The Effect of e-Learning System on Academic Performance in Higher Learning Institutions in Tanzania: Moderating Effect of Behavioral Intention

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Abstract
This research evaluated the direct impact of an e-learning system on academic performance at higher education institutions in Tanzania. The research was guided by the modified Unified Theory of Acceptance and Use of Technology (UTAUT) and used descriptive and explanatory cross-sectional survey research designs. Likewise, the study used the positivism paradigm and a simple random sampling technique to get a sample size of 322 respondents. The data were obtained through administration of questionnaires and the review of relevant documents. The acquired data underwent inferential statistical analysis using Partial Squares Structural Equation Modeling with the assistance of SmartPLS 4. Additionally, descriptive statistical analysis was performed using IBM SPSS Statistics Version 26 to examine the data collected on respondents' profiles. The results indicate that the e-learning system and behavioral intention have a direct impact on academic performance. Nevertheless, the moderation effect of behavioral intention on the link between the e-learning system and academic performance is negligible. The research confirms that both the e-learning system and behavioral intention have a significant impact on academic performance. Thus, it is essential for higher education institutions in Tanzania and other developing nations to take into account the behavioral intentions of students while deploying e-learning systems in order to optimize the academic performance.

Keywords: Academic Performance, Behavioral Intention, e-Learning System and UTAUT

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1. Introduction

Learning is a cognitive process that enables individuals to acquire information, skills, and competencies, which in turn influence their decision-making and behavioral patterns (Suresh et al., 2018; Shatta, 2023; Kuliya & Usman, 2021; Chahal & Rani, 2022; Mailizar et al., 2021; Tawafak et al., 2021; Al-Adwan & Al-Debei, 2023). The primary advantage of e-learning is its effective delivery of educational content (Suresh et al., 2018). This includes improved access to information, easy content updates, personalized instruction, convenient distribution, standardized content, and increased accountability (Suresh et al., 2018; Mailizar et al., 2021; Bhalalusesa et al., 2023; Abramson et al., 2015; Abhirami & Devi, 2022; Kuliya & Usman, 2021; Ramadiani et al., 2017; Revythi & Tselios, 2019; Abramson et al., 2015; Kuliya & Usman, 2021).

Electronic content can be updated more easily compared to printed material, and e-learning technologies enable educators to swiftly and effortlessly alter their content (Chahal & Rani, 2022; Mailizar et al., 2021; Tawafak et al., 2021; Al-Adwan & Al-Debei, 2023). Similarly, in e-learning, learners have the ability to manipulate the content, learning order, speed of learning, timing, and frequently, the media used, enabling them to customize their experience to fulfill their individual learning goals (Suresh et al., 2018; Shatta, 2023; Kuliya & Usman, 2021; Chahal & Rani, 2022; Mailizar et al., 2021; Tawafak et al., 2021; Al-Adwan & Al-Debei, 2023).

The advent of internet technology enables the extensive dissemination of digital material to many consumers concurrently, regardless of time and location (Shatta, 2023; Mailizar et al., 2021). E-learning provides a faster, more cost-effective, and potentially superior alternative to traditional education (Suresh et al., 2018). It should be readily accessible to all individuals due to its transformative impact on the college experience for students worldwide (Shatta, 2023; Bhalalusesa et al., 2023; Abramson et al., 2015; Abhirami & Devi, 2022; Kuliya & Usman, 2021; Ramadiani et al., 2017; Revythi & Tselios, 2019). However, there is an ongoing debate in the current research literature on the use or not use of moderators and mediators in studies related to the adoption of technologies, including the implementation of e-learning (Ogundega, 2019; Nassar et al., 2019; Shatta, 2023; Chen et al., 2011; Dwivedi et al., 2017; Venkatesh et al., 2003; Venkatesh et al., 2012; Venkatesh et al., 2016; Alaba et al., 2020; Abubakar & Ahmad, 2015; Mtebe & Raisamo, 2014; Suresh et al., 2018).

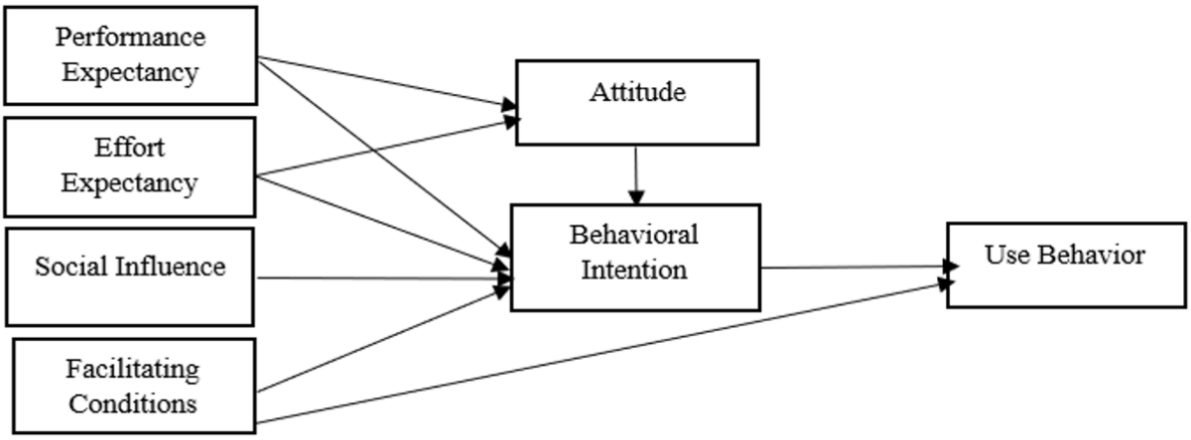
Previous studies have examined the influence of both mediators and moderators on the adoption of technologies, as well as the impact of mediators alone on technology use and academic performance. For instance, Ogundega (2019), Venkatesh et al. (2003) and Nassar et al. (2019) explored the effects of both mediators and moderators on use behavior of technologies. On the other hand, Dwivedi et al. (2017) and Shatta (2023) focused solely on the effects of mediators on technology use and academic performance respectively. Nevertheless, the impact of moderators alone on technology use behavior or academic performance has received little attention (Abubakar & Ahmad, 2015). Thus, the objective of this research was to demonstrate how behavioral intention of students acts as a moderator in strengthening the effect of e-learning system on academic performance in higher learning institutions.

1.1 Constructs Development and Hypotheses Formulation

This study used one construct (behavioral intention) from the modified UTAUT by Dwivedi et al. (2017) and other two constructs (e-learning system and academic performance) from the empirical literature review to develop the research model and formulate the hypotheses (Venkatesh et al., 2003; Venkatesh et al., 2016; Venkatesh et al., 2012; Shatta, 2023; Suresh et al., 2018).

1.1.1 Constructs Development

This study adopted the modified Unified Theory of Acceptance and Use of Technology (UTAUT) by Dwivedi et al. (2017) because of its arguments on moderators and additional of other construct in explaining the variance in users' intention to use Information Technologies (IT). Dwivedi et al. (2017) argues that moderators of gender, age, experience and voluntariness have no impact on linkages of constructs (performance expectancy, effort expectancy, social influence and behavioral intention) and use behavior. This argument was supported by the number of existing prior empirical studies (Shatta, 2023), which dropped the four moderators suggested by the origin UTAUT by Venkatesh et al. (2003) and added the academic performance and e-learning as constructs to explain the variance in user's intention to use IT (Dwivedi et al., 2017; Shatta, 2023; Venkatesh et al., 2016; Venkatesh et al., 2012). Figure 1 shows the direct and indirect elements of the modified UTAUT by Dwivedi et al. (2017).



Source: Dwivedi et al. (2017)

