thompson et al., 1991), the social cognitive theory (Bandura, 1986), the motivation model (Davis et al., 1992), the combination of the technology acceptance model and the theory of planned behavior (Ajzen, 1985), and the technology acceptance model (Davis, 1989). In the next part of this section, I describe these theories to provide a background for the choice and extension of the UTAUT in the present study.

The theory of reasoned action (Fishbein & Ajzen, 1975) stipulates that individuals' behaviors are conditioned by intentions. This theory consists of two constructs: subjective norm and attitude toward behavior (Alhazmi, 2024; Rahmayanti et al., 2021). Subjective norm is the influence of a social milieu on an individual’s intention to behave, and the attitude toward behavior is the drive that could lead an individual to create an intention. This proposition was demonstrated by Kabra et al. (2023), finding that attitude predicts continued behavioral intention to use cloud computing. These two constructs could influence students’ intention to use cloud computing in the context of the present study.

The theory of planned behavior (Ajzen, 1985) is an extension of the theory of reasoned action. Ajzen added the concept of perceived behavioral control, which is a person’s belief that they can control behavior or that performing the behavior is easy or difficult (Ajzen, 1985; Taufiq-Hai et al., 2021). Perceived behavioral control, subjective norms, and attitudes toward behavior could, therefore, probably influence cloud computing behavioral intention in the context of the present study.

The innovation diffusion theory by Rogers (1983) states that an individual’s subjective perspective, rather than an external impulse, influences the usage of a new technological innovation. The key theoretical concepts are relative advantages, observability, complexity, trialability, and compatibility (Wang & Lin, 2019). The relative advantage is the perception that a new system helps achieve better results than the ones obtained when using an existing system (Rogers, 1983; Wang & Lin, 2019). In the present study, students’ perception of relative advantages could be their understanding that cloud computing leads to better results than those achieved when utilizing existing study resources.

Observability, complexity, trialability, and compatibility are described as follows. Observability is the evidence of improvement due to using an information system (Kratzke, 2022; Wang & Lin, 2019). Students could likely intend to use cloud computing if they observed that their friends or other individuals using the technology were thriving. Complexity is like perceived behavioral control because this construct relates to the perception of how easy or difficult a system is (Ajzen, 1985; Taufiq-Hai et al., 2021). Trialability is the perception individuals may have that they can experiment with an information system. Students could perceive that they can try cloud services, such as Google Drive and DropBox. Finally, compatibility is the perception that a new system bears a resemblance to an existing system, thus facilitating transition. Students who use their laptop computers to create files may find some compatibility with creating files in OneDrive.

The model of personal computer utilization (Thompson et al., 1991) consists of factors such as ease of use, relative advantages, long-term outcomes, complexity, and job fit, which are deemed to predict the usage of information system (Fen & Ping, 2024; Wamuyu, 2022). Except for the long-term outcome, the concepts of the model of personal computer utilization are similar to those of the theory of reasoned action and the theory of planned behavior. For example, Venkatesh et al. (2003) found that the ease of use was similar to perceived behavioral control and complexity. The long-term outcome is the perception that the adoption of information systems has an enduring effect. Participants in the present study could consider using cloud computing to have long-term consequences.

The social cognitive theory (Bandura, 1986) posits that aspects of an individual's knowledge acquisition are intimately linked to the observation of others within social interactions, experiences, and external media impacts. Venkatesh et al. (2003) observed that the model was initially used for computer utilization but could also be examined regarding intention. Key constructs include the following: affect, anxiety, self-efficacy, and outcome expectation. Affect is the liking behaviors, anxiety is an emotional reaction to behaviors, self-efficacy is the judgment of whether a system can be used, and the outcome expectation is the consequence related to behaviors (Compeau & Higgins, 1995; Ratten, 2015). These attributes could lead students in the present study to create an intention to use cloud computing.

The motivation model consists of two constructs: intrinsic motivation and extrinsic motivation (Davis et al., 1992). Intrinsic motivation consists of individuals performing behavior without external incentives; individuals decide by themselves that certain behavior is relevant to their job or study performance. Intrinsic motivation relates intimately to innovation diffusion theory, in which individuals perform behavior as a result of their subjective opinions (Wang & Lin, 2019). In the present study, students exhibiting intrinsic motivation could need no external incentives, such as ease of use and subjective norms, to show an intention to use cloud computing. On the other hand, extrinsic motivation relates to external stimuli (Morris et al., 2022). Students in the present study could intend to use cloud computing if the academic managers proposed awards for those who showed strength in using the technology. The two constructs of the motivational model are promising in understanding behavioral intention.

The technology acceptance model (Davis, 1989) entails perceived ease of use and perceived usefulness as predictors of behavioral intention. Perceived ease of use is the same as the perceived behavioral control in the theory of planned behavior (Ajzen, 1985), signifying the little effort a user has to exert in using a system (Davis, 1989; Lin & Yu, 2023). Perceived usefulness denotes the value a user foresees in intending to use a technological information system, and, according to Venkatesh et al. (2003), this construct is similar to relative advantage in the theories of personal computer utilization and innovation diffusion theory.

To finalize the synthesis, Venkatesh et al. (2003) included the combination of the technology acceptance model and the theory of planned behavior. This inclusion consisted of the attitude toward behavior, subjective norm, perceived behavioral control, and perceived usefulness. With the last inclusion, the UTAUT became robust, the pronouncements of which have been made by several researchers (Kabra et al., 2023; Yadegaridehkordi et al., 2020). Later in this chapter, I will describe the similarity of the UTAUT's constructs and the theories from which the constructs were derived to further highlight the theory's robustness for the present study.

Empirical research has demonstrated the merit of the constructs used to develop the UTAUT, and the results are supportive of the outcome theory's strength. Venkatesh et al. (2003) conducted longitudinal studies with various organizations and employed a questionnaire containing items from the eight theories. The result indicated that the models explained 17% to 42% of the variance in behavioral intention. Furthermore, the percentage increased to 53 after the inclusion of moderator variables. The merit of the constructs in Venkatesh et al.'s synthesis was substantiated in other studies. For example, Sharma et al. (2023) found that the technology acceptance model accounted for 88.1% of the variance in behavioral intention. Similarly, Nur (2022) found that from 2.4 to 49.4% of the planned behavior constructs explained behavioral intention. Therefore, the UTAUT can be said to maintain its strength and is worth being used to examine behavioral intention in other contexts.

Whereas the above research findings appear high, the ones resulting from the validation of the UTAUT research model are even more promising. Venkatesh et al.'s (2003) UTAUT research model consists of four predictors and four moderators of behavioral intention and usage behavior. Predictors are EE, PE, FC, and SI, and the moderators are gender, age, experience, and voluntariness of use. EE, PE, and SI are moderated by behavioral intention, whereas FC has a direct effect on usage behavior. The result of the empirical investigation of the constructs in this model with data from four organizations indicated a superior result (69%) to those of individual theories (between 17% and 53%), and further validation with data from two other organizations revealed even higher results of the UTAUT research model; that is, the UTAUT research model explained 70% of the variance in the behavioral intention and usage. This result indicated the adequacy of the theory in supporting managers in organizations to determine the probability of success for the introduction of an information system, thus enabling them to understand drivers of usage and proactively design interventions to encourage intention and usage.

Venkatesh et al. (2003) identified three strands in information system research, and highlighting these facets may provide additional insights into the reason for choosing the UTAUT in the present study. On one side, researchers investigate technology acceptance at an individual level and strive to understand behavioral intention or actual behavior as the dependent variable. Studies that investigate factors influencing the intention to adopt (Al-Okaily et al., 2023) or use (Khayer et al., 2021) cloud computing are within this first facet. On the other side, researchers have examined the success of information-system implementation as the outcome variable. A researcher investigating the effect of cloud computing on employee productivity focuses on implementation (Daabseha et al., 2023; Khayer et al., 2021). In yet another strand, researchers have assessed task-technology fit (Wamuyu, 2022). The present study was a contribution to such strands of research but its focus was on behavioral intention, more specifically CCBI.

Because one of the UTAUT's focuses is on behavioral intention (Venkatesh et al., 2003), the theory was appropriate for the present study. The foundation was a version of the UTAUT research model in the study by Matar et al. (2020). This version was more appropriate for the present study in that the topic covered is cloud computing, examining five constructs: EE, PE, FC, SI, and behavioral intention, with the first four constructs being predictor variables and the last one being the outcome. Based on this model, the present study generated results that are comparable to previous research in other contexts.

# Literature Review

In line with the purpose of the present study, which was to examine the relationship between cloud computing factors (EE, PE, FC, and SI) and the first-year university students' CCBI in the Angolan context, this section starts with a description of the studies related to cloud computing factors. The section first includes the problems identified regarding the usage or adoption of cloud computing and then a discussion of how previous researchers have approached the problems. Subsequently, it entails an elaboration of the rationale for choosing the variables in the study and a revision and synthesis of the studies pertaining to such variables, including the ones pertaining to hypotheses. The section ends with an evaluation of the studies to highlight the implication for the research question and provide a summary of the main themes and a description of how the present study addressed the gaps that were identified.

## Studies Related to the Constructs of Interest

Within the UTAUT by Venkatesh et al. (2003), the constructs of interest in the present study were EE, PE, FC, SI, and behavioral intention. These constructs were extensively explored or examined in previous research to identify problems and find solutions related to cloud computing usage or adoption in different parts of the globe. Examples are studies by Aliyu et al. (2024) in Nigeria, Masadeh et al. (2024) in Jordan, Thanh et al. (2020) in Vietnam, Alfalah (2023) in Saudi Arabia, and Kabra et al. (2023) in India. In this section, I describe and analyze these and other studies to understand the constructs and provide a background for the present study. Initially, I clarify the usage and adoption because these terms differ; researchers can examine behavioral intention to adopt cloud computing (Abdallah et al., 2024) or behavioral intention to use cloud computing (Khayer et al., 2021). Clarifying these terms may minimize readers' ambiguities throughout this paper when encountering the description and analysis of the problems and solutions to cloud computing usage.

**Cloud Computing Usage and Adoption**

Usage and adoption are different concepts in cloud computing research. Usage entails understanding how users engage with a piece of software or any other system (WalkMe Team, 2023). According to the WalkMe Team, frequency and purpose are essential concepts for understanding usage, and analytics can help monitor how often users open a software application, how many events occur when they use software, and how users interact with the software application. Wikler and Cristo (2025) have equally captured this concept using the term *implementation*, which entails the installation and configuration of a technological information system in an organization. When embracing cloud computing at an early stage, students may not fully employ the capabilities and features of the software. Researchers may need to understand adoption at a later stage.

Adoption is how completely users employ a piece of software; software development has a purpose, and users must fully accomplish that purpose by using the software for the adoption to occur (WalkMe Team, 2023; Wikler & Cristo, 2025). In this conceptualization, adoption is a subsequent phase of embracing technological information systems, and researchers have extensively investigated such a concept (Abdallah et al., 2024; Aligarh et al., 2023; Khayer et al., 2021; Sharma et al., 2023). Succinctly, researchers can examine behavioral intention to use or adopt cloud computing. In the present study, behavioral intention references an antecedent of either usage or adoption. The argument is that a supportive framework of factors, such as EE, PE, FC, and SI, should be put in place to enable academic managers in higher education institutions to ascertain cloud computing usage and adoption.

**Problems Regarding Cloud Computing Usage or Adoption**

Previous research directly or indirectly examined essential constructs of the present study to address problems related to cloud computing usage or adoption, and one of the constructs is resistance. In the Nigerian context, Aliyu et al. (2024) stated that evidence existed regarding the power of cloud computing in rendering organizations efficient and competitive, but several organizations continued operating without such a technological information system. Similarly, in Jordan, Masadeh et al. (2024) underscored the benefits organizations could have in utilizing cloud computing and lamented that many organizations still utilized traditional methods. One essential comment was by Ploysuayngam and Tangwannawi (2022) in Thailand, stating that students may be reluctant to use cloud computing technology even knowing that such usage is free. These researchers showed considerable concerns regarding the burden of data and cost management and strived to provide support for organizations' effectiveness and competitiveness, examining constructs including EE, PE, FC, SI, and behavioral intention, as I discuss in this section.

Addressing cloud computing resistance is an essential pursuit because organizations, including higher education institutions, experience a burden of information management and collaboration. This argument finds support in Silverglate and Jarvis'

(2022) survey, which indicated that 45% of the participants expressed concerns about information management. The argument is further substantiated in Sillence et al.'s (2023) analysis of the negative consequences of digital information accumulation, finding that data overload was among the problems students experienced. Sillence et al. noted that digital data overload caused productivity loss, anxiety, and being overwhelmed. This problem may become even worse for first-year university students who enter a new educational system, requiring them to manage large amounts of data and collaborate with others. Research addressing the resistance to cloud computing usage or adoption makes an essential contribution to enhancing organizations' information management and collaboration.

Organizations, including higher education institutions, may be denied considerable benefits if they do not use or adopt cloud computing. One benefit is information accessibility at any time in the current digital organizations (Alghushami et al., 2020; Alhazmi, 2024; Assalaarachchi et al., 2022; Thavi et al., 2021). Using cloud computing, individuals in organizations can access information about daily tasks wherever they are, provided they have a smart digital device connected to the internet. A vivid example of this benefit was identified in a study by Alhelou et al. (2021), indicating that cloud computing usage in accounting education supported students and faculty members in retrieving and accessing applications and files at any moment and from any location during the COVID-19 pandemic. An important point still to be made is that cloud computing users can easily access information via private or public internet (Altes et al., 2024), allowing anyone to use cloud computing.

Another benefit of cloud computing that organizations could be denied is data storage and collaboration. Technology usage results in the production of large amounts of data that are too intricate to manage and maintain with on-premises devices, such as desktop computers and external hard drives (Clissa et al., 2023; Saraswathi et al., 2022; Yunlong & Jie, 2024). Indeed, the term big data has been coined, and its attributes have been designated as volume, velocity, variety, veracity, and value (Al-Azzama et al., 2023; Gopal et al., 2024; Verma et al., 2022; Yunita et al., 2022). The volume, velocity, and variety make data so huge that cannot be efficiently managed with on-premises devices; an amalgamation of big data and cloud computing has been suggested to efficiently manage information (Verma et al., 2022). Cloud computing is therefore one of the sophisticated tools for managing large amounts of data and establishing collaboration.

In education, the benefits of cloud computing have been stressed. Aldahwan and Ramzan (2022) pointed out that information communication technology help improve the accuracy and quality of higher education institutions, and these benefits were seen in terms of cost reduction and services availability. According to Thavi et al.(2021), these benefits were even more salient at the time of the COVID-19 pandemic, when most educational institutions were forced to use online facilities to continue performing their activities. Educational institutions that were unable to use cloud services were put to a standstill. Currently, higher education institutions adhering to cloud services have experienced considerable growth by making their services available worldwide, and those resisting the usage are denied such a benefit. Cloud computing offers several benefits, but the ones highlighted in this section appear to stand out, underscoring the essence to address cloud computing resistance.

Whereas cloud computing offers several benefits, an internet-based information system imposes constraints that may cause resistance for prospective and current users. One of the constraints is internet connectivity, which may temporarily limit access to data; prospective users of cloud computing may be inhibited when they perceive such a connectivity-based constraint (Al-Hajri et al., 2021; Hiran & Dadhich, 2024). Prospective users may also be inhibited by the lack of technology literacy (Alghushami et al., 2020; Al-Hajri et al., 2021; Hiran & Dadhich, 2024), security and privacy concerns (Khayer et al., 2021; Matias & Hernandez, 2021; Sharma et al., 2023), and lack of digital devices (Alghushami et al., 2020; Al-Hajri et al., 2021). Research has been focused on finding mechanisms for understanding such constraints from the perspective of behavioral intention to use cloud computing, which could be influenced by factors, such as FC and SI.

The problem of resistance to cloud computing has also been identified regarding current users. Individuals in organizations, including higher education institutions, may stop using cloud computing once they start experiencing issues such as internet connectivity (Al-Hajri et al., 2021; Hiran & Dadhich, 2024), lack of sufficient knowledge to continue using (Alghushami et al., 2020), and lack of qualified staff to provide support (Hiran & Dadhich, 2024; Matar et al., 2020). These problems are thought to emerge due to a lack of understanding of factors influencing behavioral intention to continue using cloud computing (Shahbaz & Zahid, 2022; Wandira et al., 2024). Research has been conducted to address such problems to ensure cloud technologies are used and adopted, thus meeting the needs of cloud services providers, users, and leaders in organizations (Abdallah et al., 2024; Alhazmi, 2024; Aligarh et al., 2023; Al-Sharafi et al., 2023). To date, knowledge has accumulated to some extent, and a basis exists on which further research can be conducted to examine factors relating to CCBI in different contexts.

Despite the plethora of research identifying problems and finding solutions to cloud computing resistance, some scholars have expressed a concern that studies in developing countries are scant. For example, Alghushami et al. (2020) argued that cloud computing necessity attracted several researchers' interest, but most focus was placed on developing countries. Similar concerns were expressed by Hiran and Dadhich (2024) in Ethiopia, Shahbaz and Zahid (2022) in Pakistan, and Thanh et al. (2020) in Vietnam. These researchers argued for widespread usage and adoption of cloud computing to alleviate the burden of data storage and information management in different contexts. The researchers directly or indirectly examined the constructs used in the present studies, as I discuss in this section.

Particular concern was expressed regarding the shortage of research on cloud computing in higher education institutions in developing countries. Thanh et al. (2020) argued that considerable research was conducted on cloud computing, but studies in educational institutions were limited. Likewise, Hiran and Dadhich (2024) noted the nascent nature of the research on cloud computing in higher education institutions, observing that only 32% of African universities had adopted such a technological information system. These observations aggravate the shortage of research in developing countries from macro to micro levels, and higher education institutions may require more considerable attention. Indeed, Thanh et al. (2020), as well as Jha and Chaturvedi (2024), indicated that most existing studies in developed countries were conducted in business organizations. More studies are required to explain cloud computing usage or adoption in developing countries, mainly in higher education institutions, and the present study was an effort toward such an end, focusing on factors influencing first-year university students' CCBI in Angola.

**Solutions to the Problems Regarding Cloud Computing Usage or Adoption**

Considerable research has directly or indirectly included the construct proposed in the present study to address the problems identified in the previous subsection: resistance to usage or adoption (Hiran & Dadhich, 2024; Matar et al., 2020; Shahbaz & Zahid, 2022), shortage of research in developing countries (Kabra et al., 2023; Thanh et al., 2022), and the reduced number of studies conducted in higher education institutions (Abdallah et al., 2024; Thanh et al., 2020). In this subsection, I describe and analyze such research to establish its relevance to the present study.

Regarding resistance to usage or adoption, several papers are relevant to the present study in that they included the UTAUT. Aliyu et al. (2024) used the extended UTAUT, henceforth *UTAUT2*, by Venkatesh et al. (2012), and examined the factors influencing CCBI in Nigeria. Aliyu et al. administered a survey questionnaire to a judgmental sample of 100 university students in the Departments of Computer Science, Information Technology, and Management, and used a regression analysis. The result indicated that EE, FC, SI, hedonic motivation, price value, and habit influenced behavioral intention and usage of cloud computing. In contrast, PE had no influence on behavioral intention but did on usage behavior. The finding on PE contradicts the one in several other studies, indicating that such a construct is positively related to behavioral intention (Abbad, 2021; Alfalah, 2023; Thanh et al., 2020). More studies are needed to examine the extent to which performance expectancy can influence CCBI in other contexts.

Demographic variables were also part of the research on understanding the problems of cloud computing usage and adoption. The findings by Aliyu et al. (2024) indicated that gender, age, and experience moderated the relationship between variables, such as FC on behavioral intention and EE on behavioral intention. Although examining such moderating effects could add rigor (Venkatesh et al., 2003), the research model for the present study did not include demographic variables; it consisted of the modified UTAUT by Matar et al. (2020), which did not include demographic variables as moderators.

Hedonic motivation, price value, and habit need to be described to highlight the reasons for being included in the UTAUT2 but not being included in the present study. Venkatesh et al. (2012) defined hedonic motivation as the enjoyment that users perceive when employing a new system. On the basis of previous research (van der Heijden, 2004; Thong et al., 2006), Venkatesh et al. noted that hedonic motivation predicts behavioral intention and usage of technological information systems, and these findings are consistent with the ones in other research (Athambawa et al., 2023; Deka, 2023; Salifu et al., 2024; Thanh et al., 2020). Venkatesh et al. (2003) defined hedonic motivation as a user’s affective reaction to using a new system and noted that it was captured by EE and PE in the UTAUT. Because the present study included the UTAUT, as utilized by Matar et al. (2020), it excluded hedonic motivation.

Price value is a user’s perception that the benefits accruing from the usage of a system outperform the cost of obtaining such a system (Venkatesh et al., 2012). For example, users assessing the benefits of cost involved in using cloud computing consider price value. Venkatesh et al. added price value to their research model on the grounds that the context of novel development required such an addition. The original context was organizational, where users incurred no costs when using a system, but the novel context of development was of personal use, in which case individuals had to incur costs themselves (Venkatesh et al., 2003). The present study also included personal cloud storage, such as Google Drive and OneDrive, but these cloud services are started with a free plan, which may not be an impediment to usage. For this reason, the research model for the present study excluded price value.

