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# Artificial Intelligence Applications Adoption and Use in Universities: A SEM Approach

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**Abstract:** ELearning platforms adoption and use by university students has become prevalent worldwide, developing nations still lag behind. This study aims to establish critical paths amongst determinants of "Behavioural Intention" and "Use Behaviour" in eLearning platforms adoption and use by university students. The PLS-SEM method was use to evaluate the modified unified theory of acceptance and use of technology path model. A sample of 520 university students from Zimbabwe was used to collect data using an online survey created on Google Forms. The findings show that "Habit" had the most influence (0.804) on "Behavioural Intention," followed by "Performance Expectancy" (0.319) and "Effort Expectancy" (0.270). Behavioural Intention had a significant influence (0.831) on "Use Behaviour." The path model explains 88.8% of "Behavioural Intention," and 76.1% of "Use Behaviour" variances. This study though limited, it is significant to students in higher education, policy makers and researchers given the importance of technology in the education sector.

**Keywords:** ELearning Technologies; ELearning Platforms; Artificial Intelligence; Online Learning; ODeL; UTAUT; UTAUT2; Higher Education; Zimbabwe

**JEL Classification:** D01; D03; D80; D83

## 1. Introduction

The integration of eLearning platforms in the education sector has become a crucial focus point, with universities positioned as significant ground globally in the

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aftermath of COVID-19. COVID-19 revolutionized the education sector through technology though historical traces of technological use in education date back to the 1960s (Weizenbaum, 1966). Technology adoption and use in the education sector dates back to chat-bots development (Weizenbaum, 1966). However, eLearning became prevalent during and after COVID-19 especially in developed countries with developing countries still lagging behind due to financial and infrastructural challenges. The adoption and use of technology in education has seriously improved human capital development and higher education learning (Maune, 2023). Maune (2016) argues that technology has become a crucial element in human capital development due to significant increase in demand for novel skills. Higher education today has become a conduit through which technologies are developed and unveiled. Universities are obligated to adapt and exploit these new technologies thereby impacting human capital development that meets the demands of the 21st century. Artificial intelligence applications such as ChatGPT have significantly transformed the educational landscapes (OpenAI, 2024) with educators and learners leveraging their capabilities to augment their learning experiences through dynamic feedback (Cukurova, Miao & Brooker, 2023).

ELearning technologies adoption and use in universities is not without challenges (Strzelecki, 2023). Such challenges particularly in Africa have been influenced by socioeconomic classes which date back to the colonial era (Maune, 2023). The colonial era left a divide that is prevalent up to today. Irrespective of these challenges the following eLearning platforms are being used in universities in Zimbabwe and these are Microsoft Teams, Wiseup, Moodle, and ChatGPT. Although eLearning platforms adoption and use have gained popularity in the recent past in Zimbabwe, research into factors influencing behaviour intention and use behaviour among university students remain scant. This gap is particularly significant as it aids to informed policy development and implementation. More so, such an understanding of the factors influencing student behaviour in adoption and use of eLearning platforms in universities is crucial and needed. In closing this research gap, a clear perspective of the factors influencing the adoption and use of eLearning platforms helps the educational system through tailor made approaches that address students concerns.

Since the construction of the UTAUT and its modification into UTAUT2, literature has shown an increasing interest in the adoption and use of technology in higher education (Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2012). The impact of COVID-19 has also seen an increase in the use of eLearning technologies by university students the world over. However, developing countries are still lagging behind due to a number of constraints such as financial and infrastructure. Despite all these challenges, studies have shown a spike in the uptake of eLearning platforms by university students (Akbari et al., 2022; Shams et al., 2022; Cojocariu, Lazăr, Nedeff & Lazăr, 2014; Wang, Ran, Liao & Yang, 2010;

Maune, 2023; Ahmad et al., 2023). The coming in of AI applications has also seen more research being carried out on their impact on academic integrity (Cotton & Cotton, 2023; Tlili et al., 2023; Williamson, Macgilchrist & Potter, 2023).

Maune (2023) argues that there are a number of factors influencing university students/learners behaviour intention and use behaviour in adopting and use of eLearning platforms. Kempson and Whyley (1999), Ellis, Lemma and Rud, (2010), and Beck, Demirgüç-Kunt and Honohan, (2009) argue that factors such as literacy, information, involuntary or voluntary, cost, trust, socioeconomic, eligibility, and documentation are among the top most influencers of eLearning technologies adoption and use in universities by students. These factors must, however, precede behaviour intentions and use behaviour (Shneor & Munim, 2019).

Various theories Fishbein and Ajzen (1975) (Theory of Reasoned Action - TRA), Ajzen (1991) (Theory of Planned Behaviour - TPB), Venkatesh et al. (2003) (UTAUT), and Venkatesh et al. (2012) (UTAUT2) and later modifications by various researchers and authors, forms the basis for this study. An extended model (Maune, 2021; Maune & Themalil, 2022) developed in prior studies was examined using SEM to distinguish factors that impact eLearning technologies adoption and use by students in universities in Zimbabwe. Figure 1 denotes the research model adopted for this study.

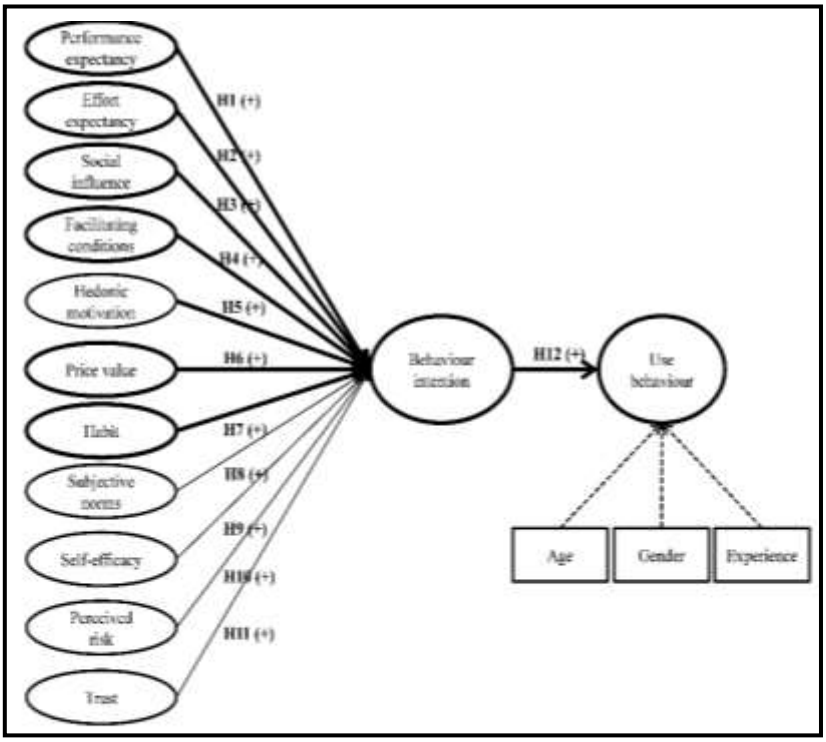

**Figure 1. Path Analysis Research model**

*Source: Adapted from Maune (2021) and Maune and Themalil (2022)*

### 1.1. Hypothesis Development

The following hypotheses were formulated from a prior research model (Maune, 2021) developed by the same author as shown in Figure 1. These hypotheses validated and tested the proposed path analysis model above. Table 1 shows the proposed research hypothesis

**Table 1. Proposed Research Hypothesis**

| Proposed Hypothesis |
|---|
| $H_1$ "Performance expectancy will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students." |
| $H_2$ "Effort expectancy will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students." |
| $H_3$ "Social influence will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students." |
| $H_4$ "Facilitating conditions will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students." |
| $H_5$ "Hedonic motivation will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students." |
| $H_6$ "Price value will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students." |
| $H_7$ "Habit will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students." |
| $H_8$ "Subjective norms will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students." |
| $H_9$ "Self-efficacy will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students." |
| $H_{10}$ "Perceived risk will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students." |
| $H_{11}$ "Trust will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students." |
| $H_{12}$ "Behavioural intention to use will have a direct positive influence on the eLearning platform Use behaviour in universities by students." |

This article seeks to close this research gap through examining the factors influencing eLearning technologies in higher education using SmartPLS-SEM approach in Zimbabwe. An extended Unified Theory of Acceptance and Use of Technology (UTAUT2) by Venkatesh et al. (2012), Maune (2021), and Maune and Themalil (2022) informed the study through examining the factors influencing behaviour intention and use behaviour of eLearning technologies by university students in Zimbabwe.

The article, first explain the EUTAUT2 model for adoption and use of eLearning platforms by students in universities in Zimbabwe. A measurement scale tailor made to suit this framework is also presented. Thereafter, the results of the analysis using Smart PLS-SEM are shared. This is followed by a deep engagement of discussion of the research findings showcasing significant contributions of the study. The study will conclude with theoretical and practical implications as well as limitations and future research direction.

## 2. Material and Methods

This study examined the factors influencing eLearning platforms adoption and use by students in universities in Zimbabwe. The role of behavioural intention was also examined. To have an in-depth appreciation of the relationships of the variables, the study used a quantitative method. Data was collected from students in their second year (2.2) and fourth year (4.2) from two universities (one state owned and one private owned) using Google Forms online survey. Complete autonomy was guaranteed for the students with a consent statement being part of the questionnaire. A total number of 1680 commercial students were invited to participate in the survey. These students were invited to participate in the survey from June to November 2023. To avoid biases, students were promised confidentiality, anonymity of responses and voluntary participation. The survey was sent through a link generated from Google Forms platform. At least ten minutes was needed to complete the survey. A pilot survey was distributed to 10 university students and lecturers to identify conspicuous characteristics, confusing, difficult, and poorly worded questions. These adjustments were then incorporated into the main survey that was distributed.

### 2.1. Respondents and Procedure

Completed surveys were automatically returned to the author by 525 respondents (31.25%). After cleaning the data, which included deleting observations with missing data and suspected unengaged respondents, there were 520 respondents with complete data to utilize (30.95% response rate). The sample size utilized in this article was guided by Marcoulides and Saunders' (2006) investigation. The minimum sample size necessary must be determined by the maximum number of arrows pointing to the latent variable in the model (Marcoulides & Saunders, 2006). Prior scholars (Hoyle, 1995) also influenced the work, arguing that a modest sample size is usually a good place to start when performing path modeling. In this study, unengaged respondents were those who reported the same response for all successive items (for example, a 5 across all observable variables). Descriptive demographic statistics are shown in Table 2.

**Table 2. Demographic statistics**

| Variable | Classification | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 322 | 62% |
| | Female | 198 | 38% |
| Age | <20 | 15 | 3% |
| | 21 – 30 | 385 | 74% |
| | 31 – 40 | 120 | 23% |
| Marital Status | Single | 463 | 89% |
| | Married | 52 | 10% |
| | Divorced | 5 | 1% |
| Education | Level Two (2) | 182 | 35% |
| | Level Four (4) | 338 | 65% |

*Source: Author's compilation*

## 2.2. Measurement

The students were invited to complete an online survey built in Google Forms aimed to measure the latent variables presented in the modified UTAUT model (Maune, 2021). These latent variables are, self-efficacy, habit, hedonic motivation, performance expectancy, price value, effort expectancy, perceived risk, social influence, trust, facilitating conditions, subjective norms, behaviour intention, and use behaviour. The latent constructs scales in the model were adapted and modified from prior studies (Venkatesh et al., 2003; Venkatesh et al., 2012; Groß, 2015; Abrahão et al., 2016; Shneor & Munimb, 2019; Maune & Themalil, 2022). Wong (2013) explains that SEM has two sorts of measurement scales: reflective and formative. The indicators are strongly connected and interchangeable, implying that reliability and validity tests were conducted in agreement with previous researches (Shneor & Munimb, 2019; Petter, Straub & Rai, 2007; Hair, Hult, Ringle & Sarstedt, 2013). A 5-point Likert scale was utilized, with 1 indicating complete disagreement and 5 indicating complete agreement. Table 3 displays measurement items, factor loadings, and sources.

**Table 3. Latent Variables, Measurement Items, Factor Loadings, and Sources**

| Latent variable | Measurement items | Factor loadings | Source |
|---|---|---|---|
| PE (*performance expectancy)* | 1. "I find eLearning platforms useful in my daily learning."<br>2. "Using eLearning platforms increases my chances of achieving my learning goals." | **0.933**<br>*Removed*<br>**0.942**<br>*Removed* | PE1-4 adapted and modified from "performance expectancy" in Venkatesh et al. |

| | | | |
|---|---|---|---|
| | 3. "Using eLearning platforms helps me accomplish my studies/learning more quickly."<br>4. "Using eLearning platforms increases my productivity." | | (2003) and Venkatesh et al. (2012). |
| EE (*effort expectancy)* | 1. "Learning how to use eLearning platforms is easy for me."<br>2. "My interaction with eLearning platforms is clear and understandable."<br>3. "I find eLearning platforms easy to use."<br>4. "It is easy for me to become skillful at using eLearning platforms." | **1.000**<br>*Removed*<br>*Removed*<br>*Removed* | EE1-4 adapted and modified from "effort expectancy" in Venkatesh et al. (2003) and Venkatesh et al. (2012). |
| SI (*social influence)* | 1. "People who are important to me think that I should use eLearning platforms."<br>2. "People who influence my behaviour think that I should use eLearning platforms."<br>3. "People whose opinions I value prefer that I use eLearning platforms." | **0.894**<br>**0.877**<br>*Removed* | SI1-3 adapted and modified from "social influence" in Venkatesh et al. (2012) and Venkatesh et al. (2003) for SI1-2. |
| FC (*facilitating conditions)* | 1. "I have the resources necessary to use eLearning platforms."<br>2. "I have the knowledge necessary to use eLearning platforms."<br>3. "ELearning platforms are compatible with other technologies I use."<br>4. "I can get help from others when I have difficulties using eLearning platforms." | **1.000**<br>*Removed*<br>*Removed*<br>*Removed* | FC1-4 adapted and modified from "facilitating conditions" in Venkatesh et al. (2003) and Venkatesh et al. (2012). |
| HM (*hedonic motivation)* | 1. "Using eLearning platforms is fun."<br>2. "Using eLearning platforms is enjoyable."<br>3. "Using eLearning platforms is very entertaining." | **0.815**<br>**0.943**<br>**0.920** | HM1-3 adapted and modified from "hedonic motivation" in Venkatesh et al. (2012). |
| PV (*price value)* | 1. "ELearning platforms are reasonably priced."<br>2. "ELearning platforms are a good value for the money."<br>3. "At the current price, eLearning platforms provide good value." | **0.676**<br>**0.859**<br>**0.898** | PV1-3 adapted and modified from "price value" in Venkatesh et al. (2012). |
| HT (*habit)* | 1. "The use of eLearning platforms has become a habit for me." | **0.910** | HT1-4 adapted and modified |

| | | | |
|---|---|---|---|
| | 2. "I am addicted to using eLearning platforms."<br>3. "I must use eLearning platforms."<br>4. "Using eLearning platforms has become natural to me." | **0.656**<br>**0.841**<br>**0.888** | from "habit" in Venkatesh et al. (2012). |
| PR (*perceived risk)* | 1. "I would not feel completely safe to provide personal information through eLearning platforms."<br>2. "I am worried about the future use of eLearning platforms because other people might be able to access my data."<br>3. "I do not feel protected when sending confidential information via eLearning platforms."<br>4. "The likelihood that something wrong will happen with the use of eLearning platforms is high." | **0.588**<br>*Removed*<br>**0.943**<br>**0.710** | PR1-4 adapted and modified from "risk" in Abrahão et al. (2016). |
| TT *(trust)* | 1. "I think they are honest."<br>2. "I think they are trustworthy."<br>3. "I think they provide good services to users."<br>4. "I think they care about their users and take their concerns seriously."<br>5. "I think they keep users' security and privacy in mind." | *Removed*<br>*Removed*<br>**0.956**<br>*Removed*<br>**0.663** | TT1-5 adapted and modified from "trust" in Groß (2015). |
| SN *(subjective norms)* | 1. "People who are important to me think that I should use eLearning platforms in learning."<br>2. "People who influence my behavior encourage me to use eLearning platforms in learning."<br>3. "My colleagues think that I should use eLearning platforms in learning."<br>4. "My friends think that I should use eLearning platforms in learning." | **0.876**<br>**0.637**<br>**0.867**<br>*Removed* | SN1-4 adapted and modified from "subjective norms" in Shneor & Munimb (2019). |
| SE (*self-efficacy*) | 1. "I have confidence in my ability to use eLearning platforms in learning."<br>2. "I have the expertise needed to use eLearning platforms."<br>3. "I am confident in my ability to navigate and use eLearning platforms in learning."<br>4. "I am confident in my ability to use eLearning platforms in learning." | **0.836**<br>*Removed*<br>*Removed*<br>**0.999** | SE1-4 adapted and modified from "subjective norms" in Shneor & Munimb (2019). |

| | | | |
|---|---|---|---|
| BI (*behavioural intention)* | 1. "I intend to continue using eLearning platforms in learning in the future."<br>2. "I will always try to use eLearning platforms in learning."<br>3. "I plan to continue to use eLearning platforms in learning frequently." | **0.924**<br>*Removed*<br>**0.919** | BI1-3 adapted and modified from "behavioural intention" in Venkatesh et al. (2003) and Venkatesh et al. (2012). |
| UB (use *behaviour)* | 1. "I frequently use eLearning platforms in learning."<br>2. "I spend much effort in using eLearning platforms in learning." | **0.925**<br>**0.811** | UB1-2 adapted and modified from "subjective norms" in Shneor & Munimb (2019). |

*Source: Authors' compilation*

### 2.3. Structural Equation Modeling Approach

This study utilized SmartPLS3 for data analysis, following previous methods in SEM (Maune, Matanda & Mundonde, 2021; Maune & Themalil, 2022). This approach was preferred due to predictive accuracy and its applicability in dealing with small sample sizes. Despite the limitations associated with the approach (Wong, 2013), it has become more popular in applied research projects. Moreover, the approach has been applied in management information systems, marketing, organization, business strategy, and behavioural sciences among other fields (Maune et al., 2021; Maune & Themalil, 2022). Data was first cleaned before uploaded into SmartPLS 3 software for analysis (Maune & Themalil, 2022).

### 2.4. Analysis

Figure 3 shows the partial least square path model estimations for this study. The results of the path analysis model were as follows:

#### 2.4.1. Reflective Measurement Scale

There are two types of measurement scale in SEM has two measurement scales; formative and reflective. A reflective measurement scale was adopted in this study because the indicators were highly correlated and interchangeable (Haenlein & Kaplan, 2004; Petter et al., 2007; Hair et al., 2013; Maune & Themalil, 2022). Therefore, the study thoroughly examined the reliability and validity of the indicators. Maune et al. (2021) and Maune and Themalil (2022) argue that each reflective indicator is related to a specific latent variable or construct using a simple regression analysis.

During the evaluation of the measurement model, 17 items were removed because of low factor loadings (<0.600) and high cross-loading (Gefen & Straub, 2005; Maune & Themalil, 2022). Cronbach's alpha and composite reliability (CR) tests were used to test the reliability of the constructs (Table 4). All the constructs in the study met the required CRs threshold of 0.700 (Hair, Hult, Ringle & Sarstedt, 2017; Maune & Themalil, 2022). Cronbach's alpha of each construct was above the threshold of 0.700. Convergent validity was acceptable since the AVE were higher 0.500 (Bagozzi & Yi, 1988; Maune & Themalil, 2022). Table 4 shows the reliability, validity and factor loadings output. The Fornell-Larcker criterion was used to assess discriminant validity and the output is as shown in Table 5. The results in Table 5 align with Fornell and Larcker (1981) and Maune and Themalil (2022) showing a greater square root of AVE than the inter-construct correlation for all the constructs. The Heterotrait-Monotrait ratio was also used to assess discriminant validity of correlations (Henseler, Ringle & Sarstedt, 2015). The output shows all values below 0.900 threshold thereby establishing discriminant validity (Maune & Themalil, 2022) (Table 6).

**Table 4. Factor Loadings, VIF, Composite Reliability, and Convergent Validity**

| Indicators | Loadings | VIF | Cronbach's Alpha | Composite Reliability | AVE |
|---|---|---|---|---|---|
| PE1 | 0.933 | *4.384* | 0.935 | 0.935 | 0.879 |
| PE3 | 0.942 | *4.384* | | | |
| EE1 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| SI1 | 0.894 | 2.596 | 0.879 | 0.879 | 0.784 |
| SI2 | 0.877 | 2.596 | | | |
| FC1 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| HM1 | 0.815 | *3.354* | 0.923 | 0.923 | 0.801 |
| HM2 | 0.943 | *3.308* | | | |
| HM3 | 0.920 | *3.763* | | | |
| PV1 | 0.676 | 1.946 | 0.854 | 0.855 | 0.667 |
| PV2 | 0.859 | 2.404 | | | |
| PV3 | 0.898 | 2.122 | | | |
| HT1 | 0.910 | 2.910 | 0.896 | 0.897 | 0.689 |
| HT2 | 0.656 | 2.044 | | | |
| HT3 | 0.841 | 2.566 | | | |
| HT4 | 0.888 | *3.070* | | | |

| | | | | | |
|---|---|---|---|---|---|
| PR1 | 0.588 | 1.741 | 0.794 | 0.799 | 0.580 |
| PR3 | 0.943 | 1.872 | | | |
| PR4 | 0.710 | 1.544 | | | |
| TT3 | 0.956 | 1.673 | 0.776 | 0.802 | 0.677 |
| TT5 | 0.663 | 1.673 | | | |
| SN1 | 0.876 | 1.634 | 0.844 | 0.841 | 0.642 |
| SN2 | 0.637 | 2.510 | | | |
| SN3 | 0.867 | 2.668 | | | |
| SE1 | 0.836 | *3.297* | 0.910 | 0.917 | 0.848 |
| SE4 | 0.999 | *3.297* | | | |
| BI1 | 0.924 | *3.576* | 0.918 | 0.918 | 0.849 |
| BI3 | 0.919 | *3.576* | | | |
| UB1 | 0.925 | 2.292 | 0.858 | 0.861 | 0.757 |
| UB2 | 0.811 | 2.292 | | | |

**Table 5. Fornell-Larcker Criterion**

| | BI | EE | FC | HM | HT | PE | PR | PV | SE | SI | SN | TT | UB |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BI | *0.921* | | | | | | | | | | | | |
| EE | 0.832 | *1.000* | | | | | | | | | | | |
| FC | 0.788 | 0.811 | *1.000* | | | | | | | | | | |
| HM | 0.859 | 0.829 | 0.772 | *0.895* | | | | | | | | | |
| HT | 0.897 | 0.781 | 0.741 | 0.889 | *0.830* | | | | | | | | |
| PE | 0.872 | 0.847 | 0.837 | 0.898 | 0.862 | *0.937* | | | | | | | |
| PR | -0.102 | -0.043 | -0.108 | -0.107 | -0.098 | -0.068 | *0.761* | | | | | | |
| PV | 0.699 | 0.718 | 0.649 | 0.731 | 0.835 | 0.781 | -0.066 | *0.817* | | | | | |
| SE | 0.072 | 0.161 | 0.098 | 0.078 | 0.052 | 0.077 | -0.230 | 0.146 | *0.921* | | | | |
| SI | 0.847 | 0.810 | 0.803 | 0.858 | 0.887 | 0.871 | 0.102 | 0.714 | 0.012 | *0.886* | | | |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SN | 0.020 | 0.120 | 0.071 | 0.061 | -0.028 | 0.042 | -0.417 | 0.051 | 0.691 | -0.060 | *0.801* | | |
| TT | 0.123 | 0.052 | 0.023 | 0.072 | 0.081 | 0.044 | -0.387 | 0.013 | 0.154 | 0.041 | 0.444 | *0.823* | |
| UB | 0.869 | 0.715 | 0.716 | 0.796 | 0.846 | 0.833 | -0.101 | 0.725 | 0.078 | 0.773 | 0.069 | -0.029 | *0.870* |

*Note: Values in Italic Represent Square-roots of AVE*

**Table 6. Heterotrait-Monotrait Ratio (HTMT)**

| | BI | EE | FC | HM | HT | PE | PR | PV | SE | SI | SN | TT | UB |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BI | - | | | | | | | | | | | | |
| EE | 0.832 | | | | | | | | | | | | |
| FC | 0.788 | 0.811 | | | | | | | | | | | |
| HM | 0.857 | 0.828 | 0.771 | | | | | | | | | | |
| HT | 0.892 | 0.777 | 0.737 | 0.887 | | | | | | | | | |
| PE | 0.872 | 0.847 | 0.837 | 0.896 | 0.861 | | | | | | | | |
| PR | 0.160 | 0.110 | 0.146 | 0.163 | 0.148 | 0.119 | | | | | | | |
| PV | 0.695 | 0.715 | 0.642 | 0.730 | 0.835 | 0.775 | 0.089 | | | | | | |
| SE | 0.082 | 0.159 | 0.094 | 0.098 | 0.088 | 0.086 | 0.305 | 0.148 | | | | | |
| SI | 0.846 | 0.810 | 0.803 | 0.857 | 0.889 | 0.871 | 0.138 | 0.711 | 0.048 | | | | |
| SN | 0.055 | 0.114 | 0.070 | 0.079 | 0.057 | 0.071 | 0.433 | 0.054 | 0.680 | 0.073 | | | |
| TT | 0.130 | 0.082 | 0.080 | 0.086 | 0.103 | 0.089 | 0.384 | 0.089 | 0.155 | 0.092 | 0.504 | | |
| UB | 0.868 | 0.717 | 0.716 | 0.797 | 0.855 | 0.836 | 0.141 | 0.734 | 0.078 | 0.775 | 0.084 | 0.064 | - |

### 2.4.2. Structural Model

The path analysis model was evaluated once reliability and validity of variables was established. Tenenhaus et al. (2005), Avkiran (2018), and Maune and Themalil (2022) state that, the theoretical model below is evaluated to provide empirical evidence of the path model using SmartPLS:

$$\xi_j = \beta_{jo} + \sum_i \beta_{ji}\,\xi_i + v_j$$

"Where: $\xi_j$ is the endogenous construct and $\xi_i$ represents the exogenous constructs, while $\beta_{jo}$ is the constant term in this (multiple) regression model, $\beta_{ij}$ are the regression coefficients, and $v_j$ is the error term; the predictor specification condition applies" (Maune & Themalil, 2022).

The PLS-SEM path analysis model output in Figure 2 shows the hypothesized results of the path analysis model in Figure 1. The path analysis model was evaluated using the significance of paths, $Q^2$, and $R^2$. The strength of each structural path determined ($R^2$ value for the dependent variable) determined the goodness fit of the model. Falk and Miller (1992), and Maune and Themalil (2022) argue that the value for $R^2$ should be equal to or over 0.1. The output in Table 7 shows all $R^2$ values for the study and they were above 0.1. The study, therefore, established the predictive capability of the model. Wong (2013) argues that predictive relevance of endogenous variables is established by $Q^2$. Therefore, the study established a $Q^2$ above zero (0) denoting predictive relevance. The study output in Table 7 denotes significance of the prediction by the constructs.

Collinearity of constructs was assessed through examining the outer VIF values of the model (Maune & Themalil, 2022). Table 4 shows the output of VIF values for all groupings of exogenous variables and related endogenous variables. The VIF output values were below the threshold of 5 denoting non-existence of collinearity among indicators in the model (Maune & Themalil, 2022). Hence, collinearity was not an issue in the model. Further examination of the output was carried out and the results are as shown in Table 7. The outputs verify the hypotheses and the significance testing for the path coefficients within the path analysis model.

**Table 7. Coefficients, STDEV, T-Statistics, P-Values, Confidence Intervals, $R^2$, and $Q^2$**

| Hypothesis | Relationship | β | STDEV | T Statistics | P Values | 2.50 % | 97.50 % |
|---|---|---|---|---|---|---|---|
| $H_1$ | PE - > BI | 0.319 | 0.172 | 1.074 | 0.283 | -0.173 | 0.499 |
| $H_2$ | EE - > BI | 0.270 | 0.141 | 1.652 | 0.099 | -0.025 | 0.528 |
| $H_3$ | SI - > BI | -0.157 | 0.100 | 0.577 | 0.564 | -0.116 | 0.288 |
| $H_4$ | FC - > BI | 0.099 | 0.094 | 1.005 | 0.315 | -0.092 | 0.286 |
| $H_5$ | HM - > BI | -0.086 | 0.114 | 0.537 | 0.592 | -0.155 | 0.290 |
| $H_6$ | PV - > BI | -0.306 | 0.070 | 1.299 | 0.194 | -0.244 | 0.037 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| $H_7$ | HT - > BI | 0.804 | 0.109 | 3.650 | 0.000 | 0.197 | 0.623 |
| $H_8$ | SN - > BI | 0.025 | 0.084 | 0.511 | 0.610 | -0.064 | 0.278 |
| $H_9$ | SE - > BI | -0.034 | 0.075 | 0.632 | 0.528 | -0.253 | 0.066 |
| $H_{10}$ | PR - > BI | 0.024 | 0.071 | 0.647 | 0.517 | -0.217 | 0.071 |
| $H_{11}$ | TT - > BI | 0.065 | 0.070 | 0.665 | 0.506 | -0.111 | 0.175 |
| $H_{12}$ | BI - > UB | 0.831 | 0.074 | 9.604 | 0.000 | 0.546 | 0.838 |
| | | $R^2$ | $R^2$ Adjusted | $Q^2$ | | | |
| | BI | 0.888 | 0.874 | 0.657 | | | |
| | UB | 0.761 | 0.751 | 0.515 | | | |

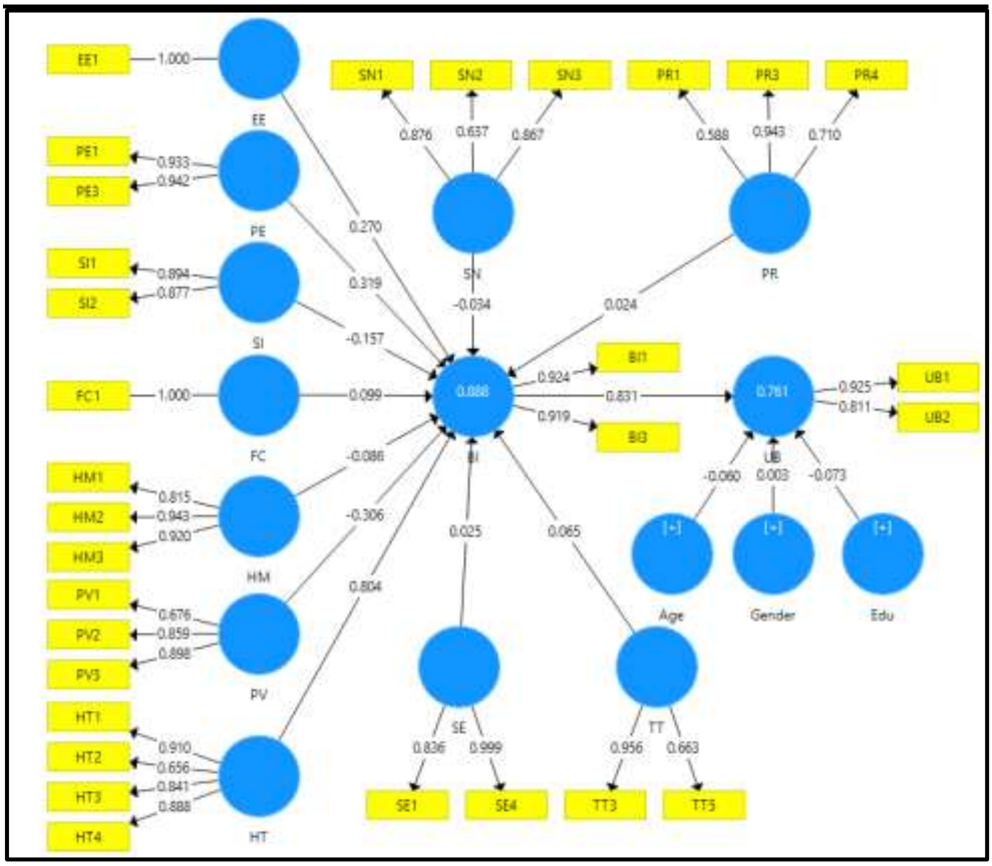


**Figure 2. PLS-SEM path model output**

*Goodness of fit: SRM, Saturated Model – 0.064 & Estimated Model – 0.066*

### 2.4.3. Importance-Performance Map Analysis (IPMA)

IPMA was extracted to establish the importance and performance of constructs in the model. Performance reflects the size of the latent variable scores while importance shows the total effect on the targeted construct in the PLS-SEM path model (Maune & Themalil, 2022). The output of the IPMA is critical in prioritizing management action. Maune and Themalil (2022) argue that management should as a matter of priority place more focus on addressing the performance of indicators that shows huge importance in explaining certain targeted constructs, nonetheless having low performance.

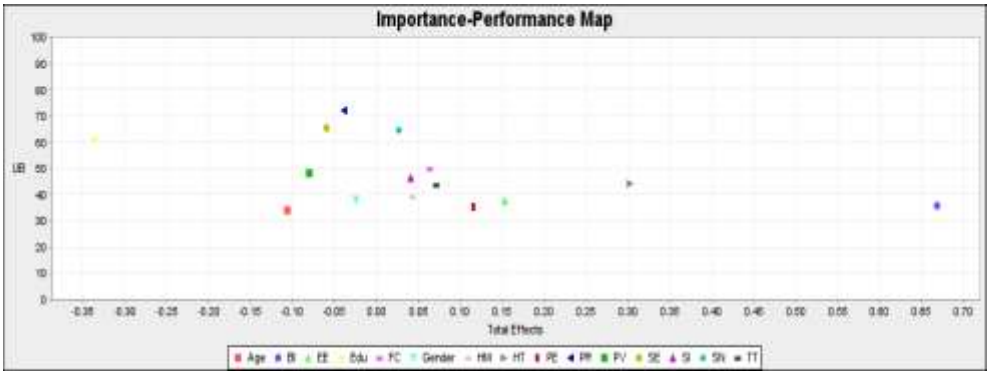


**Figure 3. Importance-Performance Map Analysis**

The study considered an indicator important when its total effect on “Use Behaviour” (UB) was absolutely high (Y-axis). Therefore, in this study “Habit” (HT) (0.302) has greater absolute importance on UB outside BI (0.668) (Figure 3 and Table 8). Moreover, an indicator has a greater performance when it has a higher score. This score reflects strong measurement of paths as shown by the X-axis. In this study “Perceived Risk” (PR) (72.155) shows greater performance than any other indicators (Table 8 and Figure 3).

## 3. Discussion

This study examines eLearning platforms adoption and use in universities in developing countries using Zimbabwe as a case study. A PLS-SEM approach was used to analyze data collected through an online survey that targeted students at two universities in Zimbabwe. A modified UTAUT2 model (Figure 1) was examined. The study placed more emphasis on BI and UB’s psychological reasoning. Behaviour Intention and Use Behaviour of eLearning platforms in higher education by students is considered a planned behaviour. A path analysis framework modified from UTAUT2 in Figure 1 was examined using PLS-SEM algorithm to establish significant paths and relationships. The extracts of output are shown in Table 2 to Table 7.

Of importance, however, was the relationship between "Habit" and "Behaviour Intention" (HT -> BI) that is significant at 95% confidence level with a p-value of < 0.05 (0.000) and a T-Statistic of 3.650. Another noteworthy relationship was BI -> UB that was significant at 95% confidence level with a p-value of <0.05 (0.000) and a T-Statistic of 9.604. The observation reveals that HT has the most noticeable influence (0.804) on BI, followed by PE (0.319), then EE (0.270) and FC (0.099). BI has a significant influence (0.831) on UB and it accounts for 76.1% of the UD variance. All the latent variables account for 88.8% of the BI variance as indicated by $R^2$. The explained variances were higher than those by previous researchers (Strzelecki, 2023; Maican, Cazan, Lixandroiu & Dovleac, 2019; Hoi, 2020). The (HT -> BI) findings are consistent with previous studies (Strzelecki, 2023; Sitar-Taut & Mican, 2021; Alotumi, 2022; Jakkaew & Hemrungrote, 2017; Kumar & Bervell, 2019). However, some of findings were inconsistent with other prior studies (Twum, Ofori, Keney & Korang-Yeboah, 2022; Ain, Kaur & Waheed, 2016) who found no direct effect of HT on BI.

During the evaluation of the paths, 17 items (indicators) were omitted because of low factor loadings or high-cross loadings as supported by Gefen and Straub (2005), and Maune and Themalil (2022). Data did not support these paths. Most of these omitted indicators were from EE and FC despite previous findings that showed their significant influence on the latent variables (Venkatesh et al., 2003; Venkatesh et al., 2012; Limayem, Hirt & Cheung, 2007). These findings were inconsistent with findings from other previous studies (Arain, Hussain, Rizvi & Vighio, 2019; Azizi, Roozbahani & Khatony, 2020; Nikolopoulou, Gialamas & Lavidas, 2020; Raman & Don, 2013; Raffaghelli, Rodriguez, Guerrero-Roldan & Baneres, 2022; Mehta, Morris, Swinnