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The Influence of Social Influence, Relative Advantage, User Satisfaction on Cloud-Based E-Learning with Behavioral Intention as a Mediating Variable

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Abstract. This research investigates the influence of social influence, relative advantage, and user satisfaction on cloud-based e-learning adoption, with behavioral intention acting as a mediating variable. Drawing on existing literature, hypotheses are formulated to explore these relationships. The study integrates models such as DOI, TAM, and UTAUT to propose hypotheses, guided by empirical findings from Lebanon, the Philippines, and Indonesia. The hypotheses posit positive impacts of social influence (H1), relative advantage (H2), and user satisfaction (H3) on cloud-based e-learning adoption. Additionally, the study explores the mediating role of behavioral intention in the relationships between social influence (H4), relative advantage (H5), user satisfaction (H6), and cloud-based e-learning adoption. The operational model is presented, depicting the relationships among variables. The research adopts an explanatory approach, using questionnaires distributed to 143 university students engaging in cloud-based e-learning. Descriptive statistics and validity tests ensure data quality, and hypothesis testing involves Mediated Regression Analysis. Results indicate that relative advantage and user satisfaction positively impact cloud-based e-learning, while social influence's direct impact is inconclusive. Behavioral intention does not mediate the relationships as hypothesized, highlighting the nuanced nature of cloud-based e-learning adoption. The study provides insights into the interplay of factors influencing cloud-based e-learning adoption, contributing to the understanding of technology acceptance in educational contexts.

Keywords. The Influence of Social, Relative Advantage, User Satisfaction, Cloud-Based E-Learning, Behavioral Intention

1. Introduction

Indonesia has implemented a policy to close all educational institutions due to offline general classroom activities. However, all universities are required to introduce learning technology for online lectures to prevent the spread of COVID-19. While this transition poses no issue for some universities with existing online academic systems, it becomes a challenge for institutions without e-learning systems [1]. The aim of online lectures is to enable all Indonesian citizens to enjoy learning from anywhere. As stated by Friedman (2000), future students could attend classes by sitting in front of a computer online, completing the learning process, although he did not specifically mention it due to COVID-19 [2]. His famous comment is the statement "The world is flat," indicating that over time, borders with other countries are

disappearing. This includes education accessible to everyone through online lectures, encouraging faculty and students to be more creative, efficient, and globally connected across various fields worldwide (Hifzul Muiz & Sumarni, 2020) [3].

This aligns with the Ministry of Education and Culture's announcement in Circular Letter No. 4 (COVID19) of 2020 regarding the implementation of educational policies during the COVID-19 outbreak. The shift from face-to-face to e-learning has several goals: preventing the spread and communication, ensuring psychosocial support, protecting educational institutions from the impact of COVID-19, and respecting the rights of children receiving education during the COVID-19 emergency by Wastuti & Siregar (2021) [4]. According to the WHO in 2019, nearly 264 million people worldwide suffer from stress and depression, with 6.1% of Indonesia's population over 15 years experiencing depression. A study by Puddu (2018) reveals that students from the Eritrea Institute of Technology are vulnerable to moderate stress (71%) [5]. This research also indicates that physical issues faced during online learning include fatigue (24.4%).

Students are a crucial factor determining the smoothness of academic activities. The duration of the 1–3-hour learning process results in students experiencing work-related stress, pain in various parts of the body, lack of concentration, and other challenges. This presents a challenge for instructors to create an engaging and enjoyable atmosphere by Dewi & Wajdi (2021) [6]. Based on a study conducted by Puddu (2018), students at the Eritrea Institute of Technology are susceptible to moderate stress (71%) [5]. According to Nastiti & Hayati (2020) this research also indicates that physical issues faced during online learning include fatigue (24.4%) [7].

A study by Basyid & Mu'azamsyah (2022) found that instructors and students do not need to be in the same room when introducing e-learning [8]. However, the learning process can take place anytime, anywhere, minimizing the interaction between instructors and students or students themselves and overcoming internet limitations. The lack of interaction during this learning process can slow down the teaching and learning process, leading to less motivated students facing learning difficulties (Riyanto, 2023) [9].

Cloud computing (CC) has revolutionized business methods over the last decade, causing a change in basic assumptions in Information Technology (IT). CC, recognized as a dynamic innovation platform, serves diverse requirements by offering a digital framework that enhances information storage capabilities. Additionally, CC offers access to programming and equipment without significant capital costs, facilitating easy access to applications and administration. This has empowered CC to create technological advancements capable of handling copious amounts of exchanged and stored data through electronic applications. Organizations have found solutions in CC to minimize costs, improve efficiency, effectiveness, and gain competitive advantages. Cost benefits are achieved through virtualization, scalability, and on-demand hardware and software, with much of the previous research focusing on the implementation and migration to the cloud and the requirements for such transitions.

This research replicates a study conducted by Wulandari et al. (2023), but with a key difference being the use of the education sector as the research sample, as opposed to the banking sector, which has been extensively studied in previous research [10]. Considering the background description, it becomes crucial to investigate the "Influence of Social Influence, Relative Advantage, User Satisfaction on Cloud-Based E-Learning with Behavioral Intention as a Mediating Variable." The research problem is presented through six essential questions, centering on the direct impact and mediated influence of social influence, relative advantage, and user satisfaction on cloud-based e-learning, as well as their interplay with behavioral

intention. The research aims to analyze and obtain empirical evidence regarding these influences, providing a comprehensive understanding of the dynamics within the context of cloud-based e-learning.

The research objectives include assessing the impact of social influence, relative advantage, and user satisfaction on cloud-based e-learning, both independently and when mediated by behavioral intention. The study aims to contribute theoretically by advancing the understanding of the relationships between social influence, relative advantage, user satisfaction, and cloud-based e-learning with behavioral intention as a mediating variable. Practical benefits of the research are outlined for various stakeholders. For researchers, it offers an opportunity to enhance knowledge and research capabilities. For academicians, the study could contribute to the academic field by promoting and socializing cloud-based e-learning, improving the quality and features of such platforms, and enhancing user satisfaction through improved learning materials, facilities, and services. Moreover, the government can utilize the results to formulate policies that promote the acceptance of cloud-based e-learning within the academic community.

1.1 Theoretical/Conceptual Framework

The Technology Acceptance Model (TAM) is a modified theory derived from the Theory of Reasoned Action (TRA), tailored to address the acceptance of technology usage. The rationale for employing TAM as the theoretical foundation is to explain the indicators determining the level of technology acceptance and to elucidate the end-user behavior of technology usage. According to TAM, the acceptance behavior of computers is primarily influenced by two key individual beliefs: perceived usefulness (PU) and perceived ease of use (PEOU). The conceptual model of TAM, as implemented by Nindyastuti & Kiswara (2014), demonstrates the practical application of the concept, revealing the levels of interest and acceptance of individuals toward information systems or technology [11]. The model comprises main variables: perceived usefulness directing individual confidence positively or negatively affecting performance through technology or information system usage, and perceived ease of use directing the ease of users individually learning how to operate a technology or information system.

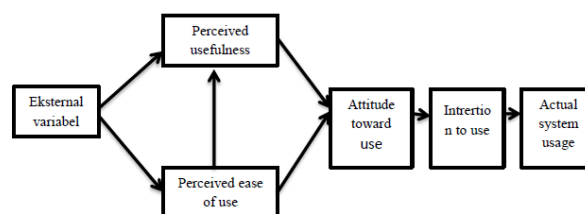


Figure 1. TAM Theory

In the context of technology acceptance, Social Influence, as described by Venkatesh et al. (2003), refers to the extent to which an individual believes that significant others think he or she should adopt the new system [12]. This statement highlights the inclusion of various variables within the broader concept of Social Influence. Subjective Norm is mentioned, representing an individual's perception of the expectations or norms conveyed by significant others. This concept is commonly utilized in several models such as the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Combined TAM and TPB (C-TAM-and-TPB). Additionally, the term Social Factors is introduced, referring to an individual's internalization of their reference group's culture and

interpersonal agreements in specific social situations, a concept employed in the Model of PC Utilization (MPCU). The third variable mentioned is Image, which signifies the extent to which an innovation is perceived to enhance an individual's image or status within their social system. This particular variable is conceptualized within the framework of Innovation Diffusion Theory (IDT). Overall, these variables contribute to the understanding of how social influence operates in various theoretical models, encompassing factors such as perceived norms, cultural influence, and the impact on personal image or status. Relative Advantage, according to Agag & El-Masry (2016), measures how much a product benefits its users, such as convenience and ease of use [13]. In the context of online learning, it implies practicality due to the elimination of the need for physical classrooms, making the teaching and learning process flexible and conducive. Furthermore, User Satisfaction is a crucial aspect, representing users' responses and feedback after using an information system. Sumarno et al. (2016) articulate user satisfaction by comparing expectations and reality, categorizing satisfaction as "very satisfied" if expectations are less than reality, "satisfied" if they are equal, and "unsatisfied" if expectations exceed reality [14].

Cloud-Based E-Learning refers to a digital learning experience that enables access to educational content from various devices connected to the internet, such as computers, smartphones, and tablets. This platform also allows educators to create learning content and track learners' progress in real-time (Mustofa et al., 2019) [15]. Moreover, cloud-based solutions frequently present economic advantages in comparison to conventional server-based alternatives by necessitating fewer hardware and infrastructure resources while demonstrating flexibility in accommodating evolving requirements. It also empowers educational institutions to collect and analyze learner performance data and utilize artificial intelligence for personalized content recommendations, targeted feedback, and adaptive learning paths that align with learners' progress and styles [16]. Cloud-Based E-Learning provides several key benefits, including easy content access, cost savings, real-time progress tracking, personalized content recommendations through artificial intelligence, and enhanced collaboration and social learning in remote education. Behavioral Intention, as defined by Dita & Murtaqi (2014), refers to conscious or unconscious actions and reactions towards an object or organism, evaluating actions against social norms and regulating them using social control [17]. Previous research by Aji et al. (2021) [18], Tom & Virgiyanti (2022) [19], and Kayali & Alaaraj (2020) indicates the positive influence of social influence, relative advantage, and user satisfaction, respectively, on the behavioral intention to adopt Cloud-Based E-Learning [20].