The definitions of habit and experience are as follows. Habit entails the automaticity with which users employ a system because of their learning of the system (Kim & Malhotra, 2005; Limayem & Hirt, 2003), and experience represents an attribute denoting the time users have spent engaging with the system (Kim & Malhotra, 2005). Capitalizing on the previous research (Kim & Malhotra, 2005; Limayem & Hirt, 2003), Venkatesh et al. (2012) noted that habit and experience were strong predictors of behavioral intention and usage. Because the present study was conducted in a context where the usage of cloud computing is minimal, assessing habit and experience was not feasible; the research model for the present study did not include habit and experience.

Regarding the search for solutions to the problem of cloud computing usage, Masadeh et al. (2024) conducted another relevant study, utilizing the UTAU by Venkatesh et al. (2003). Masadeh et al. examined factors affecting the intention to adopt financial information systems based on the cloud in small and medium-sized enterprises in Jordan. They administered a survey questionnaire to a convenience sample of 600 participants and analyzed the results using regression analysis. The findings indicated that PE, COVID-19 risks, trust, and perceived security predicted the intention to adopt financial information systems based on the cloud. In contrast, the effect of perceived vulnerability and EE on behavioral intention did not hold. Except for perceived vulnerability, the effect of EE on behavioral intention is controversial because other studies found a positive effect (Abbad, 2021; Alfalah, 2023; Ranjan et al., 2022). The effect of EE on behavioral intention needs to be investigated further to compare results with the ones in the study by Masadeh et al.

Whereas Masadeh et al. (2024) extended the UTAUT by including risk and trust, such an extension could be achieved through FC. When users perceive no risks, and they trust an information system, the condition for them to use the system may become facilitated (Alghushami et al., 2020; Khayer et al., 2021; Sharma et al., 2023). This possibility suggests that Masadeh et al. indirectly incorporated FC, a construct in the present study, but using an original research model, such as the one by Venkatesh (2003) and Matar et al. (2020), could have provided more comparable and cumulative evidence.

An example of the study providing this possible comparability of the UTAUT results was conducted by Matar et al. (2020). Matar et al. examined only the effects of EE, FC, PE, and SI on CCBI, and this examination is within the three ways in which the UTAUT has been utilized (Venkatesh et al., 2012). Indeed, Venkatesh et al. noted that the UTAUT was used entirely or partly in organizational contexts to fortify its generalizability potential. Thus, the findings arising from Matar et al.'s study can be accurately compared across different studies using the UTAUT.

In addressing the problem of resistance to cloud computing, Matar et al. (2020) were quite explicit. They argued that adopting cloud computing is a change, and such change could be resisted. They examined factors relating to the CCBI among staff and faculty members in Jordanian universities and collected data using a survey questionnaire consisting of 153 valid responses. Using structural equation modeling to analyze data, Matar et al. found that although PE and FC were positively related to behavioral intention, the hypotheses that SI and EE affected behavioral intention were not supported. These insignificant findings partly support the ones in the study by Masadeh et al. (2024), which indicated that EE did not correlate with behavioral intention. Again, the findings in the study by Matar et al. suggest that EE needs to be investigated further to understand cloud computing usage.

Two problems arise from the study by Matar et al. (2020). First, the type of sampling was not specified; that is, readers are not informed whether a random or non-random selection was performed, a component that could help understand external validity (Bryman, 2016; Saunders et al., 2023). Second, participants were faculty and staff members of the universities, excluding students, who could be the most users of cloud computing (Taufiq-Hai et al., 2021). Future studies using a probability sample should address this facet of the university population, mainly first-year university students, who initiate a new learning journey at a higher level of education imposing challenges with information management.

Another contribution to solving the problem of cloud computing was by Thanh et al. (2020), who inspected the factors influencing CCBI among university students majoring in Accounting in Vietnam. Similar to Aliyu et al. (2024), Thanh et al. used the UTAUT2, as developed by Venkatesh et al. (2012), and administered a survey questionnaire, submitted on paper and online, to a convenience sample of 696 participants. Using structural equation modeling, Thanh et al. found that PE, EE, FC, price value, SI, and hedonic motivation influenced behavioral intention. Contrary to Aliyu et al., Thanh et al. found that habit did not affect behavioral intention but influenced usage. Other constructs that directly influenced usage in Thanh et al.'s study were FC and hedonic motivation, and for the present study, the result of FC is interesting; this result indicates a controversy.

FC was found to directly influence usage in the initial UTAUT research model (Venkatesh et al., 2003), but recent studies have indicated that the construct also influences behavioral intention (Aliyu et al., 2024; Matar et al., 2020; Ranjan et al., 2022; Thanh et al., 2020). The problem is that in all these studies, efforts have not been made to examine whether the effect of FC on behavioral intention goes through mediation. The influence could occur either through an existing construct within the research model or via a different construct. Studies are needed to examine such a possible influence of FC on CCBI.

More and more studies have been conducted to find a solution to the issue of cloud computing, and in this subsection, I proceed to describe and analyze them. Alfalah (2023) extended the UTAUT to examine university students' behavioral intetion to use mobile learning in Saudi Arabia. This extension was not the same as the one by Venkatesh et al. (2012), UTAUT2, including hedonic motivation, price value, and habit as antecedents of behavioral intention. Alfalah extended the UTAUT by further examining the predictors of PE and EE in the research model and developed and administered an online survey questionnaire to a non-random sample of 258 participants. Using structural equation modeling, Alfalah found that EE, PE, and lecturers' influence (SI) were positively related to the behavioral intention to use mobile learning, but the influence of FC on the behavioral intention was not statistically insignificant. Alfalah's findings support several other studies, in which similar effects were detected regarding EE, PE, and SI (Abbad, 2021; Aliyu et al., 2024; Ranjan et al., 2022; Thanh et al., 2020); thus, Alfalah's study reinforces the hypothesis in the present study that EE and PE are related to CCBI.

Alfalah's (2023) study is robust in finding a solution to the issues of cloud computing usage in that the author delved deeper into understanding not only the antecedents of behavioral intention but also the external factors. That is, other findings by Alfalah were that academic relevance and perceived mobile value influenced PE, but university management support did not; university management support impacted EE instead. This extension is essential because one of the critiques initially leveled at the technology acceptance model was that what matters is not perceived ease of use and perceived usefulness, counterparts to EE and PE in the UTAUT, respectively, but the antecedents of such constructs, as Venkatesh and Davis (2000) and Venkatesh (2006) discussed when dealing with technology acceptance and usage. More recent studies (at the time of the present study) have also stressed the need to investigate external factors in cloud computing research (El-Gazzar, 2014; Salih et al., 2021), and examining the external factors, Alfalah responded to that concern within the UTAUT. The present study did not include new external factors but contributed to such an effort by examinng mediation among exisiting constructs (EE, PE, SI, and FC).

Whereas Thanh et al. (2020) found that FC influenced behavioral intention, Alfalah (2023) discovered that such a construct had no effect on behavioral intention. Results similar to those of Thanh et al. were found in other studies, such as Kabra et al. (2023) and Suhail et al. (2024). Likewise, Alfalah’s results are congruent with those of Alotumi (2022) and Zacharis and Nikolopoulou (2022). These discrepant results suggest that, in finding a solution to the problem of cloud computing usage or adoption, FC require additional research in different contexts.

A similar construct showing discrepant results is SI. Using the UTAUT research model, Abbad (2021) examined the factors influencing university students’ intention to use an e-learning system in Jordan. Abbad analyzed data from a survey questionnaire employing structural equation modeling and found that EE and PE influenced behavioral intention to use the e-learning system. In addition, behavioral intention and FC influenced the usage of the e-learning system. In contrast, the effect of SI on behavioral intention did not hold. These findings support the ones in the paper by Ranjan et al. (2022), who, in the Indian context, used the UTAUT and included additional constructs such as value and trust perceptions. In analyzing a survey result using structural equation modeling, Ranjan et al. found that EE, PE, FC, perceived security risks, price value, and perceived trust significantly influenced CCBI, whereas the effect of SI on CCBI did not hold. These discrepant findings indicate that additional research is needed to examine the UTAUT constructs, mainly SI, in different contexts. Other studies show additional evidence of the need to continuously investigate the UTAUT constructs in different contexts, and in the next part of this section, I describe and analyze them to highlight their relevance to the present study.

Kabra et al. (2023) extended the UTAUT to examine university students' intention to adopt cloud technologies in India. Similar to Alfalah (2023), Kabra et al.'s extension of the UTAUT was not the same as the one performed by Venkatesh et al. (2012). To the UTAUT, Kabra et al. added *trust* in examining the predictors of attitude and inspected attitude as the predictor of behavioral intention. Performing a regression analysis of the data collected through a survey questionnaire (n = 190), Kabra et al. found that SI, FC, and PE were positively associated with the attitude to adopt cloud computing. In addition, perceived trust mediated the relationship between FC and attitude, and PE mediated the influence of SI on attitude toward new technology. Adding trust, Kabra et al. made a considerable contribution to the UTAUT research model.

For the present study, Kabra et al.'s (2023) paper is essential because the researchers used the relevant constructs, such as EE and PE; a comparison could be made with the findings arising from the present study (Saunders et al., 2023; Tharenou et al., 2007). However, similar to the study by Matar et al. (2020), Kabra et al.'s paper could be even more essential if the sampling method was clarified, that is, whether a random or non-random selection of participants was performed. Clarifying this method is pertinent to understanding external validity (Bryman, 2016; Saunders et al., 2023). In addition, examining the direct influence of EE, PE, FC, and SI on behavioral intention could inform whether attitude has partial or full mediation. The relevance of Kabra et al.'s paper to the present study needs to be enhanced to understand factors influencing CCBI.

Some studies have hinted that behavioral intention is a potential proxy for using and adopting technological information systems, including cloud computing. Chang et al. (2023) conducted an experiment to examine the usage acceptance of online-class materials by investigators of agriculture in Taiwan. Using the results of an online questionnaire administered to a convenient sample of 50 participants, Chang et al. performed a multiple regression analysis and found that SI and FC influenced usage behavior, but EE and PE did not. Furthermore, they found that age, gender, level of education, and the need for growth exerted no moderating effects on the hypothesized relationships. Because some findings have indicated that EE and PE influence behavioral intention (Abbad, 2021; Alfalah, 2023; Thanh et al., 2020), the result of the study by Chang et al. could elucidate that behavioral intention is an essential proxy for actual usage. The study by Chang et al. provides a rationale for investigating the antecedents of behavioral intention.

**Rationale for Selecting the Constructs in the Present Study**

For the present study, I have selected EE, PE, SI, FC, and behavioral intention because such constructs originate from a comprehensive theory, the UTAUT, synthesized from eight theories (Venkatesh et al., 2003). This comprehensiveness is substantiated in the fact that the constructs have also been examined indirectly to find a solution to cloud computing usage or adoption in developing countries, including higher education institutions. To provide additional background for the present study, I describe and analyze relevant studies next.

One relevant study was conducted by Alghushami et al. (2020), who examined the factors influencing cloud computing adoption in higher education institutions in the Republic of Yemen. Using a questionnaire survey of 328 participants and analyzing data using structural equation modeling, Alghushami et al. found that top management support, technology readiness, security, compatibility, relative advantage, regulatory policy, reliability, and competitive pressure were positively related to cloud computing adoption. Additionally, the relationship between predictor and outcome variables was moderated by tribalism culture. Although all Alghushami et al.'s constructs are essential, top management support and relative advantage are more salient for the present study. Top management support is similar to FC, and the relative advantage is identical to PE (Venkatesh et al., 2003). Another relevance of Alghushami et al.'s study is the research context, higher education institutions. This study constitutes an essential background for the present study.

The findings in the study by Alghushami et al. (2020) support the ones in the papers by Alhazmi (2024) and Hiran and Dadhich (2024). Alhazmi examined factors influencing the adoption of cloud computing in higher education institutions in Yemen and found that technology context, organization context, and environment context were positively related to cloud computing adoption, with culture, fit, and viability serving as mediator variables. Hiran and Dadhich investigated factors affecting cloud computing adoption in Ethiopia and found that top management support, technology readiness, cost, cloud computing knowledge, relative advantages, complexity, competitive pressure, normative pressure, and mimetic pressure were related to cloud computing adoption. The findings in these three studies were based on a theory different from the UTAUT, and thus the use of the constructs in the present study was indirect.

The studies by Alghushami et al. (2020), Alhazmi (2024), and Hiran and Dadhich (2024) were based on the technology-organization-environment framework (TOE) (Tornatzky & Fleischer, 1990), but the constructs that they included have some relevance to the present study. Top management support is defined as senior leaders' awareness of technology, the acceptance of technological information systems, and the aid this leadership provides to those under their supervision (Abdallah et al., 2024; Aligarh et al., 2023; Al-Sharafi et al., 2023). Although Venkatesh et al. (2003) did not include elements from the TOE framework in the synthesis for developing the UTAUT, top management support appears to match perfectly with FC, which is an individual's belief that organizational and technical supports exist for using a system (Alfalah, 2023; Venkatesh et al., 2003). Another construct is compatibility, and Venkatesh et al.  (2003) found that such a construct was captured by FC. Thus, FC is well represented in the studies using the TOE framework.

Other constructs that were examined in the studies using the TOE framework are relative advantages and social factors. Relative advantages denote the benefits users anticipate in using a new information system and are likened to perceived benefits or perceived usefulness (Al-Sharafi et al., 2023; Matias & Hernandez, 2021). Social factors are represented by subjective norms in the theory of reasoned actions (Fishbein & Ajzen, 1975) and denote the influence that social engagement exerts on an individual's intention to behave (Alhazmi, 2024; Rahmayanti et al., 2021). In developing the UTAUT, Venkatesh et al. (2003) found that relative advantages were represented by PE, and social factors were captured by SI. These representations suggest that PE and SI were examined indirectly in the cloud-computing research using the TOE framework.

The constructs in the present study have also been indirectly examined using technology acceptance model (Davis, 1989), which stipulates that perceived usefulness and perceived ease of use are predictors of behavioral intention (Altes et al., 2024; Sharma et al., 2023). Taufiq-Hai et al. (2021) integrated the technology acceptance model and the theory of planned behavior and examined factors influencing the acceptance and use of cloud computing from the perspective of individuals in the Malaysian educational context. Using a survey questionnaire distributed to a random sample of 289 undergraduate students in three public universities, and employing structural equation modeling, they found that perceived ease of use, perceived usefulness, perceived behavioral control, and attitude were related to CCBI. This research is relevant to the present study because perceived ease of use is represented by EE, perceived usefulness is captured by PE, and perceived behavioral control is akin to FC (Venkatesh et al., 2003). This representation is expected because the technology acceptance model and the theory of planned behavior were synthesized into the UTAUT research model.

Another study using the technology acceptance model was by Sharma et al. (2023). Sharma et al. examined the influence of perceived ease of use and perceived usefulness on the behavioral intention to adopt secure cloud computing services. In addition, they studied whether behavioral intention led to actual usage and whether usage influenced academic performance. Using a survey administered to a random sample of 867 students at different levels, such as undergraduate and doctoral programs in Indian universities, and employing structural equation modeling, they found that the hypothesized relationships were supported. Like the research by Taufiq-Hai et al. (2021), Sharma et al.'s paper is essential to the present study in that perceived ease of use is represented by EE and perceived usefulness is captured by PE (Venkatesh et al., 2003); the UTAUT is well represented.

In a more recent study, Wandira et al. (2024) also used the technology acceptance model to study factors influencing CCBI in a university context in Indonesia. However, these authors integrated the technology acceptance model with the expectation-confirmation model (Oliver, 1977, 1980), which explains that post-technology adoption satisfaction is underpinned by the function of perceived performance, expectations, and beliefs disconfirmation. This study is within the effort to understand continuous behavioral intention. By using a questionnaire administered to a random sample of 261 respondents, Wandira et al. found that perceived ease of use, perceived usefulness, satisfaction, FC, and confirmation were positively related to CCBI, with perceived usefulness, FC, and satisfaction being the most salient factors. The essence of this study is explained on the grounds that perceived ease of use and perceived usefulness are represented by EE and PE, respectively, in the UTAUT (Venkatesh et al., 2003). Venkatesh et al. (2003) noted that constructs denoting affective reactions, such as satisfaction, are represented by EE and PE, so the study by Wandira et al. indirectly captured the constructs examined in the present study.

Another relevant study using a different theory but indirectly utilizing the constructs in the present study was carried out by Ploysuayngam and Tangwannawi (2022). These researchers examined the factors influencing university students' CCBI in Thailand. Using Bandura's (1986) socio-cognitive theory, Ploysuayngam and Tangwannawi proposed security and privacy, SI, anxiety, and self-efficacy as predictors of CCBI. They administered a survey to a convenience sample of 214 participants majoring in computer science, and their analysis of results using structural equation modeling indicated that all hypothesized relationships were supported. When developing the UTAUT, Venkatesh et al. (2003) noted that self-efficacy and anxiety were not direct predictors of behavioral intention; their influence on behavioral intention was mediated by ease of use. Because ease of use is identical to EE (Venkatesh et al., 2003), Ploysuayngam and Tangwannawi exercised some coverage of the constructs examined in the present study.

The indirect use of the constructs in the present study were also abundant in university contexts. One more study, by Abdallah et al. (2024), examined factors relating to mobile cloud computing adoption in university settings in Palestine. Using the technology acceptance model (Davis, 1989), TOE framework (Tornatzky & Fleischer, 1990), and innovation diffusion theory (Rogers, 1983), Abdallah et al. created an integrated research model, which they tested using a survey of 210 students and academic staff. The analysis of data using a structural equation modeling indicated that security privacy, management support, FC, SI, perceived ease of use, perceived usefulness, and quality of service influenced the adoption of mobile cloud computing. Although this study was based on different models, it included the UTAUT constructs, such as FC and SI.

The indirect coverage of the constructs examined in the present study reinforces that the UTAUT is comprehensive. Some research models based on different theories, such as the expectation-confirmation model (Oliver, 1977, 1980) and the TOE framework (Tornatzky & Fleischer, 1990), existed before 2003, when the UTAUT was developed by Venkatesh et al. (2003) and extended by Venkatesh et al. (2012), but their constructs were not included either in the UTAUT or in the UTAUT2. However, a close inspection of some constructs arising from such research models indicates similarities with the ones from the UTAUT, as seen in the studies by Alghushami et al. (2020), Alhazmi (2024), and Wandira et al. (2024). Kabra et al. (2023) have suggested that the UTAUT should be an ideal research framework for understanding cloud technology usage because this framework explains 70% of the variance in usage intention, a point that was also made by Venkatesh et al. (2012). Therefore, the UTAUT constructs, as were examined in the present study, promise a comprehensive research model to understand the relationship between cloud computing factors, including EE, PE, FC, SI, and CCBI of first-year university students in Angola.

## Studies Related to Predictor and Outcome Variables

The present study included five constructs: four were predictor variables (EE, PE, SI, and FC) and one was the outcome variable (CCBI). The foundation of these constructs was the UTAUT (Venkatesh et al., 2003). These constructs were essential to the present study because they had been originally examined to understand behavioral intention in different information system contexts (Alfalah, 2023; Aliyu et al., 2024; Thanh et al., 2020; Venkatesh et al., 2003). In the next subsections, I further describe and analyze the constructs to establish how they were examined in the present study.

### *Effort Expectancy (EE)*

EE is the degree of belief that using a system is easy (Donan et al., 2023; Venkatesh et al., 2003). Venkatesh et al. (2003) derived the EE construct from three dimensions in different models or theories: *ease of use* from the innovation diffusion theory (Rogers, 1983), *complexity* from the model of personal computer utilization (Thompson et al., 1991), and *perceived ease of* use from the technology acceptance model (Davis, 1989). In its initial conceptualization, EE referred to the ease of job performance because the UTAUT was developed with a view to understanding behavioral intention and the usage of information technology in business organizations (Venkatesh et al., 2003). The present study included the UTAUT to understand behavioral intention in an educational context, mainly a higher education institution. As such, in the present study, EE refers to the belief that using cloud computing is easy.

The effect of EE on behavioral intention is yet to be established. Abbad (2021) examined the factors influencing university students' intention to use an e-learning system in Jordan and found that EE positively influenced behavioral intention. This finding was supported by the results of several papers (Alfalah, 2023; Aliyu et al., 2024; Ranjan et al., 2022; Thanh et al., 2020), but a few other studies yielded findings showing that EE is not related to CCBI (Masadeh et al., 2024; Matar et al., 2020). These contradicting results suggest that further research is needed to examine the influence of EE on CCBI. Because the overwhelming research points to the positive side of the effect (Abbad, 2021; Alfalah, 2023; Aliyu et al., 2024; Ranjan et al., 2022; Thanh et al., 2020), a hypothesis was put forth in the present study that EE influences CCBI, but such an influence is realized through full or partial mediation.

***Performance Expectancy (PE)***

PE is the belief that using a system helps obtain gains in the job (Thanh et al., 2020; Venkatesh et al., 2003). As Venkatesh et al. (2003) synthesized, PE pertains to five constructs belonging to different models: *extrinsic motivation* from the motivation model (Davis et al., 1992), *perceived usefulness* from the technology acceptance model (Davis, 1989) and theory of planned behavior (Ajzen, 1985), *relative advantage* from the innovation diffusion theory ( Rogers, 1983), *job-fit* from the model of personal computer utilization (Thompson et al., 1991), and *outcome expectations* from the social cognitive theory (Bandura, 1986). For the present study, conducted in a higher education institution, PE refers to the belief that using cloud computing supports obtaining gains associated with task performance, accomplishment of tasks, productivity maximization, and improvements in assessment performance (Matar et al., 2020).