Figure 1: *Modified UTAUT*

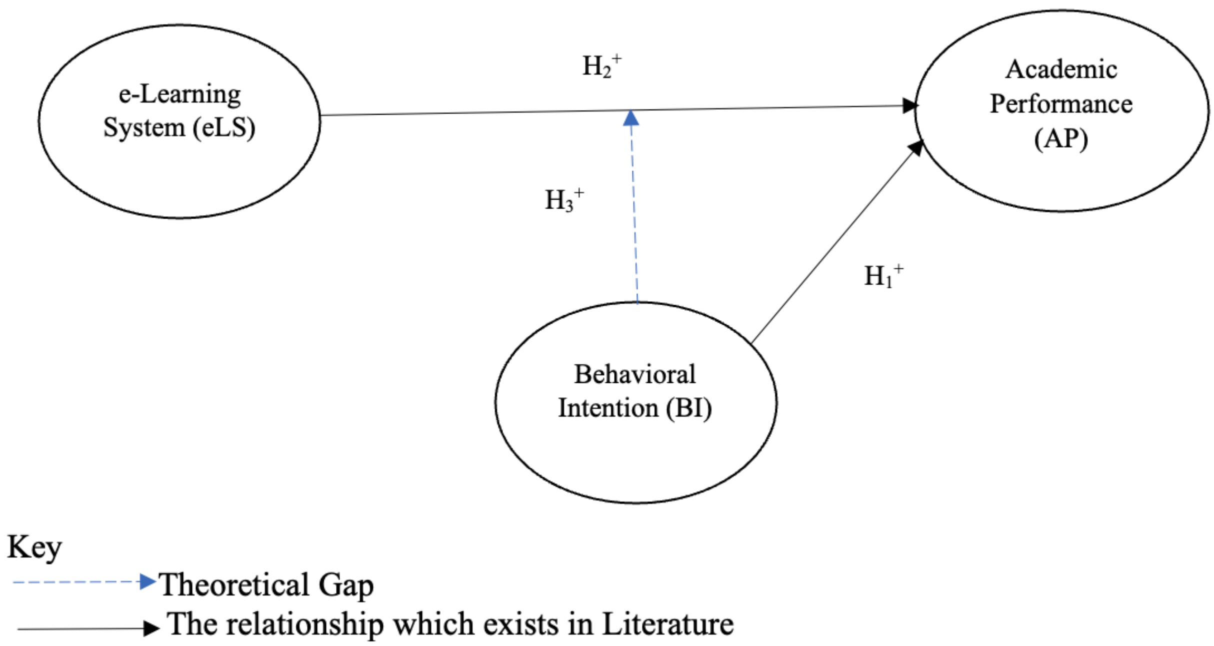
1.1.2 Hypotheses Formulation

Unlikely the criticisms of prior studies by Shatta (2023) and by Dwivedi et al. (2017), on moderation effect, this study argued that behavioral intention would positively moderate the effect of e-learning system on academic performance in higher learning institutions. The direct moderation of behavioral intention on the effect of e-learning system on academic performance was predicted as new theoretical contribution because the existing theories and models had not comprehended this phenomenon (Chen et al., 2011; Dwivedi et al., 2017; Venkatesh et al., 2003; Venkatesh et al., 2012; Venkatesh et al., 2016). In addition, several studies had predicted the effects of e-learning system and behavioral intention on academic performance (Suresh et al., 2018; Abramson et al., 2015; Kuliya & Usman, 2021; Ramadiani et al., 2017; Revythi & Tselios, 2019) and the findings revealed positive and significant effects. For the purposes of validating and advancing the findings of the existing theorical and empirical literature, this study thought behavioral intention to use e-learning system would positively moderate the effect of e-learning system on academic performance a substance that had not been tested by prior empirical studies and theories (Dwivedi et al., 2017; Venkatesh et al., 2012; Venkatesh et al., 2016; Chahal & Rani, 2022; Mailizar et al., 2021; Tawafak et al., 2021).

H_1: *Behavioral Intention (BI) would positively and directly effect the Academic Performance (AP)*
H_2: *e-Learning System (eLS) would positively and directly effect the Academic Performance (AP)*
H_3: *Behavioral Intention (BI) would positively moderate the direct effect of e-Learning System on Academic Performance (AP)*

1.1.3 Conceptual Model of the Study

The conceptual model of this study was prepared after getting the concepts from the theoretical and empirical literature. The conceptual model of the study is presented in Figure 2.



Source: Conceptualized from the Existing Literature, 2023

Figure 2: *Conceptual Model of the Study*

1.1.4 The Mathematical Model for Latent Variable and Its Observed Indicators

This study adopted the mathematical model x=lY+e, to display the association between a latent variable and its observed indicators as revealed in Figure 2. x represents the observed indicator variable, Y represents the latent variable, l is the loading which represents a regression coefficient quantifying the strength of the relationship between x and Y, and e represents the random measurement error (Shatta, 2023; Sarstedt et al., 2022).

2. Methodology

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

The study used positivism philosophy and an explanatory cross-sectional survey research methodology, which included collecting data once from a specific group by analyzing a sample of that population (Creswell & Plano, 2018). Furthermore, this research used a survey methodology to collect data from two institutions of higher education (National Institute of Transport and Procurement and Supplies Professionals and Technicians Board). This approach was chosen because it enables the collection and quantitative analysis of data using descriptive and inferential statistics.

To fulfill the assumptions of this study, we used the tenth rule guideline offered by Hair et al. (2019) for using PLS-SEM and SmartPLS software in data analysis. This guideline was utilized to validate the minimum number of participants needed to examine the proposed research model. According to Hair et al. (2019), the tenth rule states that the minimum sample size needed to test the hypotheses of the research model is equal to ten times the number of indicators of the exogenous construct. In this study, there were six indicators of behavioral intention and e-learning system, which are considered as exogenous constructs. According to the tenth rule of thumb suggested by Hair et al. (2019), the minimum sample size for this study was 60. However, a sample size of 322 respondents used was enough to test the hypotheses of this research, as it exceeded the minimal requirement of 60 respondents. Furthermore, closed-ended surveys were given numerical values to streamline and enhance the accuracy of quantitative data analysis.

The quantitative data acquired for respondents' profile 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 missing data using the SmartPLS 4 software. This research used the value of 99 as a substitute for seventeen (17) missing values that were included in the questionnaires. Conversely, this approach facilitated the establishment of a consistent distinction between data that was seen and data that was not observed (Hair et al., 2019). The identification of outliers was conducted using IBM SPSS Statistics version 26. This included estimating the frequencies of all variables and assessing their degree of agreement. No anomalies were detected in this study.

2.2 Evaluation of Measurement Model and Structural Model

This study used the criteria set forth by Hair et al. (2019) to assess the measurement model and structural model of the proposed research model. There were four processes involved in examining the reflective measuring models: When evaluating the reliability of indicators, the value should be greater than 0.708. Similarly, when assessing the internal consistency of composite reliability of constructs, the value should also be greater than 0.708. For evaluating the convergent validity of constructs, the Average Variance Extracted (AVE) value should be greater than 0.5. On the other hand, for assessing discriminant validity, the Heterotrait-Monotrait Ratio of Correlations (HTMT) criterion value should be less than 0.9. Similarly, the presence of collinearity among the components of the structural model was investigated. As to Hair et al. (2019), VIF values over 5 suggest the presence of likely collinearity across the predictor constructs difficulties. However, collinearity issues may also arise with VIF values ranging from 3 to 5. Optimally, the VIF values should be in proximity to 3 or below.

Once collinearity was accounted for, the primary factors used to evaluate the structural model in PLS-SEM were as follows: the path coefficients needed to be statistically significant, with t-statistics above 1.96 at a significance threshold of 0.05 for all pathways. Additionally, p-values of 0.05 or below were considered to indicate significance. The R2 values of 0.75, 0.50, and 0.25 may be categorized as significant, moderate, and weak correspondingly (Hair et al., 2019). Similarly, f^2 effect sizes greater than 0.02, 0.15, and 0.35 indicate small, medium, and large impact sizes respectively (Hair et al., 2019). The predictive relevance, as measured by the Q^2 effect size, should have a value greater than zero (Hair et al., 2019; Becker et al., 2018). In general, the assessment findings for both the measurement and structural models were satisfactory and satisfied all the criteria set by Hair et al. (2019).

3. Results

3.1 Respondents' Profile

The female student participants were around 70 percent of the total, while the male participants constituted approximately 30 percent. The results align with the research findings of Shatta (2023), but contradict the study findings of Bhalalusesa et al. (2023), which reported that 71.4 percent of the participants were men and 28.6 percent were girls. Additionally, it is noteworthy that almost 53 percent of the participants were actively pursuing bachelor's and master's degrees. The results of this research suggest that the data gathered from the participants may be regarded as genuine. Table 1 displays the demographic characteristics of the participants in this study.

Table 1: *Type of Respondent * Education Level Crosstabulation*

	Education level				
	Certificate Level	Diploma Level	Bachelor Degree	Master' Degree	Total
Female Students	80	44	85	15	224
Male Students	10	18	45	25	98
Total	**90**	**62**	**130**	**40**	**322**

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 construct was 0.516 without moderator and 0.656 with moderator, suggesting an increase of power after introducing the moderator. According to the established criteria outlined by Hair et al. (2019), the values of 0.516 and 0.656 exceeded the minimal level recommended. These findings suggest that the moderator behavioral intention together with e-learning system accounts for 65.6 percent of the variability in academic performance. Additionally, e-learning system alone explains 51.6 percent of the variability in academic performance. Furthermore, it is noteworthy that all path coefficients had positive relationships, indicating that when one standard deviation rises in behavioral intention and in e-learning system corresponds to an improvement in academic performance. Figure 3 and

Figure 4 display the values of R^2, the outcomes of path coefficients, and the values of indicators' loadings without and with moderator respectively.

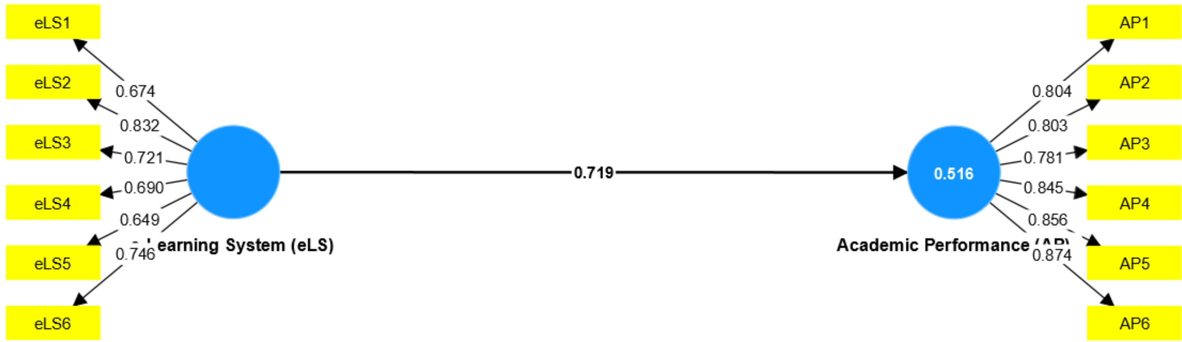


Figure 3: *Values of R^2 without moderator*

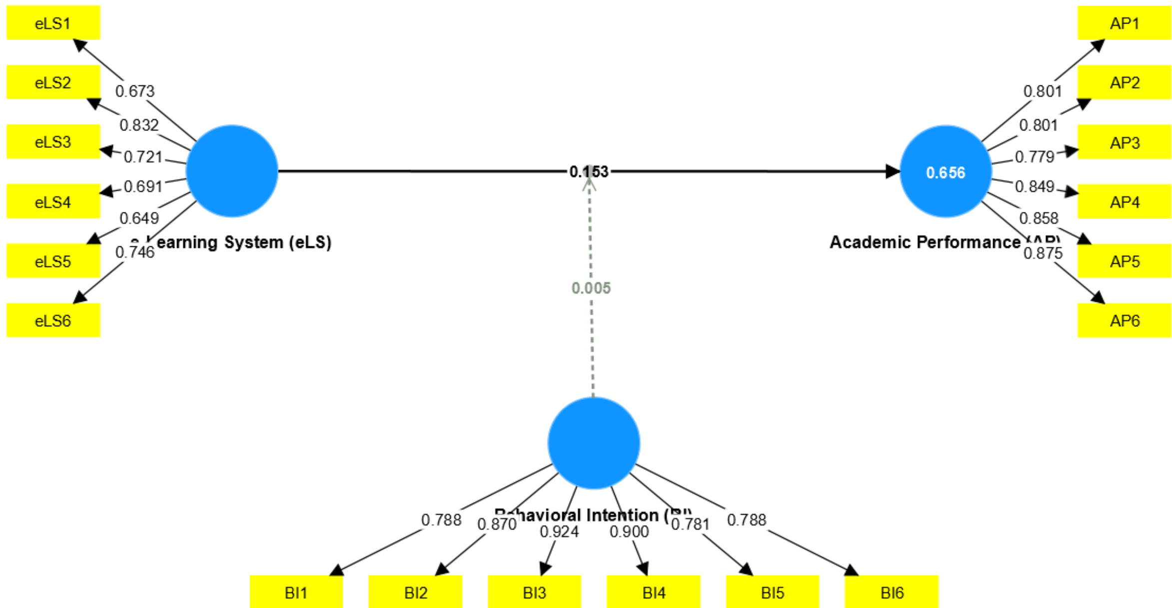


Figure 4: *Values of R^2 with a moderator*

3.3 Reliability and Convergent Validity

The loadings values of the indicators in Figures 3 and 4 were all greater than 0.708, except eLS1, eLS4 and eLS5 of which were 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, eLS1, eLS4 and eLS5 were not deleted because they did not affect the internal consistent reliability and the convergent validity of all constructs. All Average Variance Extracted (AVE) values, were greater than 0.5 and all composite reliability (CR) values were above 0.708 as shown in Table 2. 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).

Table 2: *Internal Reliability and Convergent Validity Results*

Construct	Composite Reliability (CR)	Average Variance Extracted (AVE)
Academic Performance (AP)	0.929	0.685
Behavioral Intention (BI)	0.937	0.712
e-Learning System (eLS)	0.866	0.520

3.4 Discriminant Validity

This is the extent of how indicators actually represent a construct and how they are different from other construct (Hair et al., 2019). The discriminant validity was assessed based on criteria suggested by Hair et al. (2019) in which the discriminant validity Heterotrait-Monotrait Ratio of Correlations (HTMT) criterion value should be < 0.9. The results for Heterotrait-Monotrait Ratio of Correlations (HTMT) criterion values of this study are presented in Table 3.

Table 3: *Heterotrait-Monotrait Ratio of Correlations (HTMT) Criterion Value Results*

Construct	Academic Performance (AP)	Behavioral Intention (BI)	e-Learning System (eLS)
Behavioral Intention (BI)	0.876		
e-Learning System (eLS)	0.831	0.954	
Behavioral Intention (BI) x e-Learning System (eLS)	0.473	0.581	0.605

3.5 Assessment of Coefficient of Determination (R^2)

Coefficient of determination (R^2) is the variance explained in the endogenous latent variable by exogenous latent variables (Hair et al., 2019). However, Hair et al. (2019) recommended three levels of structural model quality as; substantial (75%), moderate (50%) and weak (25%) respectively. During the assessment of measurement model for this study, the standard PLS algorism was calculated for the main effect model and R^2 value was 0.656, which implied satisfactory because it was above moderate and below substantial (Hair et al., 2019). Table 4 presents the coefficient of determination (R^2) value for this study.

Table 4: *Coefficient of Determination (R^2)*

Endogenous Latent	R-square	R-square adjusted
Academic Performance (AP)	0.656	0.653

3.6 Collinearity Statistics (VIF)

The current research evaluated collinearity statistics by using the variance inflation factor (VIF). The VIF values obtained for all items were below 5, suggesting the lack of collinearity concerns among the predictor constructs in the proposed study model (Hair et al., 2019). The collinearity statistical data for the inner model of the proposed research model, as determined by the VIF metric, are shown in Table 5.

Table 5: *Collinearity Statistics (VIF)*

	Academic Performance (AP)
Behavioral Intention (BI)	3.446
e-Learning System (eLS)	3.435
Behavioral Intention (BI) x e-Learning System (eLS)	1.497

3.7 Significance of the Path Coefficients

After doing bootstrapping analysis, the results indicated significant support for two expected hypotheses, whereas one hypothesis was not supported. The results of this study demonstrate the presence of the two predicted relationships in real-world situations. However, one hypothetical prediction does not manifest in reality. The significance of the path coefficients results are shown in Figure 5.

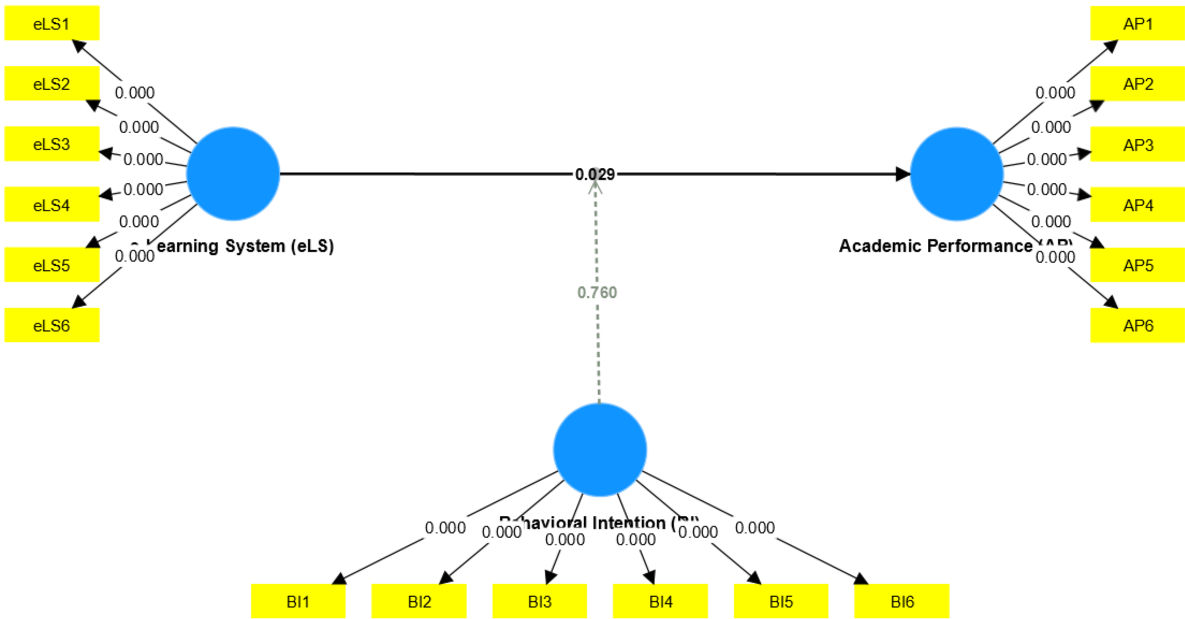


Figure 5: *Significance of the Path Coefficients Results*

3.8 Direct and Moderation Effects of the Hypotheses

Figure 3 presents the results that prove the significant influence of the e-learning system and behavioral intention on academic performance in this study. After opening the report of bootstrapping analysis, Table 6 displays the direct and moderation effects of the hypotheses that were predicted in the research.

Table 6: *Direct and Moderation Effects of the Hypotheses Tested Results*

Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BI-> AP	0.683	0.670	0.075	9.168	0.000
eLS -> AP	0.153	0.166	0.070	2.184	0.029
BI x eLS -> AP	0.005	0.003	0.016	0.306	0.760

3.9 Importance-Performance Map Analysis Results

The construct of behavioral intention, as depicted in Figure 6, 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 the behavioral intention of students during implementation of the e-learning systems, with the aim of improving overall academic performance in higher learning institutions. On the other hand, the construct e-learning system is seen below the average of importance but it is above the average of performance. This implies that e-learning system has a restricted impact on the target construct (academic performance). Therefore, it should be considered of lesser relevance in order to improve the academic performance.

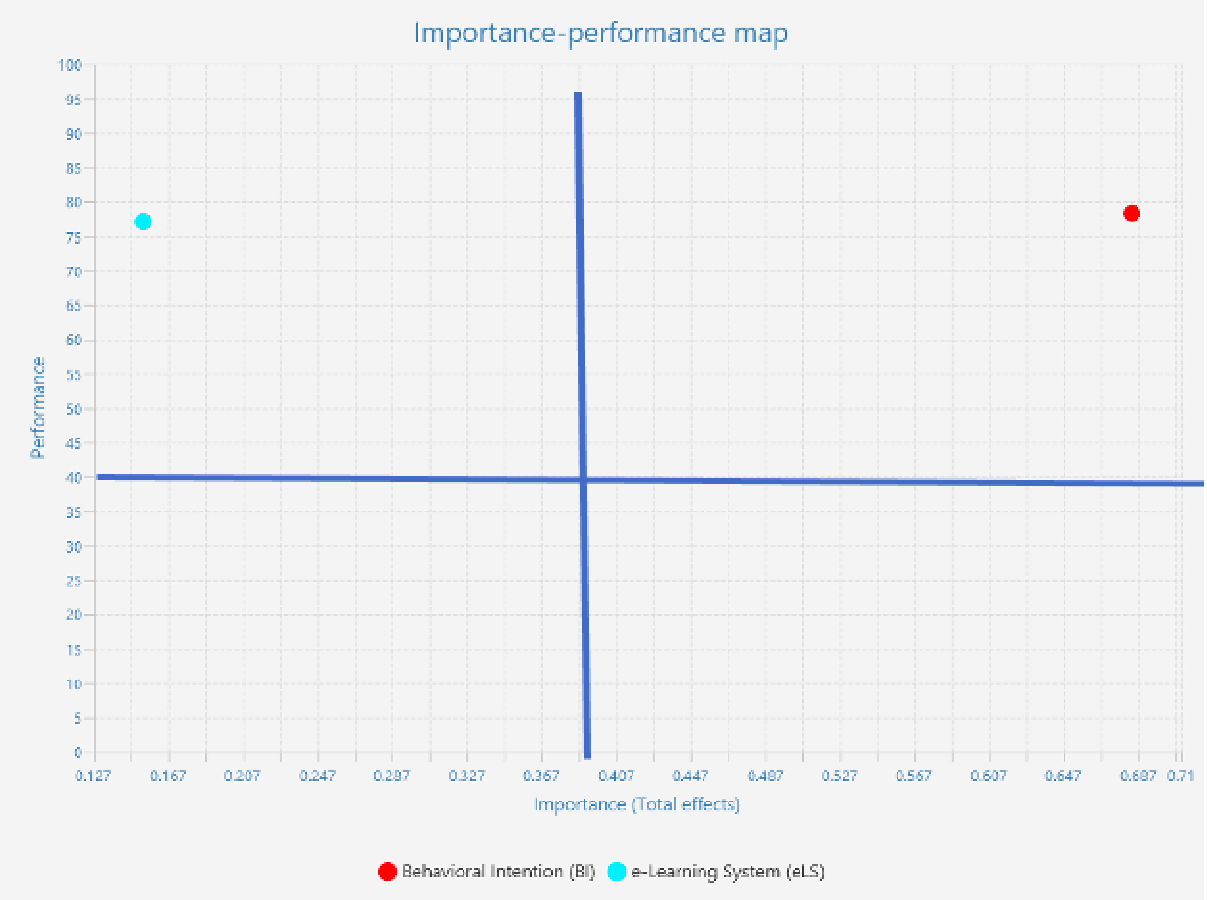


Figure 6: *Importance-Performance Map Analysis Results*

4. Discussion of Results

4.1 The Hypotheses Tested for the Theorized Research Model

This research proposed that behavioral intention would have a direct positive impact on academic performance. The findings revealed positive path coefficient and that there is a direct relationship was statistically significant (p value < 0.05). These findings imply that an increase of one standard deviation of behavioral intention leads to an improvement of academic performance and the correlation exists in real life. The findings align with the current empirical study conducted by Shatta (2023) which revealed that behavioral intention had a significant effect on academic performance (p value < 0.05).

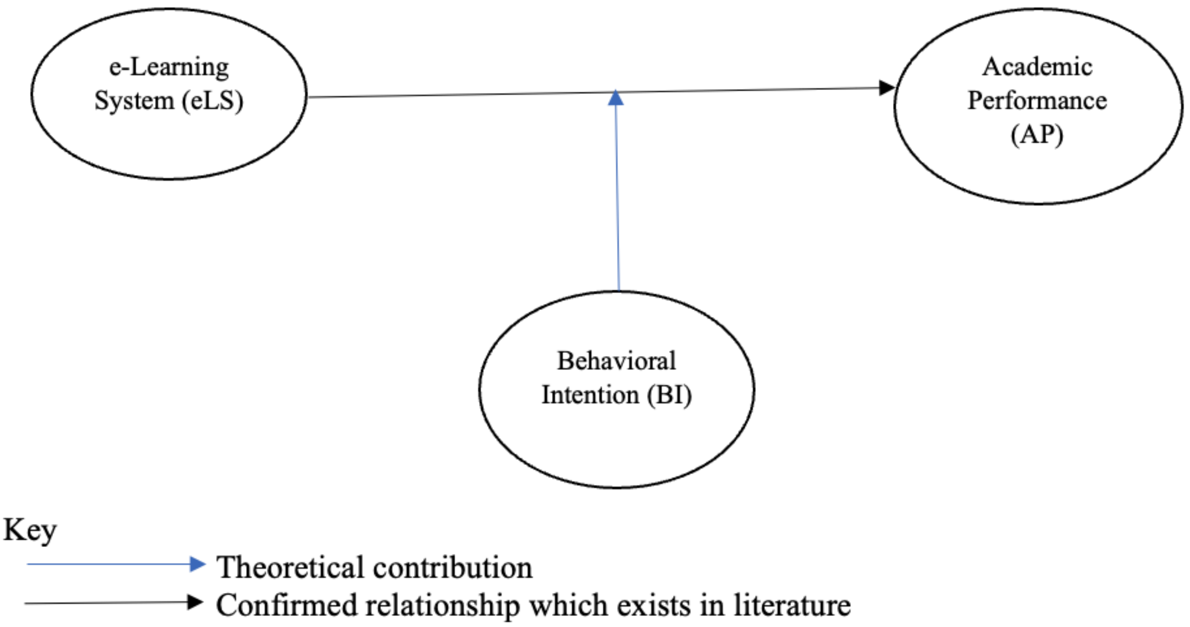
Nevertheless, this research predicted that e-learning system would have a direct impact on academic performance. The findings revealed that there is positive path coefficient, suggesting that an increase of one standard deviation of e-learning system would result in an improvement of academic performance in higher learning institutions. The results of this study align with recent research by Suresh et al. (2018) which found that e-learning had a significant effect on academic performance (p value < 0.05).

Moreover, this research postulated that behavioral intention would moderate the effect of e-learning system on academic performance. The result indicates positive path coefficient, suggesting that when one standard deviation of e-learning system rises would result in a corresponding increase in strengthening the link of academic performance and e-learning system. However, the relationship was found not statistically significant (p value > 0.05) which implies that the correlation does not exist in real life. These results are considered as theoretical contribution since they had not been documented previously by the original and modified UTAUTs (Chen et al., 2011; Dwivedi et al., 2017; Venkatesh et al., 2003; Venkatesh et al., 2012; Venkatesh et al., 2016).

5. Conclusion

5.1 Theoretical Implications

Theoretical contribution has been made to existing modified theories and models as a result of filling the identified theoretical gap, as presented in Figure 7. The moderating effect of behavioral intention on the relationship between e-learning system and academic performance, has been thoroughly understood contrary to the modified UTAUT proposed by Dwivedi et al. (2017). This understanding fills a gap in the existing theoretical literature (Chen et al., 2011; Dwivedi et al., 2017; Venkatesh et al., 2003; Venkatesh et al., 2012; Venkatesh et al., 2016).



Source: Validated Model (2023)

Figure 7: *The conclusive model that has been verified*

5.2 Practical Implications

The statistical significance of behavioral intention and e-learning system on academic performance implies that the improvement of academic performance of students in higher learning institutions will always depend on their behavioral intention to adopt e-learning. This suggests that students will not only rely directly on academic performance when making decisions about using e-learning systems. However, the behavioral intention can indirectly influence the mindset of students and lead them to implement the e-learning system.

5.3 Limitation and Recommendation for Future Research

This research used one component, namely "behavioral intention," derived from the modified UTAUT framework developed by Dwivedi et al. (2017) and other two elements (e-learning system and academic performance) derived from prior empirical studies by Shatta (2023) and by Suresh et al. (2018). These factors accounted for only 65.6 percent of the variability in academic performance. The study suggests that future research should include more elements from the modified UTAUT by Dwivedi et al. (2017) in order to increase the variance in academic performance from moderate to substantial. Similarly, this research used students only from Tanzania. Given this observation, this study suggests that future research should include students and academic staff from many countries in order to generalize the proposed model.

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