1.2 Operational Framework

The hypothesis development section draws upon various studies to formulate hypotheses regarding the influence of social influence, relative advantage, user satisfaction, and their mediation through behavioral intention on cloud-based e-learning adoption. The first hypothesis (H1) proposes a positive impact of social influence on cloud-based e-learning, supported by research in Lebanon (Kayali & Alaaraj, 2020) [20], the Philippines (Alam et al., 2021) [21], and Indonesia (Murgante et al., 2014) [22]. The second hypothesis (H2) suggests a positive influence of relative advantage on cloud-based e-learning, based on a study that integrates models such as DOI, TAM, and UTAUT (Kayali & Alaaraj, 2020) [20]. The third hypothesis (H3) suggests that user satisfaction has a favorable influence on cloud-based e-learning, underscoring its importance in the acceptance and utilization of cloud-based e-learning, as observed in the study by Kayali and Alaaraj (2020) [20]. The fourth hypothesis (H4) investigates the mediating function of behavioral intention in the association between

social influence and the adoption of cloud-based e-learning, consistent with findings from a study indicating that social influence influences behavioral intention in the adoption of cloud-based e-learning (Murgante et al., 2014) [22]. The fifth hypothesis (H5) suggests that behavioral intention mediates the positive influence of relative advantage on cloud-based e-learning, supported by research in Lebanon (Kayali & Alaaraj, 2020) [20]. Finally, the sixth hypothesis (H6) proposes that behavioral intention mediates the positive impact of user satisfaction on cloud-based e-learning, highlighting the role of user satisfaction in strengthening the intention to continue using and eventually leading to actual usage (Suryajaya & Sienaar, 2021) [23].

1.3 Operational Model

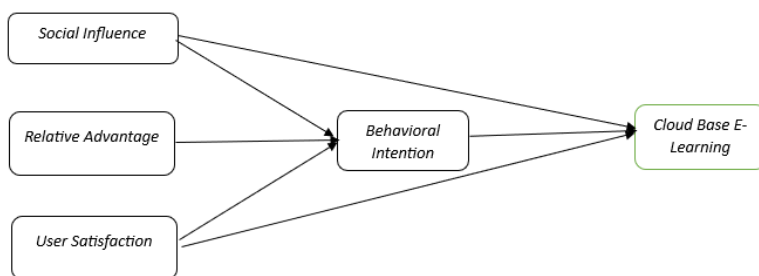


Fig 2. The operational model of the study shows the relationship among variables.

2. Methodology

2.1 Research Design

This research aims to examine the impact of social influence, relative advantage, and user satisfaction on cloud-based e-learning with behavioral intention as a mediating variable. It falls under the category of explanatory research, which seeks to explain causal relationships between two or more variables. Explanatory research is often employed to test hypotheses or build theories. In this type of research, the investigator endeavors to answer the "why" behind a particular phenomenon. The researcher collects data and utilizes statistical analysis to test hypotheses regarding the relationships between the variables under investigation. The study is designed to provide insights into the factors influencing the adoption of cloud-based e-learning, with behavioral intention playing a key role as a mediating variable.

2.2 Population of the Study

Respondents provided complete answers to the distributed questionnaire, which consisted of 21 questions representing one dependent variable, four independent variables, and one mediating variable. A total of 143 questionnaires were processed, which were obtained from the Google Form website. In terms of the semester level of the respondents, it shows that the most respondents are 3rd and 4th semester students, with a frequency of 49 or 70%, followed by 5th and 6th semester students with a frequency of 41 or 28.7%. Regarding the highest level of education of the respondents, the majority had a bachelor's degree (S-1), which amounted to 79.7%. There were nine respondents with a Diploma Three (D-3) education level and twenty-two respondents with a master's (S-2) education level, and no respondents with a Doctoral (S-3) education level. Regarding gender distribution, the questionnaire was filled out by ninety female students or 64.3%, while the remaining 37.1% was filled out by male students from a total of 143 respondents who filled out the questionnaire according to predetermined criteria.

2.3 Operational Definition and Variable Measurement

In this study, the operational definitions of each variable are outlined as follows: Social Influence encompasses the intentional and unintentional ways individuals adapt behavior to meet societal demands, including conformity, socialization, and persuasion. Relative Advantage, a key concept in marketing, gauges how a new product is perceived as superior to existing ones, influencing its adoption rate through offering greater value. User Satisfaction measures a user's feelings towards a product or service by comparing perceived performance with expectations, impacting customer retention and loyalty. The Dependent Variable, Cloud-based E-Learning, utilizes cloud computing for electronic learning, providing advantages such as affordability and flexibility over traditional systems. Finally, Behavioral Intention, the Mediating Variable, reflects the degree of desire or intent to perform a specific action, including intentions, loyalty, and positive word-of-mouth, influenced by attitudes, normative beliefs, and control beliefs. Various methods, including surveys and data analysis, can be employed to measure these variables.

2.4 Evaluation and Scoring

In the data collection process of this study, primary data is utilized, and the chosen method is questionnaires. According to Sugiyono (2017), questionnaires involve presenting a set of written questions or statements to respondents for their written responses [24]. Questions can be open-ended, expecting descriptive answers, or closed-ended, anticipating brief responses or the selection of predefined alternatives. The questionnaire is employed to gather data from university students, both from public and private institutions, using online learning systems. Six independent variables are evaluated utilizing a six-point Likert scale, where scores ranging from 1 to 6 correspond to levels of agreement, with 1 indicating 'Strongly Disagree' and 6 indicating 'Strongly Agree.' The data collection procedure involves distributing the questionnaires online via a Google Docs link to respondents, who then submit their responses [25]. The raw data obtained from the questionnaire responses for the five study variables is processed using Microsoft Excel and input into the Smart PLS application for multiple linear regression analysis to determine the relationships between dependent, independent, and moderating variables.

The descriptive analysis involves assessing the frequency distribution of respondents' responses to each question for every variable. The descriptive analysis categorizes respondents' reactions to each statement into six categories: "Strongly Disagree," "Disagree," "Slightly Disagree," "Slightly Agree," "Agree," and "Strongly Agree." The categorization is determined based on a scoring system with a maximum value of 6 and a minimum value of 1, resulting in an interval range of 0.8. The interval categories are defined as follows: "Strongly Disagree" for scores between 1.0 and 1.8, "Disagree" for scores between 1.9 and 2.6, "Slightly Disagree" for scores between 2.7 and 3.4, "Slightly Agree" for scores between 3.5 and 4.2, "Agree" for scores between 4.3 and 5.0, and "Strongly Agree" for scores between 5.1 and 6.0. This categorization allows for a clear presentation and interpretation of respondents' sentiments toward each statement within the specified scoring framework.

2.5 Statistical Treatment of Data

In the data analysis methodology, the researcher outlines the approach using Smart PLS as the analysis tool and conducts several preliminary tests. Descriptive statistics are applied to provide a comprehensive overview of respondent conditions, including university, highest education, and semester level [26]. Data quality tests involve assessing validity through Pearson

correlation, ensuring questionnaire authenticity, and reliability through the one-time method, with Cronbach's alpha indicating reliability in Smart PLS. Classical assumption tests, covering normality, multicollinearity, and heteroskedasticity, are performed using various techniques, such as graphical analysis and statistical tests [27]. Hypothesis testing involves Mediated Regression Analysis (MRA) to evaluate the impact of variables with government internal control mediation on Cloud-Based E-Learning (CBL). Tests include the coefficient of determination (R^2), F-test for simultaneous influence, and T-test for individual variable impact, contributing to a comprehensive understanding of data quality, distribution, and variable relationships within the research model.

3. Results and Discussion

In the validity testing phase, 21 questions in the questionnaire underwent validation assessment, aiming to ensure the acquired data's validity and its ability to measure the intended aspects of the study. The Average Variance Extracted (AVE) values were scrutinized, demonstrating satisfactory convergent validity, where each latent variable can elucidate more than half of the variance of its indicators on average. The AVE values for Social Influence (SI), Relative Advantage (RA), User Satisfaction (US), Behavioral Intention (BI), and Cloud-Based E-Learning (CBE) were found to be 0.635, 0.558, 0.687, 0.696, and 0.796, respectively. According to the thumb rule that considers an AVE greater than 0.5 as satisfactory, it can be concluded that all constructs exhibit good convergent validity, affirming their capability to adequately represent the measured concepts.

The reliability testing results, detailed in Table 5.0, disclose Cronbach's Alpha values for each variable—Social Influence (SI), Relative Advantage (RA), User Satisfaction (US), Behavioral Intention (BI), and Cloud-Based E-Learning (CBE)—as 0.810, 0.742, 0.848, 0.852, and 0.935, respectively. These values exceed the acceptable threshold of 0.60, signifying the reliability of the data used in the study. The Cronbach's Alpha values, all surpassing 0.60 for each variable, affirm the acceptability of Cronbach's Alpha and the overall reliability of the data, indicating consistent and dependable measurements for the intended constructs.

The multicollinearity test serves to scrutinize the potential high correlation between independent variables within a model. The findings of the multicollinearity test reveal the Variance Inflation Factor (VIF) values for each variable—Behavioral Intention, Cloud-Based E-Learning, Relative Advantage, Social Influence, and User Satisfaction. These VIF values, depicted in Table 1, all fall below 5 (<5) and exceed 0.1 (>0.1), indicating the absence of a robust correlation among the independent variables in the collinearity statistics (VIF) model. This implies that the model is free from multicollinearity concerns, reinforcing the reliability of the regression coefficients and ensuring the robustness of the results obtained, as the variables in the model do not exhibit a highly correlated relationship with each other.

Table 1. Collinearity Statistics (VIF) Test Results

| Variable | <i>Behavioral Intention</i> | <i>Cloud Based E-Learning</i> | <i>Relative Advantage</i> | <i>Social Influence</i> | <i>User Satisfaction</i> |
|-------------------------------|-----------------------------|-------------------------------|---------------------------|-------------------------|--------------------------|
| <i>Behavioral Intention</i> | | 3.958 | | | |
| <i>Cloud Based E-Learning</i> | | | | | |

| | | | | | |
|---------------------------|-------|-------|--|--|--|
| <i>Relative Advantage</i> | 2.142 | 2.180 | | | |
| <i>Social Influence</i> | 2.165 | 2.265 | | | |
| <i>User Satisfaction</i> | 2.831 | 4.598 | | | |

Source: Smart PLS (2024)

Table 1 displays the outcomes of the Collinearity Statistics (VIF) test, specifically assessing the presence of multicollinearity among the independent variables in the model. The Variance Inflation Factor (VIF) values for Behavioral Intention, Cloud-Based E-Learning, Relative Advantage, Social Influence, and User Satisfaction are detailed in the table. These VIF values provide insights into the degree of correlation between the independent variables. Notably, all VIF values are below 5 (<5) and surpass 0.1 (>0.1), signaling an absence of strong correlation among the independent variables within the collinearity statistics (VIF) model. This indicates that the model remains unaffected by multicollinearity issues, bolstering the reliability of the regression coefficients and ensuring the robustness of the results. The variables in the model exhibit a lack of highly correlated relationships with each other, strengthening the validity of the overall analysis. The recorded values, all falling below 5 (<5) and surpassing 0.1 (>0.1), signify the absence of a substantial correlation among the independent variables in the collinearity statistics (VIF) model. In simpler terms, the variables incorporated in the model do not display a strongly correlated relationship, ensuring the model's immunity from multicollinearity issues. This fortifies the dependability of the regression coefficients and confirms the resilience of the results derived from the model. The assurance here is that the model remains unharmed by concerns related to multicollinearity, providing a reliable foundation for the study's analytical outcomes.

The hypothesis testing involves conducting the Analysis of Variance (R^2) or the Coefficient of Determination test, with the objective of gauging the extent of the influence exerted by independent variables on the dependent variable. The outcomes of the Coefficient of Determination analysis, presented in Table 1, offer valuable insights into the magnitude of the impact of independent variables on the dependent variable. Commonly known as R^2 , this test quantifies the proportion of the variability in the dependent variable that can be elucidated by the independent variables. The R^2 values derived from this analysis furnish critical information about the overall goodness-of-fit of the model, facilitating an assessment of how effectively the chosen independent variables collectively expound the observed variations in the dependent variable.

Table 2. Hasil Uji R Square

| Variable | R Square |
|-------------------------------|----------|
| <i>Behavioral Intention</i> | 0.747 |
| <i>Cloud Based E-Learning</i> | 0.721 |

Source: Smart PLS (2024)

The R-square values, as outlined in Table 2, signify that 74.7% of the variability within the Behavioral Intention construct is clarified by the variables under scrutiny in the study, leaving 25.3% to be influenced by unexplored factors. Similarly, concerning the Cloud-Based E-Learning construct, 72.1% of the variability is explained by the examined variables, while

the remaining 27.9% is ascribed to factors not explicitly investigated in this research. These R-square values provide valuable insights into the explanatory prowess of the selected independent variables in elucidating the observed variations in both the Behavioral Intention and Cloud-Based E-Learning constructs. This information contributes to a holistic understanding of the model's effectiveness in capturing the underlying dynamics of the phenomena under examination.

The hypothesis testing in this study relies on the findings from the Inner Model (structural model) analysis, which encompasses key outputs such as R-square, parameter coefficients, and t-statistics. The determination of whether a hypothesis is accepted or rejected involves a detailed examination of the significant values between constructs, t-statistics, and p-values. The hypothesis testing process is conducted using the SmartPLS (Partial Least Squares) 3.0 software, and the results are derived through bootstrapping. The evaluation criteria include a t-statistic greater than 1.96 at a significance level of a p-value of 0.05 (5%) and a positive beta coefficient. The results of the hypothesis testing are presented in Table 3, and the overall model performance is visualized in Figure 1, providing a comprehensive perspective on the hypothesis testing process and the effectiveness of the overall model.

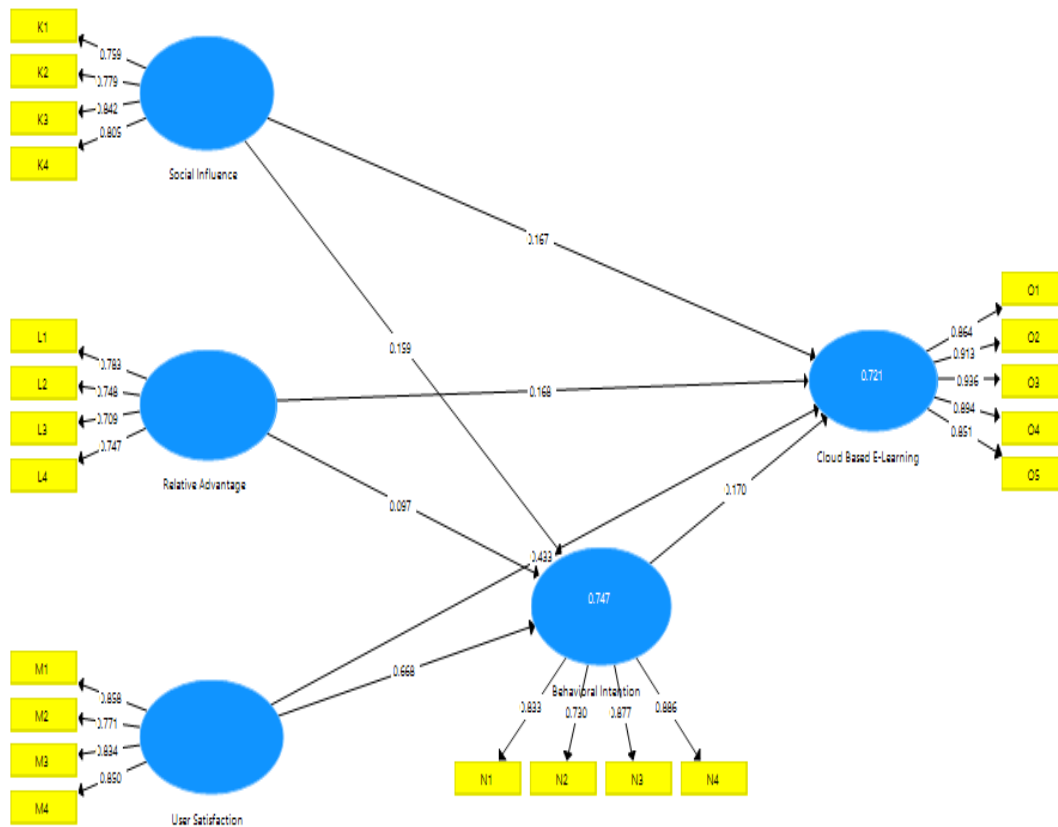


Figure 1. Model Hypothesis Testing Process
Source: Smart PLS (2024)

Table 3. Research Model Results

| Hypothesis | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics (O/STDEV) | P Values |
|---------------|---------------------|-----------------|----------------------------|--------------------------|----------|
| BI → CBE | 0.170 | 0.185 | 0.169 | 1.006 | 0.315 |
| SI → CBE | 0.167 | 0.168 | 0.130 | 1.282 | 0.200 |
| RA → CBE | 0.168 | 0.168 | 0.083 | 2.025 | 0.043 |
| US → CBE | 0.433 | 0.420 | 0.122 | 3.550 | 0.000 |
| SI → BI → CBE | 0.027 | 0.034 | 0.039 | 0.685 | 0.494 |
| RA → BI → CBE | 0.017 | 0.022 | 0.026 | 0.636 | 0.525 |
| US → BI → CBE | 0.114 | 0.117 | 0.113 | 1.004 | 0.316 |

Source: Smart PLS (2024)

Based on the table above, the regression formula used is:

$$Y = 0,170 + 0,167SI \rightarrow CBE + 0,168RA \rightarrow CBE + 0,433US \rightarrow CBE + 0,027SI \rightarrow BI \rightarrow CBE + 0,017RA \rightarrow BI \rightarrow CBE + 0.114US \rightarrow BI \rightarrow CBE$$

In this formula, (Y) represents the dependent variable, and the terms on the right side of the equation are the coefficients of the independent variables (SI) (Social Influence), (RA) (Relative Advantage), (US) (User Satisfaction), (BI) (Behavioral Intention), and (CBE) (Cloud-Based E-Learning). The arrows indicate the directional relationship between the variables in the model.

The first hypothesis aims to assess whether social influence has a positive impact on cloud-based e-learning. The results indicate a beta coefficient of 0.167 and a t-statistic of 1.282. However, the non-significant t-statistic, being below 1.96, and the p-value exceeding 0.05 lead to the rejection of the first hypothesis. Therefore, there is insufficient evidence to support the notion that social influence positively influences cloud-based e-learning.

Moving on to the second hypothesis, it explores whether relative advantage positively affects cloud-based e-learning. Drawing from Motivation Theory, which elucidates the factors driving individual learning, the relative advantage of e-learning can influence learning motivation positively. The test reveals a significant beta coefficient of 0.168 and a t-statistic of 2.025, surpassing the threshold of 1.96 and having a p-value below 0.05. Consequently, the second hypothesis is accepted, signifying that relative advantage does have a positive impact on cloud-based e-learning. This implies that the advantages offered by e-learning, such as enhanced engagement, interactivity, and flexibility, contribute positively to individual learning motivation.

The third hypothesis examines whether user satisfaction exerts a positive influence on cloud-based e-learning, drawing insights from the Expectation-Confirmation Model (ECM). According to ECM, user satisfaction is contingent on the alignment between user expectations and the reality they encounter. In the context of e-learning, user expectations may encompass factors like ease of use, content quality, and interactivity, while user confirmation is derived from their actual experience with e-learning. The test outcomes reveal a significant beta coefficient of 0.433 and a t-statistic of 3.550, surpassing the threshold of 1.96 with a p-value below 0.05. Consequently, the third hypothesis is accepted, substantiating that user satisfaction indeed exerts a positive influence on cloud-based e-learning. This implies that when user expectations align well with their e-learning experience, resulting in high satisfaction, it contributes positively to the adoption and usage of cloud-based e-learning platforms.

The fourth hypothesis investigates the impact of social influence on cloud-based e-learning, considering the mediating variable of behavioral intentions. The test outcomes reveal a non-significant beta coefficient of 0.027, accompanied by a t-statistic of 0.685, falling below the threshold of 1.96, and a p-value exceeding 0.05. Consequently, the fourth hypothesis is rejected, indicating that social influence does not exert a significant impact on cloud-based e-learning when mediated by behavioral intentions. This implies that the relationship between social influence and cloud-based e-learning adoption is not influenced or mediated by individuals' behavioral intentions. The findings suggest that, in this context, the direct influence of social influence on cloud-based e-learning remains unrelated to the role played by behavioral intentions as a mediating variable.

The fifth hypothesis scrutinizes the influence of relative advantage on cloud-based e-learning, considering the mediating variable of behavioral intentions. The test results exhibit a non-significant beta coefficient of 0.017, accompanied by a t-statistic of 0.636, falling below the critical threshold of 1.96, and a p-value exceeding 0.05. Consequently, the fifth hypothesis is rejected, indicating that relative advantage does not exert a significant impact on cloud-based e-learning when mediated by behavioral intentions. This suggests that the relationship between relative advantage and cloud-based e-learning adoption is not mediated or influenced by individuals' behavioral intentions. In this context, the direct impact of relative advantage on cloud-based e-learning remains independent of the role played by behavioral intentions as a mediating variable.

The sixth hypothesis explores the influence of user satisfaction on cloud-based e-learning, considering the mediating variable of behavioral intentions. The test results reveal a non-significant beta coefficient of 0.114, accompanied by a t-statistic of 1.004, falling below the critical threshold of 1.96, and a p-value exceeding 0.05. Consequently, the sixth hypothesis is rejected, suggesting that user satisfaction does not exert a significant impact on cloud-based e-learning when mediated by behavioral intentions. This implies that the relationship between user satisfaction and cloud-based e-learning adoption remains direct and is not significantly influenced or mediated by individuals' behavioral intentions. In other words, the role of behavioral intentions as a mediating factor does not play a substantial role in the connection between user satisfaction and the adoption of cloud-based e-learning.

The outcomes of the first hypothesis testing indicate that social influence does not exhibit a positive impact on cloud-based e-learning. This aligns with findings from diverse studies, suggesting that while social influence is recognized as a factor influencing the adoption of cloud-based e-learning, its impact may not consistently be statistically significant. Previous research supports this notion, highlighting that although social influence plays a role in shaping the adoption of cloud-based e-learning, it may not always have a significant effect on users' intentions to engage with e-learning platforms (Murgante et al., 2014). This underscores the nuanced nature of factors contributing to the adoption of cloud-based e-learning, where the influence of social factors may vary in significance across different contexts or user groups [22].

Secondly, the findings from the second hypothesis testing reveal that relative advantage is observed to exert a negative influence on cloud-based e-learning. The advantage of a product is not a primary factor for consumers in choosing cloud-based e-learning products. The hypothesis testing results are not in line with research (Han & Xie, 2023), which shows a positive correlation between relative advantage and cloud computing adoption, including in the context of education [28].

Thirdly, the outcomes of the third hypothesis testing validate that user satisfaction is established to exert a positive influence on cloud-based e-learning. Increased alignment with user needs, expectations, and preferences correlates with higher adoption rates of cloud-based e-learning products. The hypothesis testing results are in line with research Pangarso & Setyorini (2023) serta Idkhan & Ma (2023), which show user satisfaction as a crucial factor for the success of cloud-based e-learning systems [29]. Satisfied users are more likely to continue using cloud-based e-learning systems, contributing to positive word-of-mouth promotion, and engaging more actively in learning activities [30].

Fourthly, the findings from the fourth hypothesis testing reveal that social influence does not exert an impact on cloud-based e-learning when mediated by variable behavioral intention. The decisions of students to utilize cloud-based e-learning products appear to be unaffected by the opinions or actions of friends, family, and society. This outcome contrasts with certain research, such as Gohary et al. (2013), which has suggested that human factors like social interaction, exposure, motivation, and self-efficacy play a substantial role in influencing the adoption of cloud-based applications [31].

Fifthly, the results of the fifth hypothesis testing indicate that relative advantage does not have an impact on cloud-based e-learning when mediated by variable behavioral intentions. Relative advantage does not influence cloud-based e-learning when mediated by the variable behavioral intention because the advantage of a product is not a determining factor for students to always use cloud-based e-learning products. The results of the hypothesis testing deviate from the findings of Abdulsaeed (2022). However, the current study's outcomes propose that relative advantage stands out as one of the factors shaping students' intentions to engage with cloud-based e-learning [32].

The results of the sixth hypothesis testing reveal that user satisfaction lacks an impact on cloud-based e-learning when mediated by variable behavioral intentions. This suggests that, contrary to the findings of Disastra and Wahyuningtyas (2020), user satisfaction with cloud-based e-learning does not significantly influence the user's intention to continue using such systems [33].

4. Conclusions

In conclusion, the research underwent a comprehensive validation process, ensuring the reliability and validity of the collected data. The constructs demonstrated acceptable convergent validity, as evidenced by Average Variance Extracted (AVE) values surpassing the recommended threshold of 0.5. Additionally, the reliability testing results confirmed the acceptability of Cronbach's Alpha values above 0.60, indicating the reliability of the data. The multicollinearity test demonstrated the absence of strong correlations between independent variables, enhancing the stability of regression coefficients. The analysis of the Coefficient of Determination indicated that 74.7% of the variability in Behavioral Intention and 72.1% in Cloud-Based E-Learning constructs could be explained by the considered variables. These values provide insights into the extent to which the chosen independent variables contribute to explaining the observed variations in Behavioral Intention and Cloud-Based E-Learning. The high percentages suggest a substantial explanatory power of the selected variables in elucidating the dynamics of the examined phenomena. Hypothesis testing outcomes illustrated varying impacts, with social influence and relative advantage showing no significant positive influence on cloud-based e-learning, while user satisfaction was confirmed to have a positive impact. Further analysis involving mediation through behavioral intention indicated no significant effects in the tested hypotheses. These findings contribute valuable insights into the complex

dynamics of factors influencing cloud-based e-learning adoption, offering implications for both researchers and practitioners in the educational technology domain.

4.1 Recommendations

The Technology Acceptance Model (TAM) is employed as a theoretical framework to elucidate the factors influencing the level of acceptance of technology and to understand end-users' behaviors towards a specific technology. TAM also aims to provide a foundation for examining the impact of external factors on users' beliefs, attitudes, and intentions concerning technology adoption (Nindyastuti & Kiswara, 2014). Within the TAM framework, it is posited that perceived usefulness (PU) and perceived ease of use (PEOU) are two crucial individual beliefs that significantly impact the acceptance behavior of computers. The conceptual TAM model, as applied by Nindyastuti & Kiswara (2014), illustrates the outcomes of individuals' interest and acceptance of information systems or technology.

In managerial terms, the implications of this research hold practical benefits for the academic sector by focusing on enhancing relative advantages through improvements in the quality and features of cloud-based e-learning. Additionally, there is an opportunity to boost user satisfaction by enhancing the quality of learning materials, facilities, and services. For government entities, the findings can serve as a foundation for policy development aimed at advancing cloud-based e-learning. The government can leverage these research results to formulate policies that foster the adoption of cloud-based e-learning among academics.

The data for this study were obtained through instruments based on respondents' perceptions, which may pose challenges if respondents' perceptions differ from the actual situation, leading to potential systematic errors. A recommendation for future research is to employ more objective research methods, such as experiments or observations, to help reduce systematic errors related to respondent perceptions. This study faced constraints regarding the social influence variable, as social influence may not necessarily impact individuals' decisions to use e-learning, given that each individual may have different opinions on using e-learning or sticking to conventional learning methods. A recommendation for future research involves exploring additional variables that could impact students' acceptance of e-learning, including factors like perceived usefulness, perceived ease of use, and motivation. Additionally, the instruments used in this study were limited to online questionnaires. Diversifying research instruments could contribute to obtaining more comprehensive and complete data. For example, researchers could use a combination of online questionnaires, interviews, and observations.

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