Similar to EE, PE's consensus regarding the influence on behavioral intention is far from being reached in cloud computing research. Although several studies have indicated that PE positively influences CCBI (Abbad, 2021; Alfalah, 2023; Masadeh et al., 2024; Matar et al., 2020), some other studies have indicated that PE is not positively related to CCBI (Aliyu et al., 2024; Alotumi, 2022; Sharma et al., 2023). These discrepant results are probably attributed to characteristics of different research settings, and so additional research is needed in other contexts to examine the effect of PE on behavioral intention. Because the number of studies indicating positive effect tends to outperform those showing a negative effect, a hypothesis was put forth in the present study that PE influences CCBI.

The literature indicates that PE and EE are related (Shahbaz & Zahid, 2022). This relationship is expected on the grounds that perceived ease of use relates to perceived usefulness (Lin & Yu, 2023; Shahbaz & Zahid, 2022). Specifically, the effect of perceived ease of use on behavioral intention is mediated by perceived usefulness (Shahbaz & Zahid, 2022). Because perceived ease of use is similar to EE in the UTAUT (Venkatesh et al., 2003), EE is expected to relate positively to PE in such a way that its effect on behavioral intention is indirect; a tentative hypothesis was formulated in the present study that EE relates to PE.

***Facilitating Conditions (FC)***

FC is an individual's beliefs that supportive infrastructures exist to use a system (Donan et al., 2023; Venkatesh et al., 2003). In Venkatesh et al.'s (2003) synthesis of the eight theories or models, FC encapsulates three constructs from other theories. FC captures *compatibility* in the innovation diffusion theory (Rogers, 1983), *FC* in the model of personal computer utilization (Thompson et al., 1991), and *perceived behavioral control* in the theory of planned behavior (Ajzen, 1985). In the present study, FC is more specifically represented as the students' beliefs regarding resource availability, possession of knowledge to effectively use cloud computing, university support, and the perception that cloud computing could correspond with the needed support, as was examined in the study by Matar et al. (2020).

The indirect effect of FC on behavioral intention appears to be established. When validating the UTAUT, Venkatesh et al. (2003) reported that the effect of FC on behavioral intention was mediated by EE. More recent studies have shown similar results; that is, the FC shows no effect on behavioral intention but relates directly to usage behavior when EE is present (Haneefa, 2023). However, FC on usage behavior is mediated by behavioral intention when EE is absent (Donan et al., 2023). For the present study, these findings lend support for hypothesizing that FC positively relates to EE and negatively relates to CCBI if EE is absent.

***Social Influence (SI)***

SI is an individual's belief that important others are cognizant of the opinion that a new technological information system should be used (Donan et al., 2023; Venkatesh et al., 2003). In Venkatesh et al.'s (2003) synthesis of the eight theories or models, this construct was captured by *image*, which is in the innovation diffusion theory (Rogers, 1983), *social factors* in the model of personal computer utilization (Thompson et al., 1991), and *subjective norm* in the theories of reasoned actions (Fishbein & Ajzen, 1975), planned behavior (Ajzen, 1985), and the technology acceptance model (Davis, 1989). In the present study, social influence represents the students' belief that their academic managers and other important staff recognize that using cloud computing is essential.

Alluding to academic managers and other important staff is relevant in discussing social influence because this construct relates to rewards. In fact, one of the constructs from which SI was derived is *image*, from the innovation diffusion theory (Rogers, 1983), which is associated with an individual's status enhancement within a social milieu (Talwar et al., 2020; Venkatesh et al., 2003). The students' perception that their academic managers and other students highly regard cloud computing usage may influence students' CCBI.

SI has been extensively examined in the literature (Abdallah et al., 2024; Assalaarachchi et al., 2022; Suhail et al., 2024), but the result regarding its influence on behavioral intention is inconclusive. Although a plethora of research has shown that SI positively affects behavioral intention (Alfalah, 2023; Aliyu et al., 2024; Kabra et al., 2023; Thanh et al., 2020), researchers in other studies have reported different results, indicating that SI does not positively affect behavioral intention (Abbad, 2021; Matar et al., 2020; Ranjan et al., 2022). As with EE, PE, and FC, the studies reporting a positive effect of SI on behavioral intention tend to outnumber those reporting a negative effect. Consequently, hypothesizing that SI relates to CCBI in the context of the present study is reasonable.

### *Behavioral Intention*

Behavioral intention has been defined in such a way that its examination as an outcome variable may provide a solid basis for supporting academic managers in creating a framework of cloud computing factors to encourage usage or adoption. According to Shirish and Batuekueno (2021), behavioral intention represents an individual's closest decision toward using a system. Similarly, Chen et al. (2022) have stated that behavioral intention is not a perfect predictor of actual usage behavior, but its predictive effect is considered paramount. This comment finds support in a paper by Assalaarachchi et al. (2022), which, examining factors affecting cloud-based project management in Sri Lanka, indicated that behavioral intention accounted for 47.3% of the variance in the actual usage of cloud-based project management. The comment is further substantiated in a study by Al-Okaily et al. (2023), which indicated that behavioral intention had a strong influence on actual usage, accounting for 74% of the variance. This evidence suggests that finding antecedents of CCBI may provide the nearest and most helpful information that academic managers in higher education institutions could utilize to encourage cloud computing usage.

Behavioral intention has its roots in the theory of reasoned action (Fishbein & Ajzen, 1975) and the theory of planned behavior (Ajzen, 1985) and is considered a proxy for actual usage behavior (Shirish & Batuekueno, 2021; Verdegem & De Marez, 2011). Davis (1989) leveraged the theory of reason action and the theory of planned behavior to develop the technology acceptance model, which initially consisted of perceived ease of use and perceived usefulness as predictors of behavioral intention (Marangunić & Granić, 2015; Sharma et al., 2023). In synthesizing the eight theories to develop the UTAUT research model, Venkatesh et al. (2003) equally considered behavioral intention as the nearest antecedent of the usage of an information system. All these considerations provide considerable evidence for using behavioral intention as the outcome variable in finding support for academic managers to encourage cloud computing usage.

Behavioral intention has been examined in relation to actual usage behavior, but the examination has been performed considering behavioral intention as a mediating variable. For example, Aliyu et al. (2024) conducted a survey to understand the antecedents of cloud computing usage, and in the research model, behavioral intention mediated the influence of EE, FC, PE, anxiety, SI, hedonic motivation, and habit on actual usage behavior. In a similar study examining factors affecting cloud-based project management in Sri Lanka, Assalaarachchi et al. (2022) found that the effects of EE, PE, SI, and trust were detected on actual usage behavior through behavioral intention; behavioral intention was examined as a mediating variable. Studies examining usage behavior in this way are ubiquitous in the literature (Abdallah et al., 2024; Al-Okaily et al., 2023; Ma et al., 2025; Sharma et al., 2023), indicating that behavioral intention is a promising outcome variable in understanding cloud computing usage or adoption.

Most studies examining the effect of behavioral intention on usage behavior are conducted in settings in which cloud computing or similar technological information systems are already used, and research efforts are made to ensure full adoption. There are contexts in which the usage of cloud-based information systems is yet to be established, as is the case of developing countries (Abdallah et al., 2024; Hiran & Dadhich, 2024; Taufiq-Hai et al., 2021; Thavi et al., 2021), and examining the antecedents of behavioral intention is paramount in such contexts. An effort in this regard is seen in the study by Matar et al. (2020), in which a quantitative study was conducted to examine factors relating to CCBI among staff and faculty members in the Jordanian university context. A research model was developed using five constructs in the UTAUT research model, that is, examining the influence of EE, PE, SI, and FC on cloud computing behavioral intention. The present study was an effort toward such an end, but its focus was on students, who are the most prospective users of cloud computing.

**Evaluation of the Studies and Implication for the Research Question**

The description and analysis of the the studies in this chapter constitute an essential background to the present study. Researchers have highlighted the problems pertaining to cloud computing usage or adoption, and efforts have been undertaken to find solutions. Besides using the UTAUT, studies have been identified using various research models, such as the techlogy acceptance model (Sharma et al., 2023; Wandira et al., 2024), the TOE framework (Aligarh et al., 2023), and the theory of planned behavior

(Taufiq-Hai et al., 2021). Consequently, numerous factors relating to cloud computing usage or adoption have been identified. Most importantly, research has been focused on behavioral intention (Al-Okaily et al., 2023; Assalaarachchi et al., 2022), adoption or usage (Al-Sharafi et al., 2023; Khayer et al., 2021), and continuous behavioral intention (Shahbaz & Zahid, 2022; Wandira et al., 2024) in various contexts, with behavioral intention predicting usage or adoption. This variety constitutes an avenue for novel researchers to select a framework of factors to examine in different contexts. For the present study, the foundational theory (UTAUT) is well represented in that its constructs have been directly and indirectly examined (Shahbaz & Zahid, 2022; Wandira et al., 2024). This representation indicates that the present study's foundational theory is robust, helping yield a framework of cloud computing factors that academic managers in higher education institutions could utilize to encourage cloud computing usage among first-year university students.

Whereas the relevant studies constitute a solid background, there are five limitations, requiring additional research to ensure that the constructs in the present study can be used to encourage cloud computing usage. The first limitation is that most findings are inconclusive. Although some studies indicate positive results, as is the example of the effect of EE on behavioral intention (Aliyu et al., 2024; Thanh et al., 2020), other studies yield negative findings (Masadeh et al., 2024; Matar et al., 2020). These discrepant results might have been identified due to different contexts in which the studies were conducted. Additional studies are needed to check whether the influence of factors on CCBI holds in other contexts. Another possible reason is that most studies used integrated models, and the results presented cannot be compared until follow-up studies are conducted. Studies using the same research models are needed in different contexts to find cumulative evidence of factors influencing CCBI.

The second limitation is that, with the exception of Taufiq-Hai et al. (2021), Sharma et al. (2023), and Wandira et al. (2024), all the studies were conducted using convenience samples. According to Bryman (2016) and Saunders et al. (2023), convenience samples are easy to use, but they impose limitations regarding external validity; generalizing findings to other contexts becomes problematic. This limitation could have been addressed by using a random sample; future researchers should strive to employ a random sampling technique to establish the knowledge of factors influencing CCBI.

The third limitation entails the types of participants used, which could create bias in the result regarding CCBI. In some studies, such as by Ploysuayngam and Tangwannawit (2022) and Aliyu et al. (2024), participants were majoring in information technology, and their knowledge of technological information systems may differ from that of regular users, those without knowledge about computing. Consequently, the results cannot be used to understand the factors that could influence regular users to employ and adopt cloud computing. In other studies, participants were holders of leadership positions. Because the majority of cloud computing users is employees in organizations and students in educational institutions, future scholars should consider conducting research that includes samples of such populations.

A limitation similar to the third one is observed in the study by Masadeh et al. (2024), in which participants were present and prospective users of cloud-based information systems. Individuals who are already using an information system may have different perspectives from those who are yet to use the system. Indeed, participants will come from different sampling frames (Bryman, 2016; Saunders et al., 2023), and aggregating their data may skew the results (Argyrous, 2011; Field, 2024). Additional studies are needed in which regular users, pertaining to a single sampling frame, are researched to explain CCBI, as influenced by EE, PE, SI, and FC.

The fourth important limitation regards the target population in the higher education institutions. First-year university students can be a special population to consider in understanding their intention to use cloud computing because they enter a new educational system, requiring them to handle large amounts of data and collaborate more effectively with others. Research has indicated that the usage of cloud computing positively influences students' academic performance by improving communication, collaboration, and critical thinking skills (Mohammadi et al., 2023; Raza & Khan, 2022). For example, cloud platforms, such as Microsoft 365 and Google Workspace, enable students to seamlessly work on group projects, irrespective of their physical location. These skills may be lacking in first-year university students, and understanding the factors that may enhance the usage of cloud computing can be an essential pursuit.

Some other particularities of first-year university students may be the perceptions of a lack of FC, the difficulties with which they cope with new information technology, and the possible gains that can accrue from system usage. Indeed, The literature has emphasized several issues, such as limited understanding of cloud technologies and slow internet connectivity, as barriers to cloud computing usage or adoption (Al-Hajri et al., 2021; Alimboyong & Bucjan, 2021; Hiran & Dadhich, 2024). By addressing these challenges with entry-level students, academic managers in universities may develop targeted interventions to ensure every student benefits from cloud computing. Surprisingly, none of the studies described and analyzed in this chapter have included first-year university students as their target population.

Fifth, and finally, the descriptions and analyses in this chapter have indicated that there is a wide coverage of cloud computing research in developing countries. Studies were conducted in Nigeria (Aliyu et al., 2024), Jordan (Masadeh et al., 2024; Matar et al., 2020), India (Kabra et al., 2023; Ranjan et al., 2022), Vietnam (Thanh et al., 2020), Saudi Arabia (Alfalah, 2023), Yemen (Alghushami et al., 2020; Alhazmi, 2024), Malaysia (Taufiq-Hai et al., 2021), and Indonesia (Wandira et al., 2024); however, no studies were carried out in Angola. Research is needed in this developing county, mainly in higher education institutions, to support academic managers in understanding the knowledge required to encourage cloud computing usage and adoption, targeting CCBI. More specifically, the present study examined the relationship between cloud computing factors, including EE, PE, SI, and FC, and first-year university students' CCBI in Angola.

## Summary and Conclusions

The focus of this chapter was on understanding existing research on cloud computing, mainly on the relationship between existing cloud computing factors and behavioral intention. Researchers have noted that technology, including cloud computing, has made organizations more productive than before (Aldahwan & Ramzan, 2022; Al-Sharafi et al., 2023). In contrast, technology yields too much data to manage with on-premises devices, requiring cloud-based storage that is scalable and facilitates effective collaboration.

Organizations, including institutions of higher education, are yet to capitalize on the full potential of cloud computing. Researchers have noted that many organizations still resist using cloud computing and are denied several benefits accruing from such technology, such as data accessibility (Alhazmi, 2024; Altes et al., 2024), information collaboration (Al-Okaily et al., 2023; Sharma et al., 2023), and data storage (Thavi et al., 2021; Wandira et al., 2024). Consequently, research has been conducted to identify factors leading to cloud computing usage or adoption or behavioral intention to usage or adoption. One problem is that most research was conducted in developed countries (Hiran & Dadhich, 2024; Thanh et al., 2020). In addition, cloud computing research in higher education institutions, in developing countries, was found to be scarce (Abdallah et al., 2024; Kabra et al., 2023). More research is needed.

The description and analysis of the studies addressing such problems in this chapter have indicated that most studies present discrepant results. Furthermore, none of the studies were conducted in Angola, which is also a developing country. Therefore, the present study extended the UTAUT to examine the relationship between cloud computing factors, including EE, PE, SI, and FC, and first-year university students' CCBI in Angola. The next chapter, I provide details of the methodological aspects for addressing the gap.

# Chapter 3: Research Method

The purpose of this quantitative correlational study was to examine the relationship between cloud computing factors, including EE, PE, SI, and FC, and the first-year university students' CCBI in a developing country, specifically in Angola. Testing the strength of these variables included Cronbach's alpha and composite reliability, and examining the relationship between variables entailed using multiple regression analysis (Field, 2024; Warner, 2021). The result indicated which of the cloud computing factors academic managers can utilize to create policies and frameworks for encouraging first-year students to use cloud computing.

The structure of this chapter is as follows. First, I state the research design and rationale and then describe the methodological aspects, focusing on the target population, sampling strategy, procedures for recruitment, participation, and data collection. The present study included questionnaire items from a previous study (Matar et al., 2020) and a pilot study to assess the feasibility of the research instrument. Thus, before explaining the research instrument and operationalization of constructs, I describe the pilot study. The second part of the chapter deals with the data analysis plan, in which I discuss the threat to validity, highlight aspects of ethical procedures, and end the chapter with a summary of the design and methodology.

## Research Design and Rationale

Within the UTAUT by Venkatesh et al. (2003), the constructs of the present study included four predictor variables and one outcome variable. The predictor variables were EE, PE, FC, and SI, and the outcome variable was CCBI. Specifically, the examination of the variables entailed using the modified UTAUT research model by Matar et al. (2020). This modified research model was essential for the present study because Matar et al. (2020) investigated cloud computing, and all the constructs were within the original UTAUT research model. Using this research model in the present study was helpful in yielding results that are comparable across various studies within the UTAUT research model.

A quantitative research design was the framework for examining the variables in the present study. According to Saunders et al. (2023), a research design represents the overall plan for a research project. The plan entails aspects of how to answer research questions, how to achieve objectives, and how to attain an aim. In addition, the plan contains hints about specific sources of data collection, data analysis, possible ethical issues, and constraints that can be encountered (Cox, 2020b; Saunders et al., 2023). Cresswell and Cresswell (2023) broadly captures this definition by stating that research designs are categories of inquiry offering specific guidance for the research procedures within quantitative, qualitative, and mixed methods approaches. Such a definition is substantial in scope regarding the paths through which a researcher can go to achieve a study purpose. The present study included this definition in dealing with the research design.

Whereas the above definition of research design captures the entire path for effectively conducting research, the naming of the components to describe research design is inconsistent, requiring clarification of how the term is used in the present study. For example, Bryman (2016) described research designs as experimental, cross-sectional, longitudinal, case study, and comparative. In contrast, Saunders et al. (2023), as well as Cresswell and Cresswell (2023), denoted research designs as quantitative, qualitative, and mixed methods, to which Bryman referred as strategies. The present study includes the naming convention of research design by Saunders et al. and Cresswell and Cresswell because the terms *quantitative*, *qualitative*, and *mixed methods* constitute an overarching umbrella for any study.

The description of research design by Saunders et al. (2023) is comprehensive. . According to these methodologists, researchers can choose to utilize a quantitative, a qualitative, or a mixed-methods research design in the first place, which is underpinned by a given philosophical position, such as positivism or constructivism (Babbie, 2017; Burkholder & Burbank, 2020). Subsequently, in light of their research questions, researchers can choose from available research strategies such as a survey, or an experiment. The research questions also hint at the research design purpose, such as exploring, describing, explaining, or evaluating a phenomenon or construct. Researchers can then choose a time horizon, which could be cross-sectional or longitudinal. Finally, researchers can decide on data collection procedures and data analysis techniques. This description shows a hierarchical representation starting from philosophical position (realism, relativism), to research design (quantitative, qualitative, and mixed methods), to research strategies (survey, experiment), to time horizon (cross-section, longitudinal), and finally to procedures for data collection and techniques for data analysis.

Building on the above definition, the present study includes a quantitative correlational research design. Specifically, the purpose was to examine the influence of

EE, PE, FC, and SI on the CCBI of first-year university students in Angola. Regarding the time horizon, the study included a cross-sectional strategy, in which I collected data at a single point in time (Bryman, 2016; Saunders et al., 2023). This time horizon is helpful for short-scale research, as is the case in the present study.

The quantitative research design, coupled with the cross-sectional time horizon, lead to a correlational and regression analysis, which helps determine how variables relate to each other (Bryman, 2016; Saunders et al., 2023). The design of the present study helped determine which of the constructs studied related to CCBI in a context where cloud computing investigation is scant (Alghushami et al., 2020; Hiran & Dadhich, 2024; Khayer et al., 2021). Specifically, the research question of the present study hints at analyzing the influence of multiple variables on one outcome variable, and this analysis is well performed using regression analysis (Field, 2024; Tharenou et al., 2007; Warner, 2021).

However, there was a caveat in using a cross-sectional or correlational design. According to Argyrous (2011) and Bryman (2016), an existence of a relationship between variables is just a relationship in that determining the direction of such a relationship is complex. Minimizing this caveat in the present study consisted of plotting variables directionally. That is, imagining that behavioral intention leads to cloud computing factors could be impractical, whereas the opposite could be logical; cloud computing factors may cause students to use cloud computing. Therefore, although not completely examining cause-effect, the research design in the present study was helpful in identifying which cloud computing factors academic managers in higher education might utilize to create a framework for encouraging cloud computing usage in the Angolan context.

## Methodology

The methodology of the present study revolved around a quantitative correlational research design. Other research designs are available, including qualitative and mixed-method designs (Cresswell & Cresswell, 2023; Saunders et al., 2023), but the present study excluded such designs to accommodate the underlying epistemological and ontological perspectives, as well as the time constraints in completing the present research. Research designs are macro components of a study and are realized by more delicate strategies, such as surveys and experiments (Saunders et al., 2023), and the present study consisted of a survey. Regarding time horizon, the present study was cross-sectional in design, and data collection procedures consisted of a structured questionnaire, the data of which entailed performing a multiple linear regression analysis (Field, 2024; Warner, 2021).

### Population

The population of the present study was students in a higher education institution in Angola. Higher education institutions in Angola are divided into public and private, and the population for the present study was students in a private higher education institution. Students in this institution take various courses, such as accounting and finance, computer engineering, and psychology. Students are prepared to join the work market (for those who are yet to be employed) and are helped to enhance their job skills (for those who are employed). In each case, the students are expected to have an acceptable level of digital literacy to manage data effectively by the time they finish their degree. The number of students every year ranges from 3,000 to 5,000, which made the institution an appropriate setting for drawing a random sample for a study requiring a minimum of 85 participants, as determined using G*Power (Figure 2) (Buchner et al., 2024; Memon et al., 2020). The population for the present study was first-year students, who need to be initialized into technological information systems and helped to navigate the rest of their time at university with ease regarding information systems management.

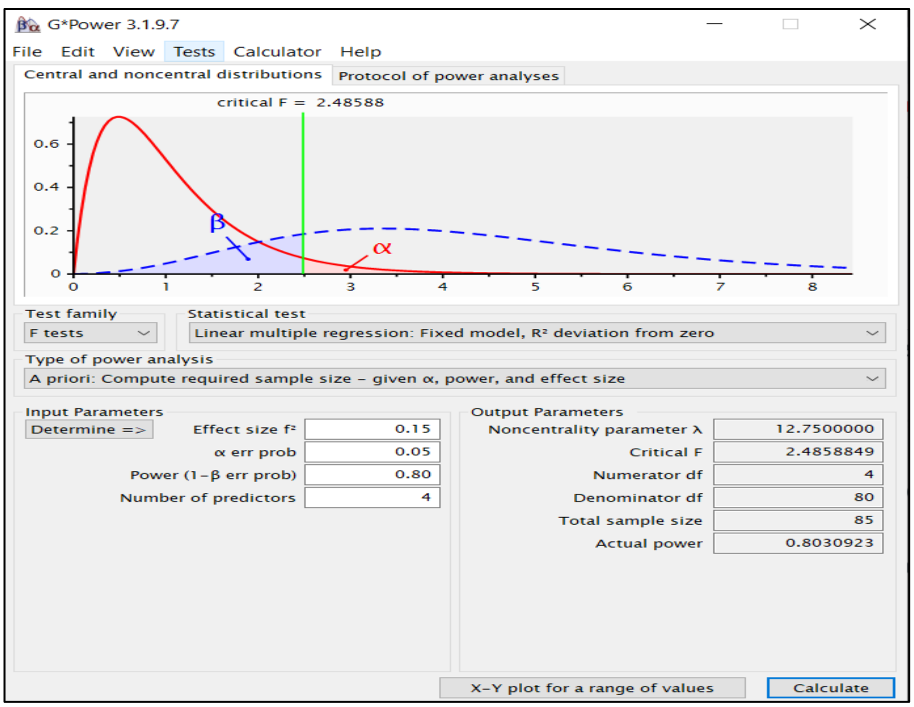
**Sampling and Sampling Procedures**

The present study included a random sample from first-year university students (sampling frame). The sample was probabilistic to grant every member of the population a chance to be included (Bryman, 2016; Tharenou et al., 2007). Procedurally, the first step was to determine the sample size a priori (Uttley, 2019) on the basis of the proposed constructs. Using the guidelines by Memon et al. (2020), I performed G*Power analysis. In Memon et al.'s guidelines, a medium effect size of a sample (.15) is chosen, an alpha level of .05 is included, and the power of .80 is considered in the input parameters when performing G*Power analysis. For the present study, the number of predictors was four, and the output revealed that a minimum sample size of 85 participants was required (Figure 2).

The second step was participant selection. I gained access to all first-year university students and assigned them numbers (1–1200) for the random selection. Although G*Power analysis indicated that 85 participants were required, I adjusted the sample to include more participants (n = 195) to allow for possible problems in response rate and in case the outcome variable was not normally distributed. This adjustment of the sample was also in alignment with Pek et al.'s (2024) point. Pek et al. have cautioned against putting much faith in the computed power analysis value when estimating a sample size because the formula to calculate such a value excludes uncertainty sources. According to these authors (Pek et al., 2024), uncertainty sources, such as variability of sampling, cause a sense of false precision and confidence in a chosen design, a point that resonates with Wegener et al. (2022). This argument suggests that the present study's estimated sample size was only a heuristic in considering sampling best practices.

**Figure 2**

*Estimated Sample Size*



**Procedures for Recruitment, Participation, and Data Collection (Primary Data)**

The target higher education institution was the site for recruiting participants. After performing a random selection, I contacted the participants to learn about their availability and willingness. This contact consisted of inviting them to collect a paper-based packed containing a flyer, consent form, and questionnaire from a locker in the target institution's staff room. The consent form contained details on the study purpose, benefits, confidentiality, anonymity, and the right to withdraw from the study at any, in alignment with the need to show respect, justice, and beneficence for persons (Cox, 2020a; Windsor et al., 2024). I used the templates from Walden University, and students read the materials to decide whether to participate in the study.

Demographic variables included in the present study are age, gender, possession of a smart device, and possession of a laptop computer although such data are not part of the theoretical framework. Demographic information is essential in providing insights into how data obtained from a probabilistic sample might apply to an entire population. For example, Acilar and Sæbø (2022) found that male and female students differed in subject-matter personal interest and the extent to which study topics were easy for them in deciding to study information systems. Yavuz (2022) reported a similar finding in a systematic literature review focused on understanding the difference between male and female users of transit technology. Yavuz's research indicated that women and men tended to encounter distinct limits and requirements when utilizing public transit services, including concerns about crime and service reliability. These findings suggest that a sample predominated by only one gender may not accurately generalize to the entire population. Researchers must learn gender balance in a sample, and this learning was part of the present study.

Many demographic variables exist but including them in a study depends on the context. Buckley (2024) stated that researchers in educational technology frequently account for demographic variables, including age, ethnicity, gender, and socioeconomic status. The present study did not include ethnicity and socio-economic status because the entire population belongs to one ethnic group: Portuguese speakers. In their study, Alfalah (2023) included possession of a smart device and possession of a laptop computer, and consistent with that study, the present study included such demographic variables.

The deadline to return the questionnaire was within 10 business days for students who consented to participate in the study. . Conversant with the procedure in the study by Matar et al. (2020), the questionnaire consisted of a 5-point Likert scale, in which 1 was *Totally disagree* and 5 was *Totally agree*. The presentation of items was a reversed order, starting with *Totally agree* and ending with *Totally disagree*. In alignment with the procedure utilized by Alfalah (2023), the questionnaire contained two sections. The first section was to collect participants' demographic information, and the second section was the Likert scale component. In addition, the questionnaire was translated into Portuguese, which is the participants' official language, to maximize comprehensibility, a practice that has been adopted in previous studies (Alfalah, 2023; Alghushami et al., 2020). On the eighth day, participants received a reminder to return the questionnaires, and this reminder was to maximize response rate. One reminder was sufficient because participants were students in the research institution. Students learned that they should not write their names on the questionnaire sheets.

**Pilot Study**

The present research included a pilot study because the research instrument was an extension of the research model by Venkatesh et al. (2003), as used by Matar et al. (2020), in a different context. Although Matar et al. used the UTAUT research model to examine factors relating to CCBI, the context was a university in Jordan. The context for the present study was a university in Angola. In addition, Matar et al.'s population was staff and faculty members, whereas the population for the present study was first-year university students. The pilot study helped understand how the research instrument could work in this new research context and ensure cultural relevance and measurement accuracy, as discussed by Brown and Moore (2021) and Zhang et al. (2022). The pilot study consisted of the following steps: (a) checking for content appropriateness, (b) translating the question to Portuguese, (c) validating the content in Portuguese, and (d) checking construct validity.

A group of linguistic and content experts participated in the translation and validation of the question into Portuguese, the participants' official language, to maximize comprehensibility, consistent with the practice in previous studies (Alfalah, 2023; Al-Okaily et al., 2023). Before performing the translation, the experts checked the original questionnaire for content appropriateness. Minor changes included lexical items to suit the population of the present study, first-year university students. In performance expectancy (PE1), *my job* was changed to *my study*, in social influence (SI1 and SI2), the term *co-workers* was changed to *classmates*, and *my work* was changed to *my study* in facilitating conditions (FC4). These changes made the entire items focus on students instead of teachers, who did the survey in the study by Matar et al. (2020).

In the next step, copilot served as the initial tool to translate the questionnaire from English to Portuguese. Then, two teachers of English as a foreign language independently validated the accuracy of translation and provided feedback. They learned that the translation presented to them was performed using Copilot. The two teachers have Portuguese as their first language but are specialized in English language teaching (English as a foreign language). They both hold a master's degree in English language teaching and are fluent in both languages, which made them an appropriate resource for providing support with translation of the questionnaire from English to Portuguese and vice versa. Copilot also served as the initial tool to perform a back translation (Portuguese to English) and then two different teachers of English as a foreign language performed validation.

In the final stage, five different groups of six professors each independently validated the content of the Portuguese version, and such non-unique raters were the result of a random selection from 40 professors teaching in the courses of computer engineering, electrotechnical engineering, and telecommunication engineering. I provided a description of the five constructs of the questionnaire, and the professors independently assessed the extent to which the items captured each construct (Appendix A). The questionnaire consisted of a 5-point Likert scale (5-Strongly Agree to 1- Strongly Disagree). To check the inter-rater reliability, I used Fleiss' Kappa, one of the methods employed when more than two raters are involved (Han & Ryu, 2024; Laerd Statistics, 2019), and computed the data using an excel spreadsheet. Specifically, I used the main formula for the Kappa ($K = (p_o – p_e) / (1- p_e)$), in which case $p_o$ represents the observed values and $p_e$ the expected values by chance (Moons & Vandervieren, 2023). Likewise, I determined the 95% confidence interval (CI) by using the main formula of $CI = K \pm z * SE$, in which SE stands for standard error, and calculated the two-tailed *p*-value with the formula of $p = 2 * (1 – \Phi(|z|))$ (Moons & Vandervieren, 2023; Zapf et al., 2016). The comparison of the result was through the value range of Fleiss' Kappa (Albakkosh, 2024) to determine the strength of interrater agreements in the process of content validation.

To check construct validity, I initially performed an exploratory factor analysis. An exploratory factor analysis is a dimension reduction technique (Field, 2024) but in the present study, it served to verify whether the questionnaire items loaded together in the translated version, considering coefficients of .40 and above (Guvendir & Ozkan, 2022; P. Rogers, 2024). The exploratory factor analysis also helped check internal consistency and reliability through Cronbach's alpha and composite reliability, as well as convergent and discriminant validities. Cronbach's alpha is a measure of internal consistency mostly used in self-reported research instruments (Field, 2024), and its value can range from 0 to 1 (Field, 2024; Tharenou et al., 2007; Watkins, 2021). According to Kline (1994) the minimum acceptable value is .5 (poor), although some researchers prefer a higher value (Field, 2024; Watkins, 2021). For example, Field opined that the minimum value should be .7. Composite reliability (CR) is also a measure of internal consistency, ranging from 0 to 1, and is appropriate when laten constructs are measured (Cheung et al., 2024). Most importantly, CR compensates for Cronbach's alpha limitation of considering items loading as making equal contribution to latent constructs (Rogers, 2024). The present study included this measure for triangulation purposes in assessing construct validity.

The purpose of the pilot study was to check how well the research instrument could be valid and reliable, considering a threshold of .7 for both Cronbach's alpha and CR. The pilot study included the procedures for collecting data in the main study because its purpose was to shed light on how well the research model might work. The pilot study required no changes to the research instrument, so the main study included the data from the initial phase of the study (pilot). This inclusion is consistent with previous research, stating that data from the pilot may be more reliably used to inform or even be integrated into the main study if both phases maintain consistent designs (Ying & Ehrhardt, 2023).

The pilot study was a subsequent step to the approval of research proposal and the Walden University Institutional Review Board (IRB)'s endorsement (IRB approval number: 07-23-25-1184072). Capili and Anastasi (2024) defined IRB as a committee that evaluates and authorizes research involving human participants. Human participants provided data for the present study, and such entities must be treated with respect, justice, and beneficence (Cox, 2020a; Windsor et al., 2024). The IRB provided essential guidance to help address as many ethical issues as possible.

**Instrumentation and Operationalization of Constructs**

The present study included the research instruments developed and tested by Venkatesh et al. (2003), the UTAUT research model, and extended by Matar et al. (2020). To reiterate, Venkatesh et al. derived the UTAUT from a synthesis of eight theories or models, including the theory of reasoned action (Fishbein & Ajzen, 1975), the theory of planned behavior (Ajzen, 1985), the innovation diffusion theory (Rogers, 1983), the model of personal computer utilization (Thompson et al., 1991), the social cognitive theory (Bandura, 1986), the motivation model (Davis et al., 1992), the technology acceptance model (Davis, 1989), and the combination of the technology acceptance model and the theory of planned behavior (Ajzen, 1985). Venkatesh et al. estimated a measurement model of seven constructs, which they hypothesized to serve as a direct determinant of behavioral intention. Relevant constructs were EE, PE, SI, attitude toward using technology, FC, self-efficacy, and anxiety (Venkatesh et al., 2003). Using the data from four organizations, Venkatesh et al. noted an internal consistency in Cronbach's alpha greater than .7. The result demonstrated sufficient consistency, which gives some confidence in using the instrument as a reference for a novel research context.

Whereas the internal consistency was high, greater than .7 (Field, 2024), the analysis of structural model did not reveal the expected result in the study by Venkatesh et al. (2003). Venkatesh et al. found that the attitude toward using technology, self-efficacy, and anxiety were not direct determinants of behavioral intention. The construct validity was not attained fully, and the model remained with four constructs, including EE, PE, FC, and SI, which have been extensively investigated to understand CCBI and usage (Alfalah, 2023; Al-Okaily et al., 2023; Matar et al., 2020; Thanh et al., 2020). This result has served as the motivation for solely examining EE, PE, FC, and SI as possible determinants of behavioral intention from the UTAUT in the present study.

Another underlying reason for the choice of the four determinants of behavioral intention in the present study is the study by Matar et al. (2020). Matar et al. examined the influence of EE, PE, FC, and SI on the CCBI in five universities in Jordan. They administered an online questionnaire to faculty members and staff, and the descriptive analysis of the constructs yielded a Cronbach's alpha level greater than .7. This result is considered acceptable regarding internal consistency (Field, 2024; Watkins, 2021), and, together with that of Venkatesh et al. (2003), suggests that the instruments may be effectively used to examine the relationship between cloud computing factors and CCBI in the present study.

The use of a research instrument may require permission, depending on the conditions expressed by the publisher. For example, Venkatesh et al. (2003) reproduced research instruments with the copyright owner's permission and stated that further reproduction of their instrument without permission was prohibited. Using the items from the UTAUT, therefore, requires permission. Although a restriction has not been imposed on the extended research model by Matar et al., (2020), permission request was necessary for the present study. Indeed, Walden University's IRB recommends that, for courtesy, permission should be requested when items from a published research instrument are utilized even when restriction is not imposed (Harris, 2018). For the present study, I requested the permission to utilize the UTAUT scale (Appendix B) and the scale items by Matar et al. (Appendix C).

The research model resulting from the extension of the UTAUT in the present study consisted of four constructs serving as predictor variables: EE, PE, FC, and SI. The outcome variable was CCBI. Some of the predictor variables do not solely have a direct influence on behavioral intention. For example, the influence of FC on behavioral intention is known to be fully mediated by EE (Venkatesh et al., 2003). Similarly, the influence of EE on behavioral intention is known to be mediated by PE (Utomo et al., 2021). Therefore, the present study included an examination of the direct and indirect influences of predictor variables on CCBI as depicted in Figure 1 of Chapter 1. The next section includes more detailed accounts of how I examined the constructs in the present study.

## Data Analysis Plan

For data analysis, I used the Statistical Package for the Social Sciences (SPSS), Version 30. The choice of this data analytic tool requires an explanation because data can be analyzed using different software. For example, quantitative data can also be analyzed with Excel and Statistical Analysis System (Bansal & Srivastava, 2018; Lavanya et al., 2023), and qualitative data can be scrutinized using NVivo, MAXQDA, and Quirkos (Bassett, 2004; Mattimoe et al., 2021). Research has indicated that software packages for data analysis, either for quantitative or qualitative data, are similar but are not identical; they yield slightly different results (Sakaria et al., 2023; Shackman, 2022). This statement suggests that specifying the software used in a study may help other researchers conduct a replication.

SPSS was helpful in the present study for performing several analyses pertaining to a quantitative study, including testing assumptions, assessing reliability, and examining the relationships between constructs (Attwal & Dhiman, 2024; Field, 2024;

Warner, 2021). In Chapter 1, I discussed assumptions, but I use the term assumptions here to refer to data description as related to the type of statistical test to be used. In this conceptualization, Field (2024) describes an assumption as a representation of a condition ensuring that what a researcher is attempting to perform functions as expected. In quantitative data analysis, mainly when a linear model is to be assessed, data are assumed to exhibit some characteristics, such additivity and linearity (Field, 2024; Warner, 2021). The present study included the test of such assumptions to ensure that data exhibit the expected characteristics and are appropriate for the statistical test under consideration (regression analysis).

Assessing reliability entails checking consistency in the scores pertaining to a construct. According to Field (2024), this consistency should be expected if the score providers belong in the same sampling frame. In the case of the present study, only first year-university students participated to ensure the data came from the same population, and consistent rating was expected regarding cloud computing factors, namely EE, PE, SI, FC, and behavioral intention, as derived from the study by Matar et al. (2020). The assessment of reliability included Cronbach’s alpha and composite reliability, with a threshold of .7.

Field (2024) made an excellent discussing regarding reliability, stating that such a criterion for evaluating constructs is not a property of a measure or scale but is a function of the measure, participants, and the context in which participants rate the items relevant to the measure. This statement is substantiated in the fact that observing reliability in one instance of research does not necessarily mean all possible research instances will show reliability (Sigudla & Maritz, 2023; Tharenou et al., 2007). Assessing reliability is essential in every research context involving variables that cannot be measured directly, as is the case of cloud computing factors in the present study.

Examining the relationships between constructs consisted of understanding the extent to which EE, PE, SI, and FC influenced CCBI. Regression analysis was helpful in reaching this understanding (Field, 2024; Warner, 2021), indicating which factors academic managers in the target context might use to encourage cloud computing usage. Initially, the present study included the examination of the overall influence of predictor variables on CCBI and then the relative influence of each predictor variable on CCBI. These examinations were consistent with the research question for the present study, as I stated in Chapter 1:

- What is the relationship between cloud computing factors and the first-year university students' cloud computing behavioral intentions in Angola?

The present study also included null and alternative hypotheses, and I reiterate them here for contextualization:

$\boldsymbol{H_0}$: There are no relationships between cloud computing factors and the first-year university students' CCBI in Angola.

$\boldsymbol{H_1}$: There is a relationship between cloud computing factors and the first-year university students' CCBI in Angola.

More specific alternative hypotheses were tested to understand the relationship between relevant cloud computing factors and CCBI:

$H_{1.1}$: EE is positively related to CCBI.

$H_{1.2}$: EE is positively related to PE.

$H_{1.3}$: PE is positively related to CCBI.

$H_{1.4}$: FC is positively related to EE.

$H_{1.5}$: FC has no effect on CCBI when EE is present.

$H_{1.6}$: SI is positively related to CCBI.

$H_{1.7}$: SI is positively related to PE.

The present study included a regression analysis to test hypotheses, but such a statistical test needs explaining because it appears in different forms. A regression model can consist of only two variables: one predictor and one outcome. This model is referred to as simple linear regression (Field, 2024; Warner, 2021). In other cases, a research model may consist of two or more predictor variables and one outcome variable. The test for this research model is referred to as *multiple regression analysis* (Field, 2024; Warner, 2021). The research model for the present study contains four predictor variables and one outcome variable and corresponds to a multiple regression analysis.

Another variation of a regression analysis results from the characteristics of the data to be used, that is, whether assumptions are met or violated. In the case of multiple regression, the testing procedure can be changed from multiple linear regression to a multiple ordinal regression, in which case a researcher chooses from available non-parametric tests, such as Mann Witney's and Fredman's tests, if assumptions are violated (Argyrous, 2011; Field, 2024). The present study included the test of assumptions of multiple regression analysis, namely outliers, linearity, independence of errors, homoscedasticity, and normal distribution of errors.

Most assumptions can be violated upon being checked, but some solution exists that can allow the implementation of a linear regression analysis. According to Field (2024), one strategy to correct data is to remove outliers, and another one is to rely on the central limit theorem. Outliers are cases significantly differing from the rest of cases, so that the result can be biased (Di et al., 2024; Petronilla & Chinaka, 2023). The central limit theorem states that as a sample becomes larger, the assumption of normal distribution becomes less problematic (Field, 2024; Memon et al., 2020). The plan for the present study was to employ a multiple linear regression analysis. Data cleaning consisted of removing extreme outliers, and the central limit theorem was the reference point in case the outcome variable was not normally distributed. A non-parametric test was an alternative in case most assumptions were violated.

Testing the research model consisted of examining direct and indirect effects. Performing this double testing was helpful because the literature indicates that some variables operate through mediation. For example, the study by Shahbaz and Zahid (2022) indicated that perceived ease of use was related to perceived usefulness. Because perceived ease of use is identical to EE and perceived usefulness equates to PE (Venkatesh et al., 2003), the influence of EE on CCBI was expected to partially or fully operate through PE. Identifying such mediating effects may help academic managers in the research context focus properly on the required factors to encourage cloud computing usage. For instance, academic managers may place greater emphasis on of EE if the present study reveals this contract fully mediates the relationship between FC and CCBI.

Interpreting the significance of the relationships between cloud computing factors and CCBI consisted of assessing the overall influence of all predictors on the outcome variable in the first place and then the contribution of each predictor. This procedure is consistent with the statistical test under consideration in the present study, that is, a multiple regression analysis (Argyrous, 2011; Field, 2024; Tharenou et al., 2007; Warner, 2021). More specifically, the present study included an understanding of how much variance in the outcome variable is explained by the total influence of the predictor variables. This assessment indicated model fit if the alpha level (α) was equal or lower than .05, a threshold margin of error commonly accepted in social sciences (Bryman, 2016; Field, 2024).

In addition, the present study included the check of the overall effect size (observed effect size) to understand the magnitude of the predictor variables on the outcome variable (Argyrous, 2011; Field, 2024; Warner, 2021). This additional check is essential in that, according to Field (2024), the relevance of an effect is not revealed by significance alone. Other checks consisted of understanding the influence of each predictor variable on CCBI to derive information that academic managers in the target context can utilize to create a framework for encouraging cloud computing usage among first-year university students.

A notable feature of a multiple regression analysis is to help perform statistical control. According to Warner (2021), statistical control consists of understanding the extent to which a variable relates to another in the absence and presence of other variables. For example, understanding the relationship between $x_1$ and y may be more revealing when performed by controlling for $x_2$. A researcher can learn whether the influence of $x_1$ on y is fully or partially mediated by $x_2$ (Field, 2024; Saunders et al., 2023; Warner, 2021). Understanding whether part or all the influence of $x_1$ on y operates through $x_2$ is essential because $x_2$ can act as a confounding variable. Therefore, including a multiple regression analysis in the present study was helpful in performing statistical control.

## Threats to Validity

Research should contain features that demonstrate applicability of findings to and beyond the sample. Attaining these features is true in both quantitative research through random sampling (Bryman, 2016; Saunders et al., 2023) and qualitative research in a process referred to as *transferability* (Crawford, 2020; Ravitch & Carl, 2021). In addition, research must demonstrate that the relevant instrument measures the intended concepts or constructs in a study. These features are attained by addressing threats to validity (Bryman, 2016; Saunders et al., 2023). In this section, I discuss external validity, internal validity, and construct validity as appropriate to the present study. Content validity was part of the discussion in the pilot study section and is excluded from this section. The section ends with a discussion of the aspects related to ethical procedures.

### External Validity

Part of the criteria to ensure the quality of the present study was external validity. External validity is a research feature allowing the findings from a sample to be generalized to the relevant population (Bryman, 2016; Saunders et al., 2023), and this possibility can be attained when the sample is randomly selected (Bryman, 2016;

Saunders et al., 2023; Tharenou et al., 2007). The present study included a random sample to ensure every student in the population of first-year students had a chance to be included (Bryman, 2016; Cresswell & Cresswell, 2023); external validity was enhanced.

There are aspects that could compromise external validity, including the difference between a sample and population characteristics, setting-treatment interaction, and history-treatment interaction (Bryman, 2016), and such aspects need to be taken into consideration in discussing generalizability. The difference between a sample and population characteristics could be assessed in terms of demographic variables (Bryman, 2016), and the present study included the ones appearing the most salient and relevant. It included data on age, gender, possession of a smart device, and a laptop computer.

The explanation of setting and history is as follows. Setting-treatment interaction may be problematic because the findings obtained in one university may not hold in the others (Bryman, 2016; Infante-Rivard & Cusson, 2018); data will come from different sampling frames. Because the site for the present study was only one institution of higher education, generalizing to other institutions is considered with caution. History-treatment interaction may be a problem on the grounds that the findings obtained 5 years or more can no longer hold today (Bryman, 2016; Tharenou et al., 2007). This aspect of external validity can be seen in the recommendations for including more recent studies in research (Saunders et al., 2023; Tharenou et al., 2007). Given all these caveats, generalizing the findings from the present study should be exercised with caution.

**Internal Validity**

The present study is quantitative in nature and is within a cross-sectional time horizon. In this type of research strategy, data collection is performed at one point in time (Bryman, 2016; Saunders et al., 2023; Tharenou et al., 2007). This feature of a study constitutes a threat to internal validity. Internal validity concerns the question of whether an identified effect or influence is caused by a given variable (Bryman, 2016; Tharenou et al., 2007). Checking this concern can be straightforward in a cause-effect study, wherein the collection of data on a predictor variable is separated from the gathering of data for the outcome variable. When data on predictor and outcome variables are collected simultaneously, determining the direction of a relationship becomes less practical than when data collection is performed at different times (Bryman, 2016; Field, 2024). Results from a correlational study indicate only that variables are related.

Whereas researchers should consider the above caveat, they can set variables in such a way that the direction of the relationship between such variables is discernible. Bryman (2016) has put forth an excellent example of this discernment: if a researcher discovers that voting and age are related, they can hardly imagine that voting causes age; only the opposite is possible. The present study plotted the variables in a discernible way to minimize ambiguity regarding causal direction. Cloud computing factors are related to knowledge, and knowledge ignites intention (Setiya, 2011; Suwandi et al., 2021). More simply put, one assumption in the present study is that participants will intend to use cloud computing because they know this technological exists. Cloud computing has factors such as EE, PE, SI, and FC (Matar et al., 2020; Thanh et al., 2020), and knowledge of these factors may lead the participants to create an intention to use the technology. This argument is not to suggest that the results of the present study demonstrate strong causal inferences but to indicate that the outcomes may constitute excellent heuristics on which academic managers in the target context, and probably beyond, can draw to create policies and frameworks for encouraging cloud computing usage.

## Construct Validity

Construct validity concerns the extent to which a set of measures determines a given underlying construct. This description is specifically captured by Tharenou et al. (2007), who stated that construct validity pertains to how much a measure correlates with other measures in accordance with the predictions of an underlying theoretical framework of the construct. In the present study, scale items in the paper by Matar et al. (2020) were assessed to determine how well they correlate to form constructs. This check indicated whether the scale items or measured variables (Field, 2024; Warner, 2021) tapped an intended construct among EE, PE, FC, SI, and CCBI (Alfalah, 2023; Matar et al., 2020).

To assess the threat to construct validity, I initially performed an exploratory factor analysis to ensure scale items loaded well in a new research context. Subsequently, I checked convergent and discriminant validities, including internal consistency and reliability, using Cronbach's alpha and composite reliability, with a threshold of .7 (Abdallah et al., 2024; Alsheikh et al., 2024). Reliability and validity are inherently linked (Bryman, 2016; Tharenou et al., 2007). Tharenou et al. discussed that a measure could not be valid unless reliability was observed. A measure can be reliable without being valid but its validity cannot be taken seriously if reliability is absent (Bryman, 2016; Tharenou et al., 2007). Thus, in the present study, a minimum Cronbach's alpha and composite reliability of .7 was a benchmark measure to ascertain that threat to construct validity was minimized.

**Ethical Procedures**

The present study involved human participants, and, as required by ethical guidelines (Bazzano et al., 2021; Hanumaiah et al., 2024), the participants and the target setting provided consent. The target setting was a higher-education institution. As well as the participants, the president of this institution learned about the purpose of the study, the benefits accruing from the research, data protection of the institution and participants, and the availability of research outcomes to all participants when the research has been finalized. Participants received such information in a package containing the consent form for participants, the flyer (Appendix D), the questionnaire (Appendix E), and the letter of cooperation (Appendix F). These ethical components of the research are in alignment with Belmont's report, in which arguments are made for respecting persons, benefiting participants, and ensuring that research outcomes are equitably available (Anabo et al., 2019; Cox, 2020a; Eckstein, 2003).

The higher education institution where the present research was conducted serves as the workplace and is affiliated with my part-time lecturing position. This dual role potentially affects data quality, necessitating preventive measures, including approval from the IRB. According to Cox (2020a), when a researcher plays dual roles, potential participants may experience undue pressure to engage in the study; their relationship with the researcher may lead them to respond in a biased fashion, and this situation might undermine the validity of the acquired data. Similarly, Siipi and Uusitalo (2024) have stated that exerting dual roles in research causes data integrity problems, as was evident in their study seeking to understand students' feedback on an ethics course. Therefore, the present study included measures to minimize such possible undue pressure, bias, and data integrity problems by emphasizing the voluntariness of participation and the fact that opting out to participate has no negative consequences. In addition, this situation was subjected to the IRB's approval.

The recruiting material consisted of a flyer and an informed consent form. The consent form can create an ethical issue regarding anonymity and requires a careful consideration. Anonymity is the absence of identifying information in a document (Siipi & Uusitalo, 2024) and is part of the respect for persons (Cox, 2020a). In an online consent form, for example, participants may check a box to indicate they agree to participate in a study, and their identity is not revealed. Because the consent form in the present study was on paper, participants did not need to sign their names. Participants received an on-paper package containing a flyer, consent form, and questionnaire. Those who agreed to participate returned only the questionnaire, on which they indicated their agreement by checking one of the five options: Totally agree, Agree, Undecided, Disagree, and Totally disagree. The questionnaire sheets were anonymous.

On-paper data collection can also cause an ethical issue related to independence, which consists of participants influencing each other's responses (Cheung et al., 2024). For instance, students sitting in a classroom to respond to a questionnaire may overhear others' opinions regarding the questions. Addressing this independence issue consisted of enclosing the data collection package in an envelope and having participants take them home, returning only the questionnaire within the next 10 business days.

Another essential ethical issue is the risk participants may experience when answering the questionnaire. A research study can pose a risk if participants experience discomfort or harm when performing research-related tasks, such as answering a questionnaire and responding to interviews (Cox, 2020a; Tharenou et al., 2007). Cox discussed three types of risks, which I must describe to shed light on the ones envisaged in the present study: low, minimal, and more than minimal. A low risk may occur in studies that impose no discomfort or harm to participants, such as public-behavior observation and a literature review. Studies imposing a minimal risk are those causing a discomfort similar to the one individuals could experience in their daily lives, such as waiting longer for a webpage to load. A more than minimal risk is the one causing considerable physical or psychological discomfort or harm, such as identity being stolen or suffering from eye impairment as a result of prolonged use of a computer.

The present study included the prediction of a minimal risk because multiple-choice questions are usually extensive, and participants may experience stress in responding to them (García-Ros et al., 2018; Olson et al., 2025). This stress is similar to what could happen to participants if they were sitting at a bus station and the bus took longer than expected (Cox, 2020a). Addressing this risk in the present study consisted ofgiving participants sufficient time to respond (10 business days) and using a research instrument with only 19 items or measured variables (Appendix E). Gender and age are also of minimal risk because they are not sensitive personal data (Europe, 2024); however, I split age into categories for an even more minimal risk observance, such as 18 to 24 years and 25 to 31 years. Participants indicated their age by choosing from such options.

A final ethical consideration has to do with data storage and retention. I scanned all the questionnaire sheets and related documents electronically and stored them in a private OneDrive, in which they are to remain safe for a minimum of 5 years after the study is completed, as recommended by Tharenou et al. (2007). A private OneDrive is accessible through a password, and other parties can access this storage platform if permission is granted. Currently, Microsoft allows a document to be securely shared with others through OneDrive, and an access code can be generated for security purpose. Therefore, the data sharing process was secure and facilitated the committee to access raw data for transparency regarding analyses and interpretations.

## Summary

This chapter has included the design and methodological aspects of the study. The first aspect was the choice of a quantitative correlational research design and the clarification of the choice on the basis of the underlying epistemological and ontological perspectives. Quantitative research designs are various (Bryman, 2016; Saunders et al., 2023), but the present study includes a survey, mainly in a cross-sectional time horizon strategy, due to the time constraints for completing the research. The data collection procedures involved using a structured questionnaire consisting of a 5-point Likert scale, and the initial plan was to administer the questionnaire to a minimum random sample of

85 participants, as determined by using G*Power (Buchner et al., 2024; Memon et al., 2020), but latter extended to 195 participants to improve power and reduce bias. The sampling frame was a population of first-year university students in a developing country, and the study included a pilot phase to validate the research instrument in terms of content and construct.

The analytical technique was multiple linear regression to examine the relationship between existing cloud computing factors and CCBI. Predictor variables were EE, PE, FC, SI, and the outcome variable was CCBI, resulting in a research model appropriate to be tested using a multiple regression analysis technique (Field, 2024; Warner, 2021). The study included identifying validity and reliability issues and the measures to overcome them. The final discussion was ethics in research, ensuring that justice, respect for persons, and beneficence are taken into consideration (Anabo et al., 2019; Cox, 2020a; Eckstein, 2003). Subsequent to the Walden University IRB approval (IRB approval number: 07-23-25-1184072) and data collection, the next chapter includes the report of the results.

# Chapter 4: Results

The purpose of this quantitative correlational study was to examine the relationship between cloud computing factors (EE, PE, SI, and FC) and the first-year university students' CCBI in a developing country, specifically in Angola. The analysis of the results informed academic managers in developing countries about the mechanism required to create effective policies and frameworks to encourage cloud computing usage among students. The study included the following research question:

RQ: What is the relationship between cloud computing factors and the first-year university students' CCBI in Angola?

In addition, the study included testing the following overarching hypotheses:

$H_0$: There are no relationships between cloud computing factors and the first-year university students' CCBI in Angola.

$H_1$: There is a relationship between cloud computing factors and the first-year university students' CCBI in Angola.

These hypotheses were formulated to assess the overall research model. Predictor variables were regressed, and additional alternative hypotheses were tested.

$H_{1.1}$: EE is positively related to CCBI.

$H_{1.2}$: EE is positively related to PE.

$H_{1.3}$: PE is positively related to CCBI.

$H_{1.4}$: FC is positively related to EE.

$H_{1.5}$: FC has no effect on CCBI when EE is present.

$H_{1.6}$: SI is positively related to CCBI.

*H*$_{1.7}$: SI is positively related to PE.

This chapter proceeds as follows. First, I report the results of the pilot study and then describe the data collection procedures in the main study, including assessments of time frame, data collection plan, and baseline descriptive (demographics, sample, response rate, and a brief account on the research model). Finally, I present the results and provide a summary, leading to the next chapter.

## Pilot Study

The purpose of the pilot was to check the feasibility of the research instrument in understanding the relationship between cloud computing factors and CCBI among first-year university students in a higher education institution in Angola. The data collection period was from August 11 to August 26, 2025. Next, I report the findings , focusing the pilot sample characteristics, content and construct validities, and results on the relationship between variables.

### Pilot Study Sample Characteristics

The pilot study included 149 randomly selected participants (Table 1) from a population of 1200 students in the research institution. Demographic data showed a predominantly young sample, with 57% aged 25–34 and 35.6% aged 18–24; only 7.4% were aged 35–44, with no participants in older age groups. Gender distribution was fairly balanced (56.4% male, 43.6% female). Most participants (89.3%) owned smart devices, whereas laptop ownership was split (46.3% owned, 53.7% did not). These variables were relevant due to their potential impact on engagement with digital platforms, particularly cloud computing.

**Table 1**

*Demographic Variables*: *Pilot Study Sample Characteristics, n = 149*

| Demographic | Category | Frequency | Valid percentage |
|---|---|---|---|
| Age | 18--24 | 53 | 35.6% |
| | 25--34 | 85 | 57% |
| | 35--44 | 11 | 7.4% |
| | 45--54 | 0 | 0% |
| | 55--64 | 0 | 0% |
| | 65 or more | 0 | 0% |
| Gender | Male | 84 | 56.4% |
| | Female | 65 | 43.6% |
| Smart device | Yes | 133 | 89.3% |
| | No | 16 | 10.7% |
| Laptop | Yes | 69 | 46.3% |
| | No | 80 | 53.7% |

## Content Validity

To evaluate the content validity of the questionnaire, I measured the interrater reliability across five constructs and used Fleiss’ kappa, one of the methods employed when more than two raters are involved (Han & Ryu, 2024; Laerd Statistics, 2019). Five independent groups, each comprising six professors randomly selected from a population of 40, provided ratings on a 5-point Likert scale. The kappa coefficients indicated substantial agreement among raters: EE ($\kappa = .69$, 95% CI [.53, .84]), PE ($\kappa = .63$, 95% CI [.49, .75]), SI ($\kappa = .63$, 95% CI [.49, .76]), FC ($\kappa = .73$, 95% CI [.59, .86]), and CCBI ($\kappa = .77$, 95% CI [.65, .89]). All results were statistically significant ($p < .005$), supporting the content validity of the Portuguese version of the questionnaire. The summary of the result is in Table 2.

**Table 2**

*Content Validity, Interrater Reliability*

| Construct | Kappa | 95% CI | p |
|---|---|---|---|
| Effort expectancy | .69 | .53 to .84 | < .005 |
| Performance expectancy | .63 | .49 to .75 | < .005 |
| Social influence | .63 | .49 to .76 | < .005 |
| Facilitating conditions | .73 | .59 to .86 | < .005 |
| Behavioral intention | .77 | .65 to .89 | < .005 |

## Construct validity

### *Factor Analysis: Convergent Validity, Internal Consistency, and Reliability*

The present study included an exploratory factor analysis (EFA) using Principal Component Analysis and Oblimin rotation to validate the Portuguese translation of the research instrument originally developed by Matar et al. (2020), and with a view to confirming structural validity. I numbered the items in the research instrument from 1 to 4, such as EE1 and EE2. The analysis revealed five distinct components, with item loadings ranging from .613 to .945. EE2 showed cross-loading, but most items loaded strongly on their expected factors, such as FC1–FC4 (.938–.945) and SI1–SI4 (.739–.835). The cross loading was low (.04) on both factors (EE and PE), which is possible for retention (Cheung et al., 2024; P. Rogers, 2024). Therefore, despite the minor cross-loading, the overall structure was consistent with the original model, confirming the structural validity of the translated research instrument.

To assess convergent validity, I used the Average Variance Extracted (AVE) for each construct. The AVE values were PE = .696, EE = .668, SI = .622, FC = .886, and CCBI = .596. According to Fornell and Larcker’s (1981) criterion, an AVE value of .50 or higher indicates adequate convergent validity. All constructs met this threshold, suggesting that the items within each construct share a high proportion of variance. Although CCBI had the lowest AVE at .596, it still exceeded the recommended minimum, supporting the validity of the construct.

To evaluate internal consistency and reliability, I used Cronbach's alpha (α) and Composite Reliability (CR). The results showed strong reliability across all constructs: PE (CR = .899, α = .876), EE (CR = .884, α = .879), SI (CR = .868, α = .884), FC (CR = .969, α = .969), and CCBI (CR = .807, α = .820). All CR and α values exceeded the recommended threshold of .70 (Ahmad et al., 2024; Nunnally & Bernstein, 1994), indicating that the measurement scales used in this study are both internally consistent and reliable. The summary of the results is in Table 3.

**Table 3**

*Convergent Validity, Internal Consistency, and Reliability – Pilot Study*

| Factors | AVE | CR | α |
|---|---|---|---|
| PE | .696 | .899 | .876 |
| EE | .668 | .884 | .879 |
| SI | .622 | .868 | .884 |
| FC | .886 | .969 | .969 |
| CCBI | .596 | .807 | .820 |

### *Discriminant Validity*

To assess discriminant validity, I used a correlation matrix where the diagonal values represent the square roots of the AVE for each construct—PE, EE, SI, FC, and CCBI. These diagonal values were all higher than the corresponding off-diagonal correlations between constructs, indicating that each construct is empirically distinct (Hair et al., 2022; Henseler et al., 2020). For example, PE's diagonal value of .834

exceeds its highest off-diagonal correlation of .393 with CCBI. All other constructs showed the same pattern. These results collectively support the discriminant validity of the constructs, indicating that each construct is empirically distinct and captures unique aspects of user perceptions and intentions regarding cloud computing usage (summary in Table 4).

**Table 4**

*Discriminant Validity – Pilot Study*

| Factors | PE | EE | SI | FC | CCBI |
|---|---|---|---|---|---|
| PE | **0.834** | | | | |
| EE | .369** | **0.818** | | | |
| SI | .219** | .478** | **0.788** | | |
| FC | -0.103 | .336** | .470** | **0.942** | |
| CCBI | .393** | .471** | .456** | .271** | **0.772** |

** Correlation is significant at the 0.01 level (2-tailed).

## Relationship Between Variables – Hypotheses Testing

To analyze the relationship between variables, I used a multiple linear regression. I computed the questionnaire scale items into composite scores (continuous variables) and checked the data for extreme outliers. In addition, I assessed the assumptions of linearity, autocorrelation, multicollinearity, homoscedasticity, and normality to decide on an appropriate statical model (linear or quadratic) (Field, 2024; Warner, 2021). All assumptions were tenable, except for normality distribution; the test of Shapiro-Wilk was statistically significant ($p < .001$) for every variable, indicating that such variables were not normally distributed (Allen et al., 2020; Mukherjee & Bhonge, 2025). For this assumption, I resorted to the central limit theorem. According to Field (2024), the most important assumption is linearity, which dictates the type of statistical model to be used.

The result of assumptions testing in the pilot study allowed the use of a multiple linear regression model.

The multiple linear regression analysis indicated that PE, EE, SI, and FC significantly predict CCBI; the overall regression model was statistically significant, $F(4, 144) = 19.347$, $p < .001$, and the model explained approximately 35% of the variance in CCBI ($R^2 = .350$), suggesting a moderate effect size. Based on these results, the null hypothesis ($H_0$) is rejected, and the alternative hypothesis ($H_1$) is accepted: there are relationships between cloud computing factors and the first-year university students' CCBI in Angola.

An examination of the individual predictors revealed that three out of the four positively and significantly influenced CCBI: PE ($\beta = .305$, $t = 3.573$, $p < .001$), EE ($\beta = .217$, $t = 2.646$, $p = .009$), and SI ($\beta = .196$, $t = 2.859$, $p = .005$). These results suggest that the three constructs are associated with stronger behavioral intentions to adopt cloud computing. In contrast, FC did not significantly predict CCBI ($\beta = .076$, $t = 1.407$, $p = .162$), indicating that perceived support and resources may not directly influence intention in this context.

The effect of some variables on the outcome variable were hypothesized to operate through mediation, namely EE, FC, and SI. The result indicated that PE partially mediates the relationships between EE and CCBI as wells between SI and CCBI. However, the relationship between FC and CCBI operates fully through EE. As summarized in Table 5, all hypotheses were supported. The results arising from the pilot study suggest that cloud computing factors, PE, EE, SI, have a greater potential to support academic managers in creating policies and frameworks for encouraging cloud computing usage among first-year university students in Angola.

**Table 5**

*Regression Analysis Predicting Cloud Computing Behavioral Intention – Pilot Study*

| Hypothesis | Path | B | t | p | Supported? |
|---|---|---|---|---|---|
| H1.1 | EE → CCBI | .217 | 2.65 | .009 | Yes |
| H1.2 | EE → PE | .325 | 4.81 | <.001 | Yes |
| H1.3 | PE → CCBI | .305 | 3.57 | <.001 | Yes |
| H1.4 | FC → EE | .226 | 4.32 | <.001 | Yes |
| H1.5 | FC → CCBI | .076 | 1.407 | .162 | Yes (no effect) |
| H1.6 | SI → CCBI | .196 | 2.86 | .005 | Yes |
| H1.7 | SI → PE | .159 | 2.72 | .007 | Yes |
| R | 0.591 | | | | |
| F(4, 144) | 19.347 | | | | |

## Data Collection

The period for data collection in the main study was from September 2 to September 15, 2025. This timeframe was essential because students were at the end of an academic semester and had more time to engage in the study. My original intention was to complete data collection in August, but delays in the IRB approval process, which concluded in late July, necessitated the shift to September. I reserved August for collecting data for the pilot study, which was the time for the research instrument validation.

As in the pilot study, the main study included additional participants (*n* = 57), who were randomly selected from a population of 1200 first year university students. I invited these participants to collect a recruitment material package, which included a consent form and a questionnaire, from the staff room of the research institution. Participants returning the questionnaire were 46, resulting in a response rate of approximately 81%. This response rate is reasonably high (Bryman, 2016; Jenkins & Quintana-Ascencio, 2020), indicating a successful recruitment strategy. I put the participants in the pilot study together with the 46 cases to form the sample for the main study. As stated in the pilot study section, this decision is consistent with previous research, stating that data from the pilot may be more reliably used to inform or even be integrated into the main study if both phases maintain consistent designs (Muasya & Mulwa, 2023; Ying & Ehrhardt, 2023). The sample for the main study therefore consisted of 195 cases, as I discuss with regard to the demographic variables next.

The demographic characteristics of the sample (*n* = 195) are in Table 6. The majority of participants was aged 25–34 years (55.9%), followed by those aged 18–24 years (36.9%). A smaller proportion was aged 35–44 years (7.2%), with no participants in the 45–54, 55–64, or 65+ age groups. The sample was predominantly male (55.4%), with females comprising 44.6%. Most participants reported owning a smart device (89.7%), whereas 10.3% did not. Laptop ownership was nearly evenly split, with 48.7% owning a laptop and 51.3% not owning one.

**Table 6**

*Demographic Variables: Main Study Sample Characteristics, n = 195*

| Demographic | Category | Frequency | Valid Percentage |
|---|---|---|---|
| Age | 18--24 | 72 | 36.9% |
| | 25--34 | 109 | 55.9% |
| | 35--44 | 14 | 7.2% |
| | 45--54 | 0 | 0% |
| | 55--64 | 0 | 0% |
| | 65 or more | 0 | 0% |
| Gender | Male | 108 | 55.4% |
| | Female | 87 | 44.6% |
| Smart Device | Yes | 175 | 89.7% |
| | No | 20 | 10.3% |
| Laptop | Yes | 95 | 48.7% |
| | No | 100 | 51.3% |

To assess the representativeness of the sample, I compared its demographic characteristics with those of the target population. The sample was predominantly composed of individuals aged 25–34 years (55.9%) and 18–24 years (36.9%), with very few participants aged 35–44 years and none above 44 years. This age distribution suggests that the sample may be representative of a younger population, such as university students or young professionals, but may not adequately reflect older age groups if they are present in the broader population. The gender distribution was relatively balanced, with a slight male predominance (55.4% male, 44.6% female), which aligns with the gender composition of the population of interest (male = 53% and female = 47%). Additionally, the high rate of smart device ownership (89.7%) and moderate laptop ownership (48.7%) indicate that the sample is technologically engaged, which could be representative if the population is expected to have high technology access.

However, if the broader population includes individuals with lower technology access or a wider age range, the sample may not fully capture this diversity. Overall, whereas the sample appears representative of a younger, technologically engaged demographic, caution should be exercised when generalizing findings to older or less technologically connected groups.

## Study Results

The data collected from the sample in the main study yielded essential information that can be used when considering the findings of the present research in different contexts. The aged 25–34 (55.9%) and 18–24 (36.9%) indicated that the findings are more applicable to younger population than the one aged 35 and above. In addition, the apparent balance regarding gender indicated that male and female students in their first year of university studies may equally benefit from the findings. These findings are aligned with the ones obtained in the pilot study. To establish consistency and comparability, I analyzed the data obtained in the main study following the procedure in the pilot study, that is, focusing on construct validity and assumptions before utilizing a multiple linear regression to test hypotheses.

### Construct Validity: Main Study

#### *Factor Structure*

The main study still included the assessment of the scale items in the study by Matar et al. (2020) by first conducting an exploratory factor analysis (EFA) using Principal Component Analysis with Oblimin rotation and Kaiser normalization. This initial assessment was helpful in certifying that the translated items retained their intended factor structure in the new linguistic and cultural context. The pattern matrix revealed that the items clustered strongly onto five distinct components: SI, PE, EE, FC, and CCBI. Specifically, items SI1 to SI2 loaded highly on the SI factor, PE4 to PE1 on the PE factor, EE3 to EE2 on the EE factor (with negative loadings), FC3 to FC4 on the FC factor, and BI3 to BI2 on the CCBI factor (also with negative loadings). These results indicate that the translated items are well-aligned with their respective theoretical constructs, as in the pilot study, supporting the validity of the factor structure in the Portuguese context.

***Convergent Validity, Internal Consistency, and Reliability***

To assess convergent validity, I used the AVE for each construct. The AVE values for PE (.663), EE (.683), SI (.638), FC (.809), and BI (.644) all exceeded the recommended threshold of .50 (Cheung et al., 2024; Fornell & Larcker, 1981). These values indicate that each construct explains a substantial proportion of variance in its indicators, with more than 50% of the variance in the observed variables being accounted for by their respective latent factors. Such results provide strong evidence for the convergent validity of the translated scale in the context of the present study.

To evaluate the internal consistency and reliability of the constructs, I used CR and α. All constructs demonstrated strong reliability, as shown in the following results: PE (CR = .885, α = .860), EE (CR = .891, α = .874), SI (CR = .876, α = .894), FC (CR = .944, α = .964), and CCBI (CR = .838, α = .802). Each of these values exceeded the recommended threshold of .70 (Ahmad et al., 2024; Nunnally & Bernstein, 1994), indicating high internal consistency and reliability for all factors in the measurement model. These results not only confirm the internal consistency of the constructs but also reinforce the robustness of the measurement model employed in the study. CR values above .85 across all constructs suggest that the latent variables are well represented by their observed indicators, minimizing measurement error (Baharum et al., 2023; Bell et al., 2024). Similarly, α values exceeding the .80 threshold indicate a high degree of interrelatedness among the items within each construct (Edelsbrunner et al., 2025; Izah et al., 2024), further validating the reliability of the scales used.

Notably, the FC construct demonstrated the highest reliability (CR = .944, α = .964), implying that the items measuring this construct are particularly cohesive and consistently reflect the underlying concept (Baharum et al., 2023; Bell et al., 2024). This result could suggest that respondents had a clear and unified understanding of the support mechanisms available to them, which may play a critical role in influencing behavioral intentions. The overall results of convergent validity and internal consistency and reliability are summarized in Table 7.

**Table 7**

*Convergent Validity, Internal Consistency, and Reliability – Main Study*

| Factors | AVE | CR | α |
|---|---|---|---|
| PE | .663 | .885 | .860 |
| EE | .683 | .891 | .874 |
| SI | .638 | .876 | .894 |
| FC | .809 | .944 | .964 |
| CCBI | .644 | .838 | .802 |

### ***Discriminant Validity***

To evaluate discriminant validity, I used the Fornell and Larcker's (1981) criterion, which establishes a comparison between the square root of the AVE for each construct and its correlations with other constructs. As presented in Table 8, the square root of AVE for each factor (PE = .814; EE = .826; SI = .799; FC = .899; CCBI = .802) exceeds the corresponding inter-construct correlations. For instance, PE's highest correlation is with CCBI (r = .335), which is lower than its AVE square root, demonstrating that PE shares more variance with its own indicators than does with other constructs. These results confirm the discriminant validity across all constructs, consistent with the guidelines proposed by Fornell and Larcker, and are supported by recent applications in structural equation modeling, as discussed by Hair et al. (2021). Therefore, as in the pilot study, analysis confirmed discriminant validity for the constructs in the novel research context.

**Table 8**

*Discriminant Validity – Main Study*

| Factors | PE | EE | SI | FC | CCBI |
|---|---|---|---|---|---|
| PE | **.814** | | | | |
| EE | .292** | **.826** | | | |
| SI | 0.098 | .359** | **.799** | | |
| FC | -.191** | .299** | .556** | **.899** | |
| CCBI | .335** | .414** | .447** | .294** | **.802** |

** Correlation is significant at the 0.01 level (2-tailed).

## Statistical Assumptions

Other essential checks were the assumptions regarding regression analysis. According to Jones et al. (2025), as well as Marisetty (2024), failure to assess assumptions such as linearity, multicollinearity, and homoscedasticity can lead to flawed analyses and misleading conclusions. This position is similarly captured by Shatz (2024), who showed how violations of assumptions like homoscedasticity and multicollinearity could lead to biased estimates and incorrect conclusions. The present study, therefore, included the assessment of assumptions of linearity, autocorrelation, multicollinearity, outliers, homoscedasticity, and normality to ensure the use of a linear regression was appropriate.

***Linearity***

Linearity is the most critical assumption in performing a regression analysis. Indeed, in classifying statistical assumptions, Field (2024) ranked this assumption in the first place on the grounds that it underpins any chosen model (linear or quadratic). Similarly, Lewis-Beck and Lewis-Beck (2015) emphasized that linearity was the most critical assumption in linear regression. These authors further explained that if the relationship between variables was not linear, the model could produce biased and misleading results, regardless of how well other assumptions were met. A significant linearity term ($p < .05$) alongside a non-significant deviation term ($p > .05$) indicates that the assumption is met (Morgan et al., 2023; Nahhas, 2024). The present study assessed linearity assumption using ANOVA-based tests for both the linearity component and the deviation from linearity for each predictor: PE, EE, SI, and FC.

For PE and EE, the linearity assumption was satisfied. The linearity test for PE yielded a statistically significant $F$-value of 24.730 ($p < .001$), and the deviation from linearity was not significant ($F = 1.427$, $p = .197$). Similarly, EE met the linearity assumption, with a strong linearity *F*-value of 40.052 ($p < .001$) and a non-significant deviation ($F = 1.039$, $p = .414$). The significance of these findings confirms that the relationship between the predictors (PE and EE) and the dependent variable (CCBI) is appropriately modeled using a linear framework. A significant linearity F-value, coupled with a non-significant deviation from linearity, indicates that the variance in CCBI can be reliably explained by linear changes in PE and EE. This finding supports the theoretical assumptions of linear regression and enhances the credibility of the model's estimates. Succinctly, the results suggest that both PE and EE have a valid linear relationship with CCBI, justifying their inclusion in subsequent regression analyses.

Linearity assumption was equally tenable for SI and FC. SI demonstrated the strongest linear relationship with CCBI among all predictors. Its linearity test produced an *F*-value of 48.561 ($p < .001$), and its deviation from linearity remained non-significant ($F = 1.092$, $p = .370$), confirming the assumption. FC also met the linearity assumption, with a significant linearity *F*-value of 18.305 ($p < .001$) and a non-significant deviation ($F = 1.045$, $p = .408$). These findings underscore the robustness of the linear relationship between these predictors (SI and FC) and the outcome variable (CCBI). The particularly high F-value for SI suggests that this construct is a strong explanatory variable for the variations in CCBI, reinforcing its theoretical importance in the model. The non-significant deviation from linearity further confirms that the relationship is not only statistically significant but is also appropriately modeled using a linear approach.

For FC, while the linearity *F*-value is comparatively lower than that of SI, the result remains statistically insignificant, indicating a meaningful linear association with

CCBI. The non-significant deviation from linearity suggests that the data do not exhibit substantial curvature or non-linear trends (Morgan et al., 2023; Nahhas, 2024), supporting the appropriateness of including FC in the linear regression model. Overall, the confirmation of linearity for both SI and FC enhances the validity of the regression analysis. The confirmation ensures that the estimated coefficients for these predictors will be unbiased and interpretable, thereby contributing to the reliability of the study's conclusions regarding the factors influencing CCBI. The result of linearity assumption is shown in Table 9.

**Table 9**

*Test of Linearity Assumption*

| Predictor | R | $R^2$ | Eta | $Eta^2$ | F (Linearity) | p (Linearity) | F (Deviation) | p (Deviation) | Linearity Assumption Met? |
|---|---|---|---|---|---|---|---|---|---|
| PE | .335 | .112 | .397 | .157 | 24.73 | < .001 | 1.427 | .197 | Yes |
| EE | .414 | .172 | .47 | .22 | 40.052 | < .001 | 1.039 | .414 | Yes |
| SI | .447 | .2 | .5 | .25 | 48.561 | < .001 | 1.092 | .37 | Yes |
| FC | .294 | .086 | .368 | .136 | 18.305 | < .001 | 1.045 | .408 | Yes |

***Autocorrelation***

To assess the assumption of autocorrelation or independence of residuals, I used the Durbin-Watson statistic. The literature suggests that a Durbin-Watson statistic between 1.5 and 2.5 is generally considered acceptable and indicates a lack of significant autocorrelation in the residuals (Bobbitt, 2024; Field, 2024; Gujarati & Porter, 2021). In the present study, the analysis yielded a Durbin-Watson value of 1.864, and therefore the autocorrelation assumption was tenable. This result indicates that the residuals from the regression model are approximately independent, meaning that the error terms are not systematically correlated with one another. The autocorrelation assumption is critical in linear regression in that its violations, particularly positive autocorrelation, can lead to underestimated standard errors, inflated *t*-statistics, and yielding significant tests that are misleading (Field, 2024; Warner, 2021). The Durbin-Watson value of 1.864, in the present study, falls comfortably within the acceptable range, suggesting that the model does not suffer from serial correlation and that the residuals behave randomly across observations.

***Multicollinearity***

Multicollinearity is present when predictor variables correlate highly with each other. Field (2024) considers predictors correlating at .8 or .9 as exhibiting multicollinearity. More specifically, Warner (2021) discusses that predictor variables correlating in excess at .9 may be measuring the same thing and one of them should be dropped. The correlation matrix in Table 8 shows values on off diagonal well below this threshold. In addition, multicollinearity can be detected by inspecting the variance inflation factor (VIF) and tolerance from SPSS output, in which a violation is observed if VIF is not less than 10 and tolerance is not greater than .1 (Field, 2024; Gujarati & Porter, 2021). In the present study, all tolerance values ranged from .598 to .804, and all VIF values ranged from 1.244 to 1.673. These results indicate that there is no significant multicollinearity among the predictors in the regression model, and thus the assumption of multicollinearity was not violated.

***Outliers***

An outlier is an observation deviating from a pattern. In a distribution, a score lying far from the other scores (below 3 or -3 standard deviation from the mean) is considered as an outlier (Leys et al., 2019; Todorov et al., 2020). Outliers can be checked on one variable (univariate outlier) or on a distribution whereby two or more variables are combined (multivariate outlies) (Todorov et al., 2020). In the present study, I checked the univariate outliers using boxplots in SPSS outputs, and the result indicated no extreme cases. In addition, I examined multivariate outliers using the Mahalanobis distance statistics. Given that the model included four predictor variables and the sample size was 195, the critical chi-square value at the $p < .001$ level with 4 degrees of freedom is approximately 18.47 (Field, 2024; Tabachnick & Fidell, 2019). The maximum Mahalanobis distance observed in the data was 16.344, which falls below this threshold. Therefore, no cases exceeded the critical value, indicating that the assumption of no multivariate outliers was not violated. Overall, the assumption of outliers was tenable.

***Homoscedasticity***

Homoscedasticity consists of the observation that the variance of residuals in a regression model is constant at all levels of the predictor variables. When this pattern is not observed, heteroscedasticity is present (Onifade & Olanrewaju, 2020; Su & Berenson, 2017). One acclaimed tool to detect homoscedasticity is the White test for heteroskedasticity, the result of which should be non-statistically significant for homoscedasticity to be observable (Onifade & Olanrewaju, 2020; Su & Berenson, 2017). In this study, the White test for heteroskedasticity produced a Chi-Square value of 15.117

with 14 degrees of freedom and a significance level of .370 (Figure 3). Because the p-value exceeds the conventional alpha level of .05, the null hypothesis that the variance of errors is independent of the values of the independent variables cannot be rejected. This result indicates that there is no evidence of heteroskedasticity, and thus the assumption of homoscedasticity holds for this model.

**Figure 3**

*The White Test for Heteroskedasticity Showing no Violation of Homoscedasticity*

White Test for Heteroskedasticity[a,b,c]

| Chi-Square | df | Sig. |
|---|---|---|
| 15.117 | 14 | .370 |

a. Dependent variable: CCBI

b. Tests the null hypothesis that the variance of the errors does not depend on the values of the independent variables.

c. Design: Intercept + PE + EE + SI + FC + PE * PE + PE * EE + PE * SI + PE * FC + EE * EE + EE * SI + EE * FC + SI * SI + SI * FC + FC * FC

### *Normality*

To assess the normality of data distribution, I used the Kolmogorov-Smirnov and Shapiro-Wilk statistics, both of which yielded significant results ($p < .001$) for all variables, indicating that the assumption of normality was violated. However, considering the sufficiently large sample size (n = 195), I resorted to the Central Limit Theorem (CLT), which posits that the sampling distribution of the mean tends toward normality as sample size increases, regardless of the shape of the population distribution (Field, 2024; Stevens, 2016). This theoretical foundation supports the use of parametric tests such as linear regression even when normality is not strictly met (FasterCapital, 2024; Field, 2024). Therefore, data analysis in the present study was conducted using multiple linear regression, and the robustness of the results was supported by the sample size and the applicability of the CLT.

**Relationship Between Variables: Hypotheses Testing**

As in the pilot study, in the main phase, the present study included a multiple linear regression analysis to examine the relationship between cloud computing factors (EE, PE, SI, FC) and first-year university students' CCBI in Angola. The basis of analysis was initially the null hypothesis that there are no relationships between cloud computing factors and the first-year university students' CCBI in Angola and the alternative hypothesis that there is a relationship between cloud computing factors and the first-year university students' CCBI in Angola. The regression model explained approximately 33.6% of the variance in the first-year university students' CCBI ($R^2$ = .336). The overall regression model was statistically significant, $F(4, 190) = 24.051$, $p <$ .001, indicating that the set of predictor variables reliably influenced the first-year university students' CCBI in Angola. Therefore, the null hypothesis is rejected, and the alternative hypothesis is supported, concluding that there is a significant, positive relationship between cloud computing factors and the first-year university students' CCBI in Angola. The study included testing additional alternative hypotheses, and the results are presented next.

$H_{1.1}$ of EE on CCBI: the results indicated that EE has a positive and statistically significant influence on CCBI ($\beta = 0.184$, $t = 2.87$, $p = .005$). This result suggests that when users perceive cloud computing systems as easy to use, their intention to adopt and use these systems increases. The positive coefficient implies that improvements in the perceived ease of use are associated with higher behavioral intention. This finding aligns with the core tenets of the UTAUT, where EE is a key determinant of behavioral intention (Alfalah, 2023; Venkatesh et al., 2003). The statistically significant t-value and low p-value reinforce the reliability of this relationship, indicating that the observed effect is unlikely to be due to chance. The unstandardized beta coefficient ($\beta = .184$) reflects a moderate effect size, suggesting that although EE is not the strongest predictor, the construct plays a meaningful role in shaping users' intentions. Therefore, Hypothesis $H_{1.1}$ is supported.

$H_{1.2}$ of EE on PE: EE was also found to be a significant predictor of PE ($\beta = 0.254$, $t = 4.24$, $p < .001$). This finding indicates that as users find cloud computing platforms easier to use, they are more likely to believe these platforms will enhance their study performance. The strong statistical significance ($p < .001$) indicates a robust relationship. This result suggests that ease of use not only directly influences behavioral intention but also indirectly affects the construct by shaping users' beliefs about the performance benefits of cloud computing. This finding supports the alternative hypothesis 1.2 ($H_{1.2}$).

$H_{1.3}$ of PE on CCBI: PE demonstrated a strong, positive, and statistically significant effect on CCBI ($\beta = 0.303$, $t = 4.20$, $p < .001$). This result indicates that users who expect cloud computing to improve their study performance are more likely to intend to use the technology. The relatively high coefficient suggests that PE is one of the most influential predictors in the model. The strength of this relationship underscores the central role of PE in shaping behavioral intention, consistent with the UTAUT (Alfalah, 2023; Venkatesh et al., 2003). An unstandardized beta of .303 indicates that for every 1 standard deviation increase in PE, there is a corresponding .303 standard deviation increase in CCBI (Field, 2024; Warner, 2021), highlighting a substantial effect. The high t-value and highly significant p-value ($p < .001$) further confirm the robustness of this relationship, suggesting that the effect is not only statistically reliable but also practically meaningful. Therefore, Hypothesis $H_{1.3}$ is supported.

$H_{1.4}$ of FC on EE: the analysis revealed that FC have a positive and significant effect on EE ($\beta = 0.195$, $t = 4.35$, $p < .001$). The positive relationship indicates that when users perceive strong support and resources (such as training, help desks, and technical assistance), they are more likely to find cloud computing easy to use. This finding supports $H_{1.4}$ and underscores the importance of providing adequate support mechanisms to enhance users' perceptions of ease of use. This relationship is theoretically consistent with the UTAUT framework, where FC is posited to influence EE by reducing perceived barriers to technology use (Reyes & Booc, 2024; Sang et al., 2023). In practical terms, this finding means that institutions aiming to promote cloud computing adoption should invest in infrastructure, user training, and ongoing technical support. These resources not only empower users to navigate the technology more confidently but also reduce anxiety and resistance associated with learning new systems.

$H_{1.5}$ of FC on CCBI in the absence of EE: the regression results showed that the effect of FC on CCBI is not statistically significant when EE is included in the model ($\beta = .084$, $t = 1.78$, $p = .077$). The p-value exceeded the conventional threshold of .05, indicating that FC does not have a direct effect on behavioral intention in this context.

This finding supports $H_{1.5}$, which stated that the influence of FC on behavioral intention is mediated by EE. In other words, once users' perceptions of ease of use are accounted for, the direct impact of support structures on CCBI becomes negligible. This result highlights the mediating role of EE in the relationship between FC and CCBI.

$H_{1.6}$ of SI on CCBI: SI was found to have a positive and statistically significant effect on CCBI ($\beta = .211$, $t = 3.70$, $p < .001$). This finding suggests that users are more likely to intend to use cloud computing if they perceive that important others (such as classmates, professors, or educational leaders) believe they should do so. Particularly, this finding highlights the importance of leveraging social dynamics in promoting the use of an information system. Institutions can enhance cloud computing usage by fostering a culture of endorsement among faculty and student leaders, integrating cloud tools into collaborative learning activities, and showcasing success stories of peers who have benefited from an information system. By doing so, users can amplify the perceived social value of cloud computing, thereby strengthening users' behavioral intentions. This result supports Hypothesis $H_{1.6}$.

$H_{1.7}$ of SI on PE: the relationship between SI and PE was not statistically significant ($\beta = .069$, $t = 1.37$, $p = .172$). This result indicates that, in this study, SI does not significantly affect users' beliefs about the performance benefits of cloud computing. The non-significant result suggests that although social influence can directly shape behavioral intention, such a construct does not necessarily alter users' perceptions of how cloud computing will impact their study performance. Therefore, $H_{1.7}$ is not supported. The overall results are summarized in Table 10.

**Table 10**

*Regression Analysis Predicting Cloud Computing Behavioral Intention – Main Study*

| Hypothesis | Relationship | B | t-value | p | Supported? |
|---|---|---|---|---|---|
| $H_{1.1}$ | EE → CCBI | .184 | 2.87 | .005 | Yes |
| $H_{1.2}$ | EE → PE | .254 | 4.24 | <.001 | Yes |
| $H_{1.3}$ | PE → CCBI | .303 | 4.20 | <.001 | Yes |
| $H_{1.4}$ | FC → EE | .195 | 4.35 | <.001 | Yes |
| $H_{1.5}$ | FC → CCBI | .084 | 1.78 | .077 | Yes (no effect) |
| $H_{1.6}$ | SI → CCBI | .211 | 3.70 | <.001 | Yes |
| $H_{1.7}$ | SI → PE | .069 | 1.37 | .172 | No |
| R | .580 | | | | |
| $F(4, 190)$ | 24.501 | | | | |

## Summary

This chapter consisted of presenting results regarding the research question of whether there is a relationship between cloud computing factors (EE, PE, SI, and FC) and the first-year university students' CCBI in Angola. The first report was the results of the pilot study, including the steps for validating the research instrument. The process included checking assumptions in both pilot and main study to ensure the linear regression model was an appropriate tool to examine the relationships. The pilot study yielded essential information regarding the validity and reliability of the research instrument, as well as the result of hypotheses testing. The overall result in both pilot and main studies indicated that cloud computing factors, as theorized by the UTAUT (Matar et al., 2020; Venkatesh et al., 2003), have a significant and positive influence on CCBI among first year university students in Angola.

The assessment included the relative influence of each factor on CCBI. In both the pilot and main studies, predictor variables were overall found to exert a positive, significant influence on CCBI, suggesting that the assessment of the research model shows considerable potential for supporting academic managers in the research context to create policies and framework to support the use of cloud computing. The findings were consistent from the pilot to the main study, with the only difference being that the influence of SI on PE was supported in pilot study but not in the main study. This inconsistency can be discussed as having implications for sampling procedures and research. In the next chapter, I provide a more comprehensive discussion of the overall findings.

# Chapter 5: Discussion, Conclusions, and Recommendations

In this quantitative correlational study, I examined the relationship between cloud computing factors (EE, PE, SI and FC) and the first-year university students' CCBI in a developing country, specifically in Angola. Particularly, I sought to examine the influence of EE, PE, SI, and FC on CCBI, and my goal was to identify which of the predictor variables academic managers in higher education institutions could utilize to create policies and framework for promoting the use of cloud computing. In the rest of this chapter, I first provide a summary and interpretation of key findings and then discuss the limitations and recommendations based on the findings. Finally, I discuss the implications of the study and provide conclusions.

The null hypothesis was that there is no relationship between cloud computing factors and CCBI, and the alternative hypothesis stated that the relationship exists. The multiple linear regression analysis indicated that, overall, the cloud computing factors significantly influence CCBI ($F[4, 190] = 24.051$, $p < .001$), and the model explains approximately 33.6% of the variance in CCBI. This result provides the support for rejecting the null hypothesis and supporting the alternative one. Additionally, all cloud computing factors depicting a direct relationship with CCBI were supported: EE ($\beta = .184$, $t = 2.865$, $p = .005$), PE ($\beta = .303$, $t = 4.202$, $p < .001$), SI ($\beta = .211$, $t = 3.695$, $p < .001$), and FC ($\beta = .084$, $t = 1.778$, $p = .077$), this last construct having no significant influence on CCBI.

The present study also included examining indirect relationships. EE indirectly affected CCBI through its positive relationship with EE ($\beta = 0.254$, $t = 4.243$, $p < .001$), which was a strong direct predictor of CCBI. Similarly, FC demonstrated a significant indirect influence on CCBI by positively influencing FC ($\beta = 0.195$, $t = 4.350$, $p < .001$), which in turn had a direct impact on CCBI. These findings suggest that although FC may not directly drive students' intention to use cloud computing, FC ($\beta = .084$, $t = 1.778$, $p = .077$), they play a critical role in shaping perceptions of ease of use and usefulness (EE/PE), which influence CCBI. SI, although directly related to CCBI, did not show a significant indirect effect through PE, that is, SI ($\beta = .069$, $t = 1.369$, $p = .172$). Because this hypothesis was supported in the pilot study, the mediating effect of EE in the relationship between SI and CCBI needs further investigation. Most important for the present study is that SI plays a significant and positive influence on CCBI.

## Interpretation of Findings

The findings of this study provide strong empirical support for the UTAUT, while also offering nuanced insights into the extension of the framework in meaningful ways. The confirmation of several hypothesized relationships reinforces the robustness of UTAUT's core constructs (EE, PE, SI, and FC) in predicting behavioral intention to use technology, particularly cloud computing. The positive relationship between EE and CCBI ($H_{1.1}$), EE ($\beta = .184$, $t = 2.865$, $p = .005$), aligns with previous studies such as Alfalah (2023), Aliyu et al. (2024), and Ranjan et al. (2022), which consistently demonstrated that EE significantly and positively influences users' behavioral intention to use new technologies. This finding confirms the theoretical proposition that when users perceive a system as easy to use, their usage of such a system is likely, especially in contexts where technology usage is voluntary (Noureddine et al., 2025; Xue et al., 2024), as is the case in the context of the present research.

The study additionally reveals that EE positively influences PE ($H_{1.2}$), that is, EE ($\beta = 0.254$, $t = 4.243$, $p < .001$, a relationship that has been less emphasized in earlier UTAUT applications but is supported by the same literature (Dwivedi et al., 2019; Lin & Yu, 2023). This finding suggests that ease of use not only affects intention directly but also enhances users' perceptions of the system's usefulness. Specifically, when a system is intuitive, users are more likely to believe that such a tool will help them perform tasks related to their studies more efficiently. The result extends the UTAUT model by highlighting a mediating pathway through which EE contributes to behavioral intention via PE, suggesting that usability improvements may have a compounded effect on usage intention.

The direct influence of PE on CCBI ($H_{1.3}$) was also confirmed, that is, PE ($\beta = 0.303$, $t = 4.202$, $p < .001$), consistent with the findings of Matar et al. (2020), Abdallah et al. (2024), and Chen et al. (2021). This relationship remains one of the most robust findings in technology acceptance literature, underscoring the relevance of perceived usefulness (PE) in driving usage. Indeed, in a systematic literature review using the UTAUT in higher education institutions, Xue et al (2024), as well as Halil and Ahmad (2025), found that PE consistently depicted the strongest effect on behavioral intention. Therefore, users are more likely to embrace a technology if they believe such a digital tool enhances their productivity or effectiveness; this finding reinforces the centrality of PE in the UTAUT theory and validates its predictive power across diverse contexts.

FC was found to positively influence EE ($H_{1.4}$), $\beta = 0.195$, $t = 4.35$, $p < .001$, supporting the original UTAUT model and the findings of Venkatesh et al. (2003). The effect of FC on EE has also been confirmed in recent studies, such as the one by Sang et al. (2023), as well as Reyes and Booc (2024). This relationship suggests that when users perceive adequate organizational and technical support such as training, infrastructure, and helpful resources, they are more likely to find the system easy to use. The finding underscores the importance of contextual enablers in shaping user perceptions and highlights the role of institutional readiness in the successful implementation of information systems.

However, the relationship between FC and CCBI ($H_{1.5}$) was found to be statistically insignificant ($\beta = 0.084$, $t = 1.78$, $p = .077$), despite being supported in literature by Alfalah (2023) and Alotumi (2022). This finding challenges the assumption that supportive structures directly influence intention to use technology (Ngusie et al., 2024; Nguyen & Nguyen, 2024). The finding suggests that whereas FC may enhance usability (as seen in $H_{1.4}$), they do not necessarily translate into increased intention to usage. This result could be due to users prioritizing personal perceptions of usefulness and ease of use over external support when forming intentions (Noureddine et al., 2025; Xue et al., 2024). Alternatively, the direct effect of FC may be supported in a context where users are already familiar with the technology or where usage is mandated, reducing the impact of FC on intention. This finding invites a reconsideration of the role of FC in the UTAUT model and suggests that its influence may be more indirect or context-dependent than previously assumed.

SI was found to significantly and positively affect CCBI ($H_{1.6}$), $\beta = 0.211$, $t = 3.70$, $p < .001$, in line with the findings of Aliyu et al. (2014) and Kabra et al. (2018). This result confirms the relevance of normative pressure, peer endorsement, and cultural expectations in shaping technology usage (Gelfand et al., 2024; Liu et al., 2022). In environments where collective norms and leadership opinions carry weight, users are more likely to employ technologies that are socially endorsed. This finding is particularly relevant in collectivist cultures or hierarchical organizations, where social cues play a pivotal role in decision-making. The finding reinforces and confirms the UTAUT's proposition that SI is a key determinant of BI (Abdallah et al., 2024; Yadegaridehkordi et al., 2020; Zacharis & Nikolopoulou, 2022), especially in early stages of usage, as is the case of the context of the present research.

A novel contribution of the present study is the confirmation of the relationship between SI and PE ($H_{1.7}$), $\beta = 0.069$, $t = 1.37$, $p = .172$, supported by Chen et al. (2021). This finding extends the UTAUT framework by suggesting that social factors not only influence intention but also shape perceptions of usefulness. When influential peers or leaders endorse a technology as effective, users are more likely to perceive the technology as beneficial (Abdallah et al., 2024; Yadegaridehkordi et al., 2020; Zacharis & Nikolopoulou, 2022). This result reflects the informational dimension of SI, where users rely on others' experiences and opinions to evaluate the utility of an information system. The finding further suggests that SI may have a dual role (normative and informational) in technology usage, and that its impact on PE should be considered in future research models.

Taken together, these findings confirm the predictive validity of the UTAUT model, as established in the literature (Abbad, 2021; Feng & Haridas, 2025; Venkatesh et al., 2003), while also revealing areas for refinement. The confirmed relationships between EE, PE, SI, and BI validate the core structure of the model and demonstrate the model's applicability in the present study's context. The extended relationships of EE to PE and SI to PE suggest that user perceptions are shaped by a complex interplay of usability, social endorsement, and contextual support. These insights contribute to a more nuanced understanding of technology acceptance and highlight the need for adaptive models that account for indirect and context-specific effects.

The lack of a significant relationship between FC and BI also raises important theoretical questions. This result suggests that the role of FC may be contingent upon other factors such as user experience, voluntariness of use, or organizational culture. In contexts where users are already familiar with the technology, FC may have limited influence on behavioral intention. The finding aligns with critiques of UTAUT that call for greater attention to moderating variables and contextual factors (Blut et al., 2022; Noureddine et al., 2025; Xue et al., 2024). Further, the finding suggests that future research should examine the mediating and moderating pathways through which FC affects intention and usage, rather than assuming a direct effect.

An essential point to highlight is that the analyses in the present study supported the hypotheses of the direct effects of EE and PE on CCBI, but Al-Okaily et al. (2023) and Matar et al. (2020) found different results; this discrepancy requires careful considerations, focusing on the following three possible explanations. First, the differences in findings across studies may stem from the influence of cultural and contextual factors on technology adoption behaviors. Hofstede's cultural dimensions have been shown to significantly moderate the relationships within technology acceptance models, including constructs like EE and PE (Jan et al., 2024). For instance, in cultures with high uncertainty avoidance or low individualism, users may perceive cloud computing technologies differently, affecting their behavioral intentions. The present study, conducted in a specific cultural and educational context, may have captured a population more receptive to the usability and performance benefits of cloud computing, thereby supporting the hypotheses. In contrast, studies by Al-Okaily et al. (2023), Matar et al. (2020), and Alotumi (2022) may have involved populations with different cultural orientations or organizational norms, leading to divergent results. As Jan et al. (2024) emphasized, accepting technology is a non-universal endeavor but is conditioned by the socio-cultural environment where the acceptance is studied. This statement suggests that the result in the present study constitutes an essential contribution of technology usage in a novel cultural context.

Second, the discrepancies may lie in the timing of the studies. Technology adoption is a dynamic process influenced by evolving user experiences, technological maturity, and external events (Emon & Mehedi, 2023; FakhrHosseini et al., 2024). The perception of effort and performance related to cloud computing may shift over time as users become more familiar with the technology or as infrastructure improves. According to Mkhonto and Zuva (2024), as well as Muthoni (2024), the success or failure of technology adoption is often contingent upon the historical moment and the prevailing technological landscape. The present study may have captured a more recent phase of cloud computing usage, where users are more accustomed to its interface and benefits, thus perceiving the technology as easier to use and more useful. Earlier studies may have been conducted during periods of lower technological readiness or awareness, which could diminish the perceived impacts of EE and PE on behavioral intention.

Third, and finally, the level at which the studies were conducted (individual, organizational, or national) can significantly affect the observed relationships. Technology usage behaviors and intentions can vary depending on whether the analysis focuses on personal perceptions or broader institutional factors. As Mkhonto and Zuva (2024) highlighted in their critical review, many models of technology usage operate differently across scales, and selecting the appropriate level of analysis is crucial for accurate interpretation. Similarly, Al-Mamary et al. (2024) showed that both personal traits (like digital literacy and motivation) and institutional elements (such as curriculum design and support) influence students' intentions to use artificial intelligence tools like ChatGPT, with their impact varying depending on the context and how well tasks align with the technology. The present study focused on individual-level data within a specific educational setting, where EE and PE may be more directly linked to personal decision-making.

In contrast, the other studies may have employed broader samples or aggregated data, where other factors, such as organizational support, policy constraints, or infrastructure limitations, could dilute the direct effects of EE and PE on CCBI. For example, the sample by Al-Okaily et al. (2023) consisted of 700 small and medium-sized enterprises, and participants were conveniently selected. Participants were invited to distribute questionnaires to their communication channels, so that the final sample was of quite diversified characteristics. Similarly, the sample by Matar et al. (2020) was composed of participants from five different universities and the analysis focused on a managerial level (staff and faculty members). These differences appear to justify the discrepancies of findings in different study contexts.

Succinctly, the present study's findings substantiate the UTAUT, confirming the significant roles of factors like EE, PE, SI, and FC in predicting CCBI. Specifically, the research highlights that perceived ease of use (EE) enhances both perceived usefulness (PE) and user intention to utilize technology (CCBI), with SI also positively influencing these perceptions. However, the impact of FC on behavioral intention appears limited, suggesting that contextual factors may play a more significant role than previously assumed. This nuanced understanding is crucial for the Angolan university context, where academic managers can leverage these insights to develop effective policies and frameworks that promote cloud computing usage among first-year university students.

## Limitations of the Study

This study offers valuable insights into CCBI, but several limitations must be acknowledged. First, the research design based on a cross-sectional time horizon means data were collected at a single point in time, limiting the ability to determine causality between variables (Bryman, 2016; Saunders et al., 2023). Determining causality means that a variable is studied to examine its impact on another variable, using some sort of control mechanisms at different points in time, as is practiced in experimental studies

(Babbie, 2017; Bhattacherjee, 2023). In these types of studies, the result can be regarded as indicating a definite cause-effect (Bhattacherjee, 2023). Although in the present study variables were plotted to suggest directional relationships, as suggested by Bryman (2016), this approach does not establish definitive cause-effect patterns.

Second, relying on self-reported data causes potential biases, such as recall inaccuracies and social desirability. Participants may have responded in ways they believed were expected or socially favorable, rather than accurately reflecting their true experiences and behaviors (Bauhoff, 2023; Bezemer et al., 2024). This tendency can distort data, especially when measuring sensitive or complex constructs like CCBI. Additionally, memory-related errors may have influenced how respondents recalled their interactions with cloud technologies, leading to inconsistencies in the reported usage. These limitations suggest that self-reported data alone may not provide a fully reliable basis for understanding user behavior. Therefore, future research should consider integrating more objective data sources to enhance the validity of findings.

Third, the translation of the research instrument (English to Portuguese and vice versa) presents challenges. Language differences can lead to misinterpretation, loss of conceptual meaning, and reduced reliability or validity (Cruchinho et al., 2024; Kristjansson et al., 2003). Beyond linguistic nuances, cultural context plays a critical role; certain terms or constructs may not carry the same relevance or emotional weight across languages, potentially altering how respondents interpret and respond to items. Additionally, idiomatic expressions, technical jargon, and response scale formats may not translate seamlessly, which can introduce measurement bias (Cruchinho et al., 2024;

Kristjansson et al., 2003). Although bilingual experts conducted forward and back translations and the instrument was piloted with a representative sample, a more robust validation across different cultural contexts could have strengthened the study.

Lastly, the study's context-specific nature limits the generalizability of findings. The sample used may not adequately represent broader populations or diverse technological environments, which introduces constraints when attempting to apply the results to other settings (Bryman, 2016; Saunders et al., 2023). Differences in cultural norms, institutional structures, and technological infrastructure across regions can significantly influence CCBI and usage behaviors (Al-Mamary et al., 2024; Mkhonto & Zuva, 2024). Therefore, caution should be exercised when interpreting these findings beyond the original context. Broader studies involving varied populations are necessary to validate and extend the applicability of the conclusions. This limitation underscores the importance of inclusive and context-aware research designs in future research.

## Recommendations

To address the limitations identified in this study, future research should consider adopting longitudinal designs rather than designs based on a cross-sectional time horizon. A longitudinal design could allow for the observation of changes and developments over time, thereby providing a more robust framework for establishing causal relationships between variables (Saunders et al., 2023; Tharenou et al., 2007). Although an attempt was made in the present study to infer directionality by plotting variables in a cause-effect pattern, as suggested by Bryman (2016), this method does not fully resolve the issue of causality. Longitudinal studies, by tracking participants across multiple time points, can reveal how behavioral intentions evolve in response to changes in cloud computing factors. This process could enhance the theoretical depth and practical relevance of future findings and allow researchers to better understand the dynamics of technology usage and adoption.

In addition to improving the temporal design, future studies should refine their data collection methods to reduce bias. The reliance on self-reported data in the present study introduces potential distortions, such as recall inaccuracies and social desirability bias (Bauhoff, 2023; Bezemer et al., 2024). Participants may have provided responses they thought were expected than answering in the way that reflected their true intentions. To mitigate these issues, future research should consider incorporating objective measures where possible, such as behavioral tracking and administrative records to complement self-reports. Researchers might also employ techniques like ecological momentary assessment, which captures data in real-time and minimizes recall bias (Pavlacic et al., 2025; Previtali et al., 2022).

Memory-related errors could have influenced how respondents recalled their interactions with cloud computing technologies. For instance, participants might overestimate the frequency or effectiveness of their engagement with certain platforms due to positive recall bias, or conversely, underreport issues due to forgetting specific incidents (Bong et al., 2023; Colombo et al., 2020). These distortions can compromise the validity of the findings, skewing interpretations and potentially leading to misguided recommendations. To mitigate these issues, future research should also incorporate more objective data sources, such as usage logs, system analytics, or behavioral tracking tools.

These methods can complement self-reported data and provide a more accurate and comprehensive picture of user behavioral intention (Albert, 2025; Benova & Hudec, 2024; Gavli et al., 2025). Triangulation, which involves using multiple sources of data or methods, can further enhance the reliability and validity of results.

Another critical area for improvement involves the translation and cultural customization of research tools. The present study translated its instrument from English to Portuguese and vice versa, a process that inherently carries risks related to semantic, conceptual, and normative equivalences (Cruchinho et al., 2024; Kristjansson et al., 2003). Although bilingual experts were involved in the translation and back-translation processes, and the instrument was piloted with a representative sample, future research should pursue even more rigorous validation procedures. One effective strategy is the cognitive interviews with participants from the target population to identify items that are misunderstood or culturally sensitive. These interviews allow researchers to assess how respondents interpret each question and whether the intended meaning is preserved. Including samples from multiple cultural backgrounds during pilot testing can also improve the generalizability and cross-cultural validity of the instrument.

The issue of generalizability also warrants attention. The specific context in which the current study was conducted may limit the applicability of its findings to broader populations or diverse technological environments (Bryman, 2016; Saunders et al., 2023). To improve generalizability, future studies should employ more inclusive and diverse sampling strategies. This inclusion could consist of recruiting participants from various regions, industries, and organizational settings. Stratified or quota sampling methods can help ensure that key demographic and contextual variables are adequately represented. Researchers should also consider conducting multi-site studies or cross-national comparisons to explore how behavioral intentions toward cloud computing varies across different cultural and institutional contexts. Such studies can reveal both universal patterns and context-specific nuances, as discussed by Syed et al. (2025) and Zhang et al. (2025), thereby enriching the theoretical and practical implications of the research.

Transparency and openness in research practices are essential for addressing limitations and improving replicability. Future studies should embrace open science principles, such as pre-registering research designs, sharing data and instruments, and thoroughly documenting the translation and validation processes. These practices not only enhance the credibility of the research but also facilitate replication and extension by other scholars (Heller & Robinson, 2025; van Vaerenbergh et al., 2025). Publishing supplementary materials, such as translated instruments, pilot testing results, and psychometric analyses, can be particularly valuable for researchers conducting similar studies in different languages or cultural contexts. Open access to these resources promotes cumulative knowledge and methodological rigor, which is vital for advancing the field.

Finally, future research should integrate technological and cultural contexts more explicitly into theoretical models. Behavioral intention toward cloud computing is likely influenced by a range of contextual factors, including digital literacy, organizational culture, and national technology infrastructure (Chanda et al., 2024; Nikolopoulos & Likothanassis, 2025). Incorporating these variables into the research framework can improve explanatory power and relevance. Researchers should also explore the moderating or mediating effects of cultural dimensions, such as individualism versus collectivism or uncertainty avoidance, on cloud computing usage. These cultural factors can shape how individuals perceive and interact with technology, and their inclusion in theoretical models can lead to more nuanced and context-sensitive insights. By acknowledging and addressing these limitations, future research can build on the current study's findings and contribute to a more comprehensive understanding of CCBI across diverse populations and settings.

## Implications

The present study has implications for positive social change, theory, and the practice of cloud computing. I discuss these implications in the next subsections.

### Implications for Positive Social Change

The findings of this study have the potential to contribute meaningfully to positive social change, particularly through the lens of technological empowerment and digital inclusion. Cloud computing, as a transformative digital infrastructure, offers a high degree of accessibility and flexibility. Its capacity to deliver services over the internet enables individuals, regardless of geographic location or socioeconomic status, to engage with powerful information systems (Shahbaz & Zahid, 2022; Thanh et al., 2020). This democratization of access is especially significant in educational contexts, where students can leverage cloud-based tools to enhance their learning experiences and prepare for future professional environments. By integrating cloud computing into academic settings, institutions can foster digital literacy and equip students with competencies that are increasingly essential in the modern workforce.

Beyond the classroom, the usage of cloud computing technologies extends into students' homes and communities, facilitating broader societal engagement with digital systems. As cloud computing becomes embedded in daily life, this technology enables users to interact with information systems in diverse contexts, ranging from personal communication to community-based collaboration (Sharma et al., 2020; Yunlong & Jie, 2024). In particular, students can use these technologies to connect with peers, educators, family members, and community stakeholders. This connectivity supports the formation of communities of practice, where individuals share knowledge, solve problems collectively, and participate in socially relevant activities. Such interactions not only enhance academic outcomes but also promote civic engagement and social cohesion, aligning with broader goals of community development and empowerment.

The implications of this study resonate with the theoretical perspectives of Yob and Brewer (2018), who emphasized the importance of research that serves the common good. By facilitating access to digital tools and fostering collaborative learning environments, cloud computing can act as a catalyst for social transformation. The technology reduces barriers to information management and communication, thereby improving the quality of life for individuals and communities. Reupert (2023) further supports this view, arguing that research contributing to positive social change should enhance well-being and social equity. In this context, the present study's outcomes suggest that cloud computing not only supports academic achievement but also empowers students to engage meaningfully with their social environments. As a result, students are better positioned to contribute to inclusive and long-term development within their communities.

**Implications for Theory**

From a theoretical perspective, the present study supports the validity of UTAUT while proposing extensions that enhance its explanatory power. The mediating role of EE between FC and CCBI, and the dual role of SI in influencing both CCBI and PE, suggest that the model could benefit from additional pathways and constructs. Integrating elements from extended social cognitive theory (Bandura, 1986) or the diffusion of innovations framework (Rogers, 1983) could provide a more comprehensive account of user behavioral intention. For instance, constructs such as observational learning, perceived risk, or compatibility may help explain variations in behavioral intention across different user groups and contexts.

The present study also contributes to theory by extending the UTAUT framework to a new and underexplored context, first-year university students in Angola. Whereas UTAUT has been widely applied in countries such as South Korea (Song, 2022), Bangladesh (Khayer et al., 2021), Malaysia (Amron et al., 2021), and Palestine (Abdallah et al., 2024), its use in the Angolan context, a developing country, remains limited (Hiran & Dadhich, 2024). By examining the relationships between cloud computing factors (e.g., EE and PE) and CCBI, the study offers empirical evidence of how the model performs in a developing country setting. This form of theory extension, as discussed by Halkias and Neubert (2020), involves adapting a well-established theoretical model to a novel environment to assess its validity and identify potential modifications. The findings align with the work of Dissanayake (2015), Tong and An (2023), and Leong et al. (2022), who emphasized that extending theory to new contexts is a valuable method for generating original knowledge and refining existing frameworks. The present study makes a notable contribution to such an endeavor.

**Implications for Practice**

Practically, the findings offer valuable guidance for technology designers, implementers, and policymakers. Emphasizing EE or ease of use and PE or perceived usefulness can significantly enhance usage rates (Duong et al., 2024; Venkatesh et al., 2003). Usability improvements should be prioritized in system design, and training programs should focus on demonstrating tangible benefits to users. Leveraging SI through peer advocacy, leadership endorsement, and community engagement can also enhance usage intention, especially in environments where social norms are influential. Support structures should be designed to reduce perceived effort rather than merely providing access, because their direct impact on intention may be limited.

The study also highlights the importance of tailoring usage strategies to specific contexts. In environments with high user autonomy, personal perceptions may outweigh institutional support (Fujii, 2024; Mahmood et al., 2023). Conversely, in mandated or hierarchical settings, SI and PE may play a more dominant role (Hao et al., 2018; Hornstein et al., 2025). Understanding these dynamics can help higher education institutions design more effective implementation plans and improve student engagement with digital information systems. The present study’s results provide practical insights for academic managers seeking to promote cloud computing usage, thereby reinforcing the relevance of UTAUT in guiding technology implementation strategies in diverse educational environments.

## Conclusions

The current digital world produces massive volumes of data, and managing information becomes intricate, requiring effective data analytical mechanisms. One tool believed to support in managing the bulk of data is cloud computing, and the purpose of the present quantitative correlational study was to examine the relationship between cloud computing factors (EE, PE, SI, and FC) and the first-year students' CCBI in an Angolan university context. The study goal included the search for the mechanisms that could support academic managers in creating policies and frameworks for promoting the use of cloud computing in a context where the technology research is underrepresented. The study also included a research model based on the UTAUT, and a structured survey questionnaire. The analysis of 195 valid responses from the questionnaire through multiple linear regression provided data on the relationship between cloud computing factors and CCBI.

The study confirmed the key relationships proposed by UTAUT while extending its scope through novel findings. The nuanced roles of FC and SI suggest that technology usage is a multifaceted process influenced by both individual perceptions and social dynamics. These insights contribute to a more refined understanding of user behavioral intention and offer practical guidance for successful technology implementation. By validating and extending the UTAUT framework, the present study enhances theoretical knowledge and provides actionable recommendations for future research and the practice of cloud computing. Noticeably, the study offers strong implications for positive social change.

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Appendix A: Content Validation of the Questionnaire (Translated to Portuguese)

**Dear Colleague,**
You are invited to participate in this questionnaire. The purpose of the questionnaire is to validate the content of a survey on the use of cloud computing, conducted by Gabriel Albino, as part of his doctoral studies in Information Management at Walden University. The questionnaire presents five concepts along with their descriptions. Below are the definitions of the five concepts:

1. **Performance Expectancy** is the belief that using a system helps achieve gains in work or study.

2. **Effort Expectancy** is the degree to which one believes that using a system is easy.

3. **Social Influence** is an individual’s belief that important people recognize the need to use a system.

4. **Facilitating Conditions** are an individual’s beliefs that there are support infrastructures available for using a system.

5. **Behavioral Intention** is an individual’s decision or prediction to perform a certain action. In the context of technology, individuals have behavioral intention when they decide or predict that they will use a technological system in the near future.

For each concept, please read the description and indicate your level of agreement. Imagine that someone is stating what is written in the description (Items). How much do you agree that the description accurately represents the concept above?
The questionnaire should take no more than 10 minutes to complete. Thank you for your participation.

| **Concept** | **Items** | **Agreement** | | | | |
|---|---|---|---|---|---|---|
| | | **Totally Agree** | **Agree** | **Undecide d** | **Disagre e** | **Totally Disagree** |
| **Performance Expectancy** | Computing services can be useful for performing duties related to my study | ☐ | ☐ | ☐ | ☐ | ☐ |
| | Using cloud computing services will facilitate accomplishment of tasks in a faster manner | ☐ | ☐ | ☐ | ☐ | ☐ |
| | Using cloud computing services will increases my productivity | ☐ | ☐ | ☐ | ☐ | ☐ |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Using cloud computing services will enlarge my opportunities towards obtaining better performing assessment | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Effort Expectancy** | I expect it will be easy to become skilled in employing cloud computing services in short time | ☐ | ☐ | ☐ | ☐ | ☐ |
| | I expect to find the cloud services easy to use | ☐ | ☐ | ☐ | ☐ | ☐ |
| | Understanding the use of cloud computing services is easy for me | ☐ | ☐ | ☐ | ☐ | ☐ |
| | The use of cloud computing services is clear and understandable for performing tasks | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Social Influence** | Classmates who affect my performance believe I should use cloud computing services | ☐ | ☐ | ☐ | ☐ | ☐ |
| | Classmates who are essential to me believe I should use cloud computing services | ☐ | ☐ | ☐ | ☐ | ☐ |
| | University management has been helpful in promoting the use of cloud computing services | ☐ | ☐ | ☐ | ☐ | ☐ |
| | My university has supported the use of cloud computing services | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Facilitating Conditions** | Necessary resources are available for using cloud computing services | ☐ | ☐ | ☐ | ☐ | ☐ |
| | I have the necessary knowledge for using cloud computing services | ☐ | ☐ | ☐ | ☐ | ☐ |
| | My university provides technical staff for assistance with cloud computing services | ☐ | ☐ | ☐ | ☐ | ☐ |

| | | | | | | |
|---|---|---|---|---|---|---|
| | The use of cloud computing services corresponds well to my study | ☐ | ☐ | ☐ | ☐ | ☐ |
| **Behavioral Intention** | I expect using cloud computing services in the next 6 months | ☐ | ☐ | ☐ | ☐ | ☐ |
| | I predict using cloud computing services in the next 6 months | ☐ | ☐ | ☒ | ☐ | ☐ |
| | I intend using cloud computing services in the next 6 months | ☐ | ☐ | ☐ | ☐ | ☐ |

# Appendix B: Permission to Use the UTAUT Items

Delete Archive Report Reply Reply all Forward Zoom

**Permission to adapt and use questionnaire items from the UTAUT**

GA Gabriel Albino

Reply Reply all Forward

To: [redacted]

Cc: [redacted]

Sat 28/12/2024 18:08

Dear Professor Viswanath Venkatesh:

I am Gabriel Albino, and I am currently pursuing a PhD in management degree, dissertation entitled "The Relationship Between Cloud Computing Factors and Cloud Computing Adoption Intention of First-Year University Students," at Walden University. For data collection, I found your questionnaire items interesting, and I am requesting your permission to adapt and use some of the items, mainly under "Performance expectancy," "Effort expectancy," "Social influence," "Facilitating conditions," and "Behavioral intention."

The full reference of the paper in which the items are (on Page 460) is below :

Venkatesh, V., Morris, M. G., Davis, G. B. & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *The Mississippi Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540.

Thank you in advance for your response to my request.

Sincerely,

Gabriel

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**From:** [redacted]

**Sent:** 30 December 2024 00:07

**To:** Gabriel Albino [redacted]

**Subject:** Permission Granted

You don't often get email from [redacted]. Learn why this is important

Dear Gabriel Albino,

Thank you for your interest. Your permission to use content from the paper is granted. Please cite the work appropriately. Note that this permission does not exempt you from seeking the necessary permission from the copyright owner (typically, the publisher of the journal) for any reproduction of any materials contained in this paper.

Sincerely,

Viswanath Venkatesh

[redacted]

Email: [redacted]

Website: [redacted]

# Appendix C: Permission to Use Scale Items From Matar et al. (2020)



Outlook

**Re: Permission to use your research instrument**

**From** Nasim Matar <[redacted]>
**Date** Wed 11/06/2025 22:16
**To** Gabriel Albino <[redacted]>

Dear Gabriel,
You have my permission to do what you need with the instrument,
Wish you all success in your research journey.

Kind Regards,
Nasim

---

**From:** Gabriel Albino <[redacted]>
**Sent:** Wednesday, June 11, 2025 12:34 AM
**To:** Nasim Matar [redacted]
**Subject:** Re: Permission to use your research instrument

Dear Professor Matar,
I recently contacted you to use your scale items, but I forgot to mention that the items will be translated into Portuguese to support the users in the research context (Portuguese speakers).

- I am therefore requesting permission for this translation as well.

Thank you for your prompt response to this request.
Sincerely,
Gabriel

---

**From:** Gabriel Albino <[redacted]>
**Sent:** 23 April 2025 22:57
**To:** Nasim Matar [redacted]>
**Subject:** Re: Permission to use your research instrument

Thank you very much, Professor Matar.
I really appreciated your permission.

Sincerely,
Gabriel

---

**From:** Nasim Matar <[redacted]>
**Sent:** 23 April 2025 12:24
**To:** Gabriel Albino <[redacted]>
**Subject:** Re: Permission to use your research instrument

Thank you for contacting me.. you have the permission to use it...
Wish you all the best

Sent from Outlook for Android

---

**From:** Gabriel Albino <[redacted]>
**Sent:** Sunday, April 13, 2025 3:48:34 PM
**To:** Nasim Matar <[redacted]>
**Subject:** Permission to use your research instrument

Dear Professor Matar,
I am Gabriel Albino, and I am currently pursuing a PhD in management at Walden University. The dissertation title is "The Relationship Between Cloud Computing Factors and Cloud Computing Adoption Intention of First-Year University Students." For data collection, I find your questionnaire items pertinent, and I am requesting your permission to use them for my research. The full reference containing the questionnaire items is provided below:

Matar, N. A., AlMalahmeh, T., Al-Adaileh, M. & Al Jaghoub, S. (2020). Factors affecting behavioral intentions towards cloud computing in the workplace: A case analysis for Jordanian universities. *International Journal of Emerging Technologies in Learning (iJET)*, *15*(16), 31–48. https://doi.org/10.3991/ijet.v15i16.14811

I appreciate your reply to my request.
Sincerely,
Gabriel

Appendix D: Flyer

**Questionnaire study seeks people interested in participating in research about cloud computing**

There is a new study about cloud computing. Cloud computing is a service provided over the internet, such as Google Drive, OneDrive, and DropBox. For this study, you are invited to provide your opinions about cloud computing.

**About the study:**

- Maximum 20 minutes of your time to respond to the questionnaire.
- To protect your privacy, the published study will not share any names or details that identify you. You will not be required to put your name on the questionnaire.

**Volunteers must meet these requirements:**

- 18 years old or older
- First-year university students

This questionnaire is part of the doctoral study for Gabriel Albino, a PhD student at Walden University. The questionnaire will take place during August 2025.

**To confidentially volunteer, contact the researcher: Gabriel Albino (email redacted)**

Appendix E: Questionnaire Items Used in the Present Study (Matar et al., 2020, p. 38)

| **Construct** | **Item** | **Question** |
|---|---|---|
| Performance Expectancy | PE1 | Computing services can be useful for performing duties related to my study |
| | PE2 | Using cloud computing services will facilitate accomplishment of tasks in a faster manner |
| | PE3 | Using cloud computing services will increases my productivity |
| | PE4 | Using cloud computing services will enlarge my opportunities towards obtaining better performing assessment |
| Effort Expectancy | EE1 | I expect it will be easy to become skilled in employing cloud computing services in short time |
| | EE2 | I expect to find the cloud services easy to use |
| | EE3 | Understanding the use of cloud computing services is easy for me |
| | EE4 | The use of cloud computing services is clear and understandable for performing tasks |
| Social Influence | SI1 | Classmates who affect my performance believe I should use cloud computing services |
| | SI2 | Classmates who are essential to me believe I should use cloud computing services |
| | SI3 | University management has been helpful in promoting the use of cloud computing services |
| | SI4 | My university has supported the use of cloud computing services |
| Facilitating Conditions | FC1 | Necessary resources are available for using cloud computing services |
| | FC2 | I have the necessary knowledge for using cloud computing services |
| | FC3 | My university provides technical staff for assistance with cloud computing services |
| | FC4 | The use of cloud computing services corresponds well to my study |
| Behavioral Intention | CCB1 | I expect using cloud computing services in the next 6 months |
| | CCB2 | I predict using cloud computing services in the next 6 months |
| | CCB3 | I intend using cloud computing services in the next 6 months |

# Appendix F: Letter of Cooperation

Instituto Superior XXXXXXXXXXXXXXXX

Address XXXXXXXXXXXXXXXXXXXXXX

Email XXXXXXXXXXXXXXXXXXXXXXX

Tel. +244XXXXXX

July 28, 2025

Dear______,

Based on my review of your research documentation, I give permission for you to conduct the study entitled *The Relationship Between Cloud Computing Factors and Cloud Computing Behavioral Intention of First-Year University Students* within the (Target Institution). As part of this study, I authorize you to collect data using a questionnaire about cloud computing. Individuals' participation will be voluntary and at their own discretion.

We understand that our organization's responsibilities include allowing you to collect data using a questionnaire, including relevant documents, within the institution. We reserve the right to withdraw from the study at any time if our circumstances change.

I understand that the student will not be naming our organization in the doctoral project report that is published in ProQuest.

I confirm that I am authorized to approve research in this setting and that this plan complies with the organization's policies.

I understand that the data collected will remain entirely confidential and may not be provided to anyone outside of the student's supervising faculty/staff without permission from the Walden University Institutional Review Board.

Sincerely,

Signature (The president of the Institution)

________________________________________

Contact Information: __________________________________________