__The Influence of Behavioral Intention to Use e-Learning System on Academic Performance in Developing Countries: Tanzania Context__

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Abstract
The objective of this study was to evaluate the direct and indirect impact of behavioral intention on academic performance by examining the usage behavior of e-learning systems among students at higher education institutions in Tanzania. The research employed an explanatory cross-sectional survey design and utilized a stratified sampling method to choose a sample of 312 participants. Data collection was conducted using documentary review and a questionnaire consisting of closed-ended questions. The inferential analysis of the collected data was performed using Partial Least Squares Structural Equation Modeling, facilitated by the utilization of SmartPLS 4 software and descriptive analysis was performed with the help of IBM SPSS statistics version 26. The results of the study indicate that there is a significant positive relationship between behavioral intention and academic performance (p value<0.05). This relationship is mediated by the use behavior of the e-learning system. The findings of the study suggest that there is an indirect relationship between students' behavioral intention to utilize e-learning systems and their academic achievement in higher education institutions. Additionally, the effectiveness of the e-learning system is contingent upon the user's behavior. Hence, it is advisable that in the context of developing nations, with specific reference to Tanzania, due attention should be given to the behavioral intention and use patterns of students both during and subsequent to the deployment of the novel e-learning system.

Keywords: Behavioral Intention, e-Learning System, Academic Performance, Use Behavior

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1. Introduction

The COVID-19 pandemic has had a significant influence on the education sector worldwide, leading to the closure of universities and schools, notably in underdeveloped countries such as Tanzania (Chahal & Rani, 2022; Mailizar et al., 2021; Tawafak et al., 2021). In light of the COVID-19 pandemic, there has been a notable increase in the adoption of online learning by numerous universities worldwide (Mailizar et al., 2021). According to existing scholarly literature, the impact of e-learning on students' learning outcomes, academic achievements, and satisfaction levels has been widely acknowledged (Abramson et al., 2015; Kuliya & Usman, 2021). Moreover, it has been observed that the intention to use e-learning systems plays a crucial role in the adoption and implementation of online educational programs in various countries (Bhalalusesa et al., 2023; Abramson et al., 2015; Abhirami & Devi, 2022; Kuliya & Usman, 2021; Ramadiani et al., 2017; Revythi & Tselios, 2019). However, previous research has engaged in a discourse concerning the direct and indirect impacts of e-learning platforms on academic achievement (Kuliya & Usman, 2021; Chahal & Rani, 2022; Mailizar et al., 2021; Tawafak et al., 2021; Al-Adwan & Al-Debei, 2023). The objective of this study is to evaluate the impact of behavioral intention to utilize e-learning systems on academic achievement. The original Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) is employed to analyze both the direct and indirect effects. Similarly, this study examines the mediating role of students' usage behavior on their academic performance at higher education institutions located in underdeveloped nations, with a specific focus on Tanzania.

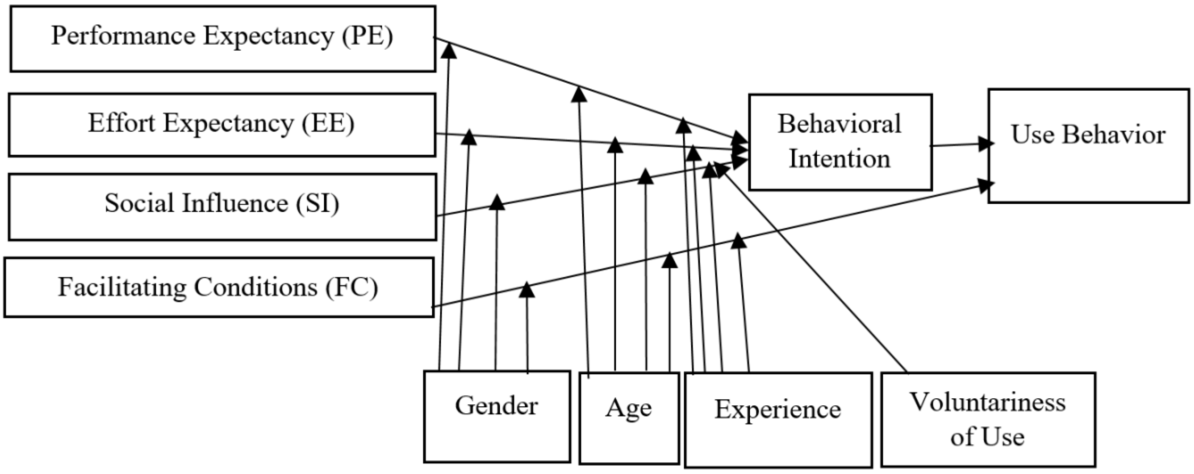
1.1 Constructs Development and Hypotheses Formulation

The present study integrated two constructs, namely behavioral intention and use behavior, from the original Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003). Additionally, one construct, specifically academic performance, was incorporated from the empirical literature review. These constructs were utilized to develop the research model and establish the hypotheses, drawing upon previous studies by Dwivedi et al. (2017) and Venkatesh et al. (2016, 2012).

1.1.1 Constructs Development

The present study utilized the Unified Theory of Acceptance and Use of Technology (UTAUT), originally created by Venkatesh et al. (2003), following a comprehensive assessment of around eight theories and models (Chen et al., 2011). Chen et al. (2011) have identified a range of theories and models explored by Venkatesh et al. (2003) in their research. These include the Diffusion of Innovation Theory (DIT), Combined Theory of Planned Behavior/Technology Acceptance Model (TPB/TAM), Model of PC Utilization (MPCU), Social Cognitive Theory (SCT), Motivational model (MM), Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), and Theory of Planned Behavior (TPB). According to the findings of Venkatesh et al. (2003), the explanatory power of the eight theories/models examined in their study was limited, accounting for just 17% to 53% of the variability in users' intention to adopt Information Technologies (IT). Nevertheless, the UTAUT framework, initially proposed by Venkatesh et al. (2003), demonstrated superior performance compared to the other eight theories/models when applied to the same dataset. This theory successfully accounted for almost 70% of the variability in individuals' behavioral intention to adopt and utilize Information Technologies (IT), as reported by Dwivedi et al. (2017). The original UTAUT was used for this study due to its superior ability to elucidate the variability in users' intention to utilize Information Technologies (IT). Figure 1 illustrates the primary components and moderating factors of the initial Unified Theory of Acceptance and Use of Technology (UTAUT).

Figure 1: *Unified Theory of Acceptance and Use of Technology (UTAUT)*



Source: Venkatesh et al. (2003).

1.1.2 Criticisms of the Original UTAUT

Despite the fact that the original Unified Theory of Acceptance and Use of Technology (UTAUT) has demonstrated the ability to account for around 70% of the variability in individuals' behavioral intention to adopt Information Technologies (IT), it has faced significant criticism from various scholars in recent times. The study conducted by Dwivedi et al. (2017) proposes a revised version of the Unified Theory of Acceptance and Use of Technology (UTAUT). This revised model suggests that factors such as gender, age, experience, and voluntariness do not influence the relationships between constructs such as performance expectancy, effort expectancy, social influence, behavioral intention, and use behavior. The proposition presented in this study is substantiated by a substantial body of prior empirical research. Specifically, it deviates from the original Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003) by excluding four moderators and incorporating additional dimensions, such as attitude, as recommended by Dwivedi et al. (2017), Venkatesh et al. (2016), and Venkatesh et al. (2012). Drawing off the critiques put out by Venkatesh et al. (2012), Venkatesh et al. (2016), and Dwivedi et al. (2017), the present study posits that there exists a positive and significant relationship between behavioral intention and academic performance, both directly and indirectly. The authors of previous studies (Chen et al., 2011; Dwivedi et al., 2017; Venkatesh et al., 2003; Venkatesh et al., 2012; Venkatesh et al., 2016) have not fully understood the relationship between behavioral intention and academic performance. Therefore, this study aims to contribute to the existing theories and models by predicting the direct and indirect linkages between these two variables. Similarly, the existing empirical research is insufficiently elucidating these types of relationships (Kuliya & Usman, 2021; Chahal & Rani, 2022; Mailizar et al., 2021; Tawafak et al., 2021).

1.1.3 Hypotheses Formulation

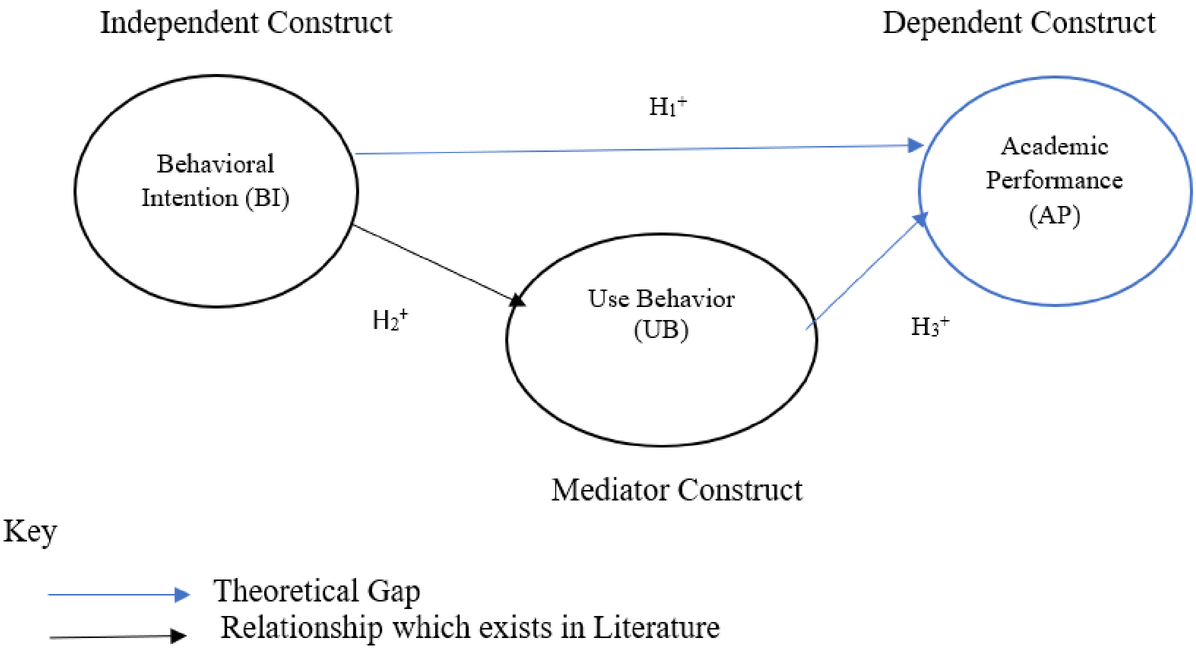
Previous empirical studies have produced predictions about how behavioral intention affects the actual use of different technology environments (Abramson et al., 2015; Kuliya &

Usman, 2021; Ramadiani et al., 2017; Revythi & Tselios, 2019). Previous research has shown the presence of positive path coefficients, which signify a statistically significant association between behavioral intention and actual use (Dwivedi et al., 2017; Venkatesh et al., 2012; Venkatesh et al., 2016; Chahal & Rani, 2022; Mailizar et al., 2021; Tawafak et al., 2021). The objective of this study was to assess the possible influence of behavioral intention to employ e-learning systems on academic accomplishment, a topic that has received little attention in prior scholarly researches. Therefore, the main aim of this work was to illustrate the impact of using behavior as a crucial determinant affecting both theoretical and empirical knowledge addition via the mediation process.

H_1: *Behavioral intention (BI) would direct influence academic performance (AP)*
H_2: *Behavioral intention (BI) would direct influence use behavior (UB)*
H_3: *Use behavior (UB) would direct influence academic performance (AP)*
H_2*H_3: *Behavioral intention (BI) would indirect influence academic performance (AP) through use behavior (UB)*

The conceptual model of the study is presented in Figure 2.

Figure 2: *Conceptual Model of the Study*



Source: Researcher' Conceptual Model (2023)

1.1.4 The Mathematical Model for Latent Variable and Its Observed Indicators

The present work used the mathematical model x=lY+e to illustrate the relationship between a latent variable and its observable indicators, as seen in Figure 2. In the study conducted by Sarstedt et al. (2022), the observable indicator variable is denoted by x, while the latent variable is represented by Y. The loading, denoted by l, serves as a regression coefficient that quantifies the strength of the link between x and Y. Additionally, e is used to indicate the random measurement error.

2. Methodology

2.1 Research Design, Methods and Tools for Data Collection and Analysis

The research strategy used in this study was an explanatory cross-sectional survey, since it included the collection of data from a specific group by investigating a representative sample of that community (Creswell & Plano, 2018). Furthermore, this research used a survey methodology to collect data from two institutions of higher education. This approach was chosen because to its ability to acquire quantitative data, which could then be evaluated using descriptive and inferential statistical techniques. To fulfil the requirements of this study, the researcher used the tenth rule guideline offered by Hair et al. (2019) for using PLS-SEM and SmartPLS software in data analysis. This guideline was employed to establish the minimum number of participants necessary to evaluate the proposed research model. According to Hair et al. (2019), the tenth guideline proposes that the minimum sample size needed to test the hypotheses of the research model is determined by multiplying the number of indicators of the exogenous construct (specifically, four indicators of behavioral intention in this study) by ten. According to the tenth rule of thumb, the sample size of 312 respondents in this research was deemed enough for testing the hypotheses, since it exceeded the minimal requirement of 40 respondents. Furthermore, closed-ended surveys were given numerical values to enhance the accuracy and streamline the process of quantitative data analysis. The quantitative data acquired for the respondents' profiles were evaluated using descriptive statistics, using IBM SPSS Statistics Software Version 26. The inferential statistical analysis for evaluating the hypotheses was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the assistance of SmartPLS 4 software. The Extra Answer approach was used to address the issue of missing data via the utilization of SmartPLS 4 software. This research used the value of 99 as a supplementary response to substitute for seventeen (17) missing values that were identified in the questionnaires. However, this approach facilitated the establishment of a systematic distinction between data that has been seen and data that has not been observed (Hair et al., 2019). The identification of outliers was conducted using IBM SPSS Statistics version 26. This included examining the frequencies of all variables in relation to their degree of agreement. No outliers were detected in the present study.

2.2 Evaluation of Models

The evaluation of the measurement model and structural model of the suggested research model in this study was conducted using the criteria specified by Hair et al. (2019). There were four processes involved in examining the reflective measurement models, which are outlined as follows: The examination of the reliability value of indicators should exceed 0.708. When assessing the internal consistent reliability value of the composite reliability of constructs, it should also exceed 0.708. In order to assess the convergent validity of the constructs, the Average Variance Extracted (AVE) value should be greater than 0.5. On the other hand, for discriminant validity, the Heterotrait-Monotrait Ratio of Correlations (HTMT) criterion value should be less than 0.9. Similarly, the examination of collinearity was conducted for the constructs of the structural model. Based on the findings of Hair et al. (2019), VIF values over 5 suggest the presence of potential collinearity among the predictor constructs. However, it is important to note that collinearity concerns may also arise with VIF values ranging from 3 to 5. Ideally, it is desirable for the Variance Inflation Factor (VIF) values to be about 3 or below.

After doing a collinearity check, the primary factors for evaluating the structural model in Partial Least Squares Structural Equation Modeling (PLS-SEM) were as follows: the significance of the path coefficients, with a t-statistic above 1.96 at a significance threshold of 0.05 considered acceptable, and p-values equal to or less than 0.05 deemed significant. According to Hair et al. (2019), R^2 values of 0.75, 0.50, and 0.25 may be categorized as significant, moderate, and weak, respectively. Similarly, the f^2 effect sizes, with values greater than 0.02, 0.15, and 0.35, indicate small, medium, and big impact sizes, respectively (Hair et al., 2019). The predictive relevance, as measured by the Q^2 effect size, is expected to have a greater than zero value (Hair et al., 2019; Becker et al., 2018). In general, the outcomes pertaining to the assessment of both the measurement and structural models were deemed satisfactory and aligned with the criteria set out by Hair et al. (2019).

2.3 Variables, Indicators and Measurement of Scale

This study used the variables, indicators and the measurement of scale presented in Table 1.

Table 1: *Variables, Indicators, Measurement, Data Analysis Method and Tool*

Dependent Variable	Indicators	Level of Measurement	Analysis Method	Analysis Tool
Academic Performance	Consistency of high grades scores, satisfied with academic performance, apply knowledge to the real-world situation	Ordinal	PLS-SEM	SmartPLS 4
Mediator Variable	**Indicators**	**Measurement Level**	**Analysis Method**	**Analysis Tool**
Use Behavior of e-Learning System	Continue interesting the system, continue learning the system, continue using the system, continue enjoying the benefits of the system	Ordinal	PLS-SEM	SmartPLS 4
Independent Variable	**Indicators**	**Measurement Level**	**Analysis Method**	**Analysis Tool**
Behavioral Intention to Use e-Learning System	Personal opinion on the system, intention to learn the system, intention to use the system, intention to continue taking advantages of the system	Ordinal	PLS-SEM	SmartPLS 4

Source: Researcher' Own Design (2023)

3. Results

3.1 Respondent's Profile

Approximately 73% of the participants identified as female students, while approximately 27% identified as male. These results are contrary to the study findings by Bhalalusesa et al. (2023) which revealed that 71.4% were males while 28.6% were females. Furthermore, it is worth noting that around 46 percent and 34 percent of the participants were pursuing undergraduate and graduate degrees, respectively. The findings of this study indicate that the information supplied by the participants may be considered authentic. Table 2 presents the profile of the respondents in this research.

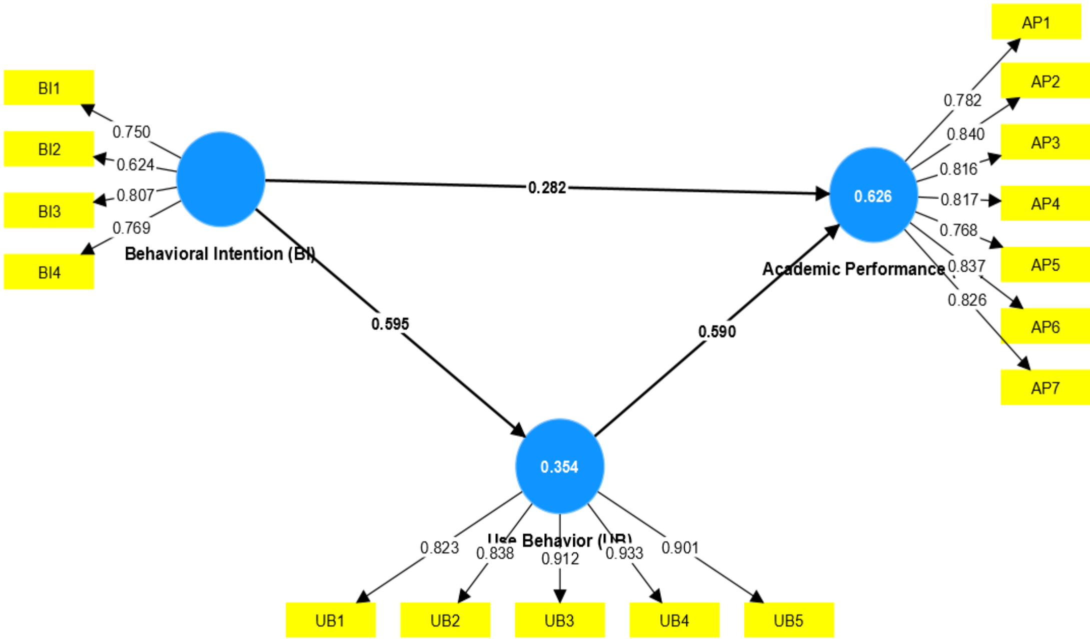
Table 2: *Type of Respondent *Education Level Crosstabulation*

	Education level				Total
	Certificate Level	Diploma Level	Bachelor's Degree	Master's Degree	
Female Students	15	30	104	80	229
Male Students	10	8	40	25	83
Total	**25**	**38**	**144**	**105**	**312**

3.2 R^2 Values, Relevance of the Path Coefficients and Indicators' Loadings Values

Hair et al. (2019) propose that R^2 values of 0.75, 0.50, and 0.25 might be categorized as considerable, moderate, and weak, respectively. The findings of this research showed that the R^2 values for the endogenous constructs were 0.354 and 0.626, suggesting a modest level of predictive power for the result. According to the established criteria outlined by Hair et al. (2019), the values of 0.354 and 0.626 exceeded the minimal level recommended. These findings suggest that the combined influence of behavioral intention to use an e-learning system and actual use behavior accounts for 62.6% of the variability in academic performance. Additionally, behavioral intention alone explains 35.4% of the variability in the use behavior of the e-learning system. Furthermore, it is noteworthy that all route coefficients had a positive relationship, indicating that a one standard deviation rise in behavioral intention and use behavior corresponded to an improvement in academic achievement. Furthermore, the loadings values of the indicators were all greater than 0.708, except for BI2, which was less than 0.708. Based on the findings of Hair et al. (2019), indicators with a reliability value below 0.708 may be considered for removal, but only if their exclusion would result in an improvement in both composite reliability (CR) and Average Variance Extracted (AVE). Based on this evidence, it can be concluded that the deletion of BI2 did not have a significant influence on the internal consistent reliability values of the composite reliability of all constructs, which were found to be more than 0.708. Additionally, the deletion of BI2 did not affect the convergent validity of all constructs, as shown by the Average Variance Extracted (AVE) values, which were greater than 0.5. The findings of this study indicate that there were favourable response patterns observed, and each construct demonstrated convergence in explaining the variability of its respective item (Hair et al., 2019). Figure 3 displays the values of R^2, the outcomes of path coefficients, and the values of indicators' loadings.

Figure 3: *R^2 Values, Relevance of the Path Coefficients and Indicators' Loadings Values*



3.3 Reliability and Convergent Validity

According to Hair et al. (2019), a construct's reliability may be assessed using the composite reliability (CR) value. A CR value better than 0.708 is deemed acceptable. Additionally, the construct's convergent validity can be evaluated using the Average Variance Extracted (AVE) value. It is suggested that the AVE value be greater than 0.5. In this research, the composite reliability (CR) values for all components were found to be better than 0.708, indicating satisfactory reliability. Additionally, the convergent validity of all constructs was assessed using the Average Variance Extracted (AVE) measure, with all constructs demonstrating AVE values over 0.5, indicating acceptable convergent validity. The implications of these results suggest that the research saw favorable response patterns, with each construct converging to account for the variability of its respective item (Hair et al., 2019). Table 3 displays the findings pertaining to the reliability and validity of the constructs.

Table 3: *Reliability and Convergent Validity*

Construct	Composite Reliability (CR)	Average Variance Extracted (AVE)
Academic Performance (AP)	0.932	0.661
Behavioral Intention (BI)	0.828	0.549
Use Behavior (UB)	0.946	0.779

3.4 Discriminant Validity

The HTMT values for all relationships postulated in the research model were found to be less than 0.90, indicating that each construct within the proposed research model was empirically distinguishable from other constructs within the structural model (Hair et al., 2019). The findings of the discriminant validity study utilizing the HTMT measure are shown in Table 4.

Table 4: *Discriminant Validity*

	Academic Performance (AP)	Behavioral Intention (BI)
Behavioral Intention (BI)	0.761	
Use Behavior (UB)	0.819	0.714

3.5 R-square

Based on the findings of Hair et al. (2019), it can be inferred that R^2 values of 0.75, 0.50, and 0.25 may be categorized as considerable, moderate, and weak, respectively. The study yielded R^2 values of 0.354 and 0.626, indicating an existence of predictive power among the constructs which seamed to influence other constructs in the proposed research model. According to the established criteria outlined by Hair et al. (2019), the R^2 values of 0.354 and 0.626 observed in this study above the minimal threshold values recommended. The findings suggest that a combination of behavioral intention and use behavior accounts for 62.6% of the variability seen in the academic performance. Furthermore, behavioral intention alone explains 35.4 % of the variability in the use behavior. The findings of the R^2 values are shown in Table 5.

Table 5: *R-square*

	R-square	R-square adjusted
Academic Performance (AP)	0.626	0.624
Use Behavior (UB)	0.354	0.352

3.6 Collinearity Statistics (VIF)

In the present study, collinearity statistics were assessed using the variance inflation factor (VIF). The obtained VIF values for all items were below 3, indicating the absence of collinearity issues among the predictor constructs in the proposed research model. Table 6 displays the collinearity statistical findings for the inner model of the proposed research model, measured using the VIF metric.

Table 6: *Collinearity Statistics (VIF)*

	Academic Performance (AP)	Use Behavior (UB)
Behavioral Intention (BI)	1.549	1.000
Use Behavior (UB)	1.549	

3.7 F Square

Hair et al. (2019) established that effect sizes of 0.02, 0.15, and 0.35 are indicative of modest, medium, and large f^2 values, respectively. The present study observed f^2 effect sizes of 0.138, 0.549 and 0.602, indicating the occurrence of modest, and high f^2 impact sizes across all hypotheses of the research model. The findings of the study are shown in Table 7, which displays the f^2 values.

Table 7: *F Square*

	Academic Performance (AP)	Use Behavior (UB)
Behavioral Intention (BI)	0.138	0.549
Use Behavior (UB)	0.602	

3.8 Q^2 Predict Results

In the present study, it was observed that the values of Q^2 for all endogenous constructs, namely use behavior (UB) and academic performance (AP), were found to be greater than zero. This suggests that the exogenous construct behavioral intention (BI) possesses predictive power within the research model. The findings of Q^2 for the endogenous construct of the proposed research model are shown in Table 8.

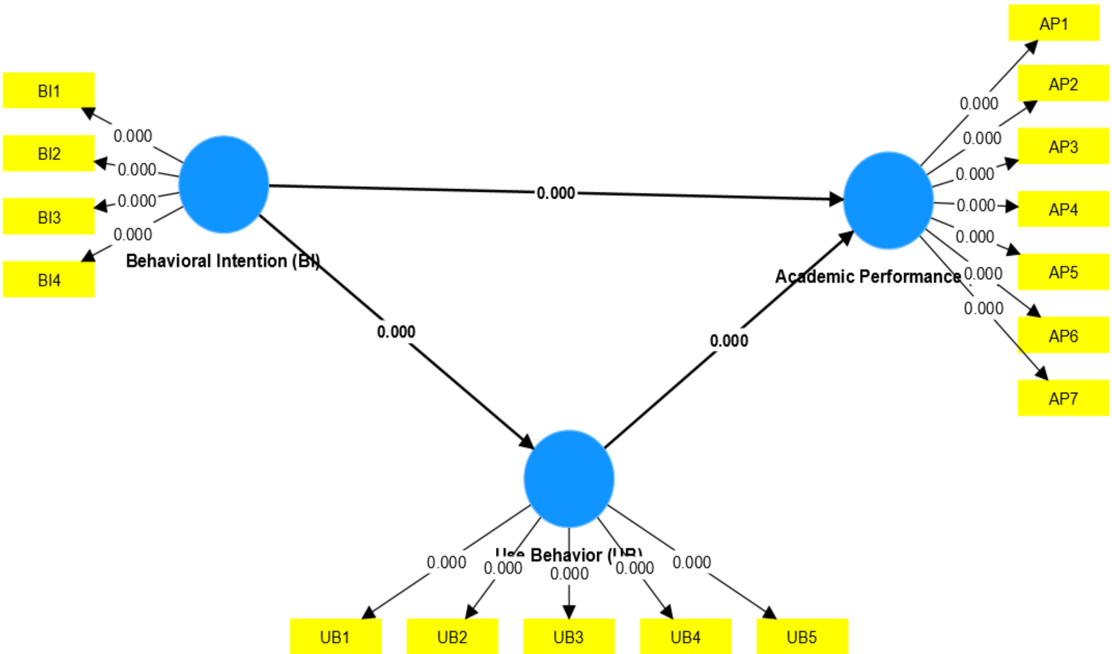
Table 8: *Q Square*

Construct	SSO	SSE	Q^2 (=1-SSE/SSO)
Academic Performance (AP)	2184	1301.421	0.404
Use Behavior (UB)	1560	1138.791	0.270

3.9 Significance of the Path Coefficients

Upon doing bootstrapping analysis, the obtained findings revealed statistical significance for all anticipated hypotheses. Specifically, the p-values associated with all routes were determined to be less than 0.05. The findings of this study indicate that the hypothesized correlations are really present in real-world contexts. The significance of the path coefficients is seen in Figure 4.

Figure 4: *Significance of the Path Coefficients*



3.10 Total and Specific Indirect Effects of the Hypotheses

Based on the findings shown in Figure 4, this research has demonstrated the presence of substantial impacts of behavioral intention towards using an e-learning system (both direct and indirect effects) as well as the actual use behavior (direct effect) on academic achievement. Table 9 presents the comprehensive and particular indirect impacts of the hypotheses that were examined in the study.

Table 9: *Total and Specific Indirect Effects of the Hypotheses Tested Results*

Hypothesis	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Remark
BI -> AP	0.037	17.079	0.000	Supported
BI -> UB	0.045	13.103	0.000	Supported
UB -> AP	0.054	10.966	0.000	Supported
BI->UB->AP	0.041	8.525	0.000	Supported

3.11 Total and Specific Indirect Effects of the Hypotheses Tested by Using MGA

The statistical analyses conducted in this study, namely the BI -> AP and BI -> UB models, indicate a significant positive correlation. This suggests that female students exhibit more strength compared to male students, accounting for about 50% of the total hypotheses examined and the observed connections. The statistical analysis conducted using multiple group analysis (MGA) indicates that there is a significant negative relationship between the variables UB-> AP, as well as between BI ->UB, respectively. These findings suggest that male students exhibit more strength compared to female students in about 50% of the total hypotheses examined. Table 10 displays the comprehensive and distinct indirect impacts of the hypotheses examined via the use of MGA. It also includes the disparities in path coefficients and corresponding p-values. Based on the obtained p values in this research, which were all found to be larger than 0.05, it can be concluded that the perceptions of the two groups, namely female and male students, regarding the predicted correlations exhibit similarities. The findings suggest that there were no significant differences in the responses of female and male students to the presented propositions.

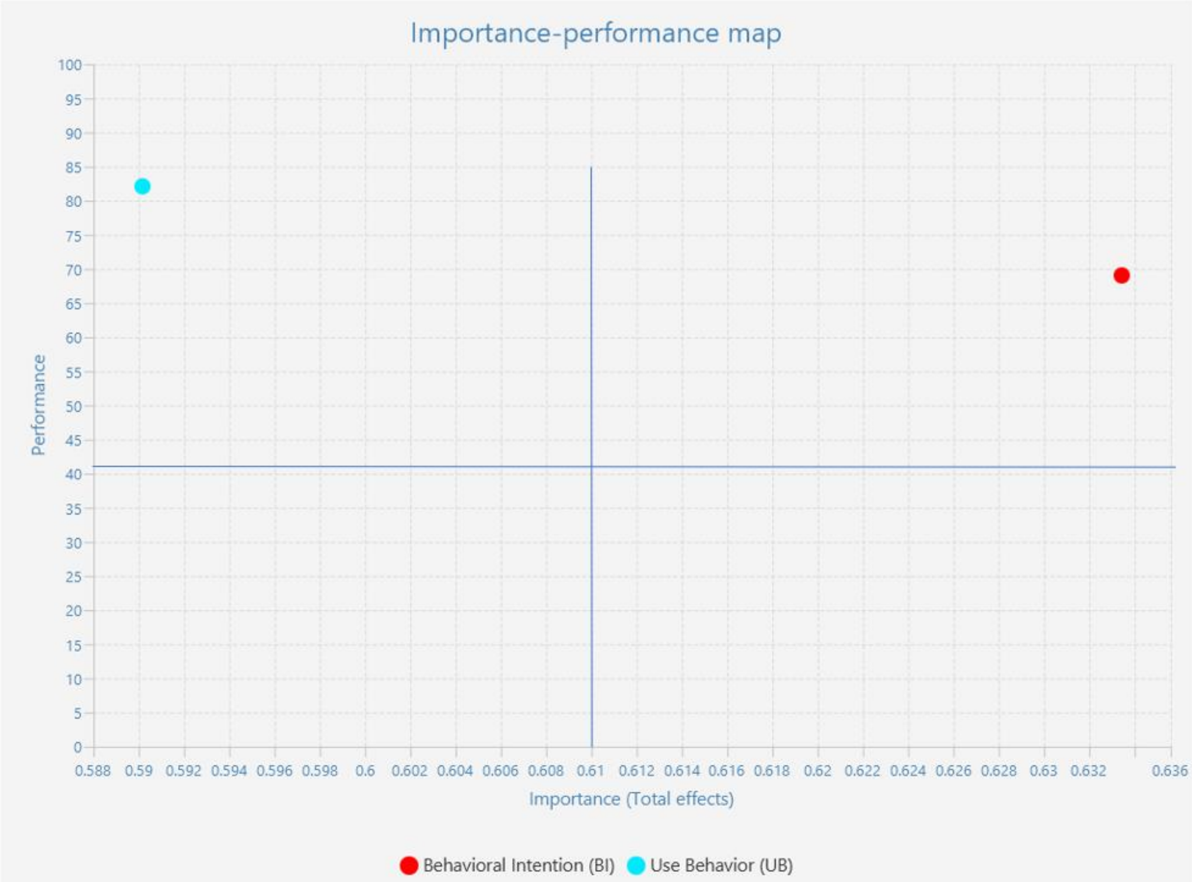
Table 10: *Total and Specific Indirect Effects of the Hypotheses Tested by Using MGA*

Hypothesis	Difference (Female - Male)	2-tailed (Female vs Male) p value	Remark
BI -> AP	0.027	0.721	Rejected
BI -> UB	0.035	0.629	Rejected
UB -> AP	-0.103	0.385	Rejected
BI->UB->AP	-0.040	0.556	Rejected

3.12 Importance-Performance Map Analysis Results

The construct of behavioral intention to use the e-learning system, as depicted in Figure 5, is situated above the average of the importance and performance of the target construct, namely academic performance. This positioning is logical as it suggests the need to prioritize, invest more in, and enhance the construct of academic performance during and after the implementation of the e-learning system, with the aim of improving overall academic performance. On the contrary, the construct of use behavior is seen to have a lower level of relevance compared to the goal construct, which is academic performance. This implies that the construct being examined has a somewhat restricted impact on the target construct. However, it is seen that the use behavior construct exhibits performance levels that are higher than the average, indicating that it should be considered of lesser relevance before and after the implementation of an e-learning system in order to improve academic achievement.

Figure 5: *Importance-Performance Map Analysis Results*



4. Discussion

4.1 The Hypotheses Tested for the Theorized Research Model

The present research hypothesized that there would be a direct relationship between behavioral intention and the use behavior of an e-learning system. The findings indicated a positive path coefficient, suggesting that a one standard deviation rise in behavioral intention would result in an increase in the rate of use behavior of e-learning system. The results of this study align with prior research conducted by Dwivedi et al. (2017), Venkatesh et al. (2012), and Venkatesh et al. (2003). These studies also found that behavioral intention significantly influences the utilization of technology, as shown by a p-value of less than 0.05.

Additionally, this research posited the hypothesis that the behavior of using an e-learning system would have a direct impact on students' academic performance. Furthermore, it suggested that the behavioral intention to use the e-learning system would indirectly affect students' academic performance via their use behavior. The findings indicate that there are positive path coefficients, suggesting that an increase of one standard deviation in behavioral intention and use behavior is associated with an improvement in academic achievement. The findings presented in this study are not consistent with the results of earlier research, and thus represent a novel addition to the existing body of knowledge.

5. Conclusion

5.1 Theoretical Implications

The present study has successfully addressed a gap in the current theoretical and empirical literature by comprehensively examining the role of use behavior as a mediator and behavioral intention as a predictor, as originally proposed in the Unified Theory of Acceptance and Use of Technology (UTAUT).

5.2 Practical Implications

The statistical significance of behavioral intention in both direct and indirect interactions implies that students primarily depend on their behavioral intention when making the choice to use e-learning systems.

5.3 Limitation and Recommendation for Future Research

This research only used two components, namely "behavioral intention" and "use behavior," derived from the original Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003). The model provided an explanation for just 62.6% of the observed variance in academic achievement. The study therefore suggests that future research should include more components from the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003) in order to enhance the diversity of factors influencing academic success. Similarly, the present research used participants who were students hailing from a single nation, namely Tanzania. In light of this observation, it is recommended that future research endeavors use a diverse sample of students from other nations in order to enhance the generalizability of the proposed model for e-learning systems.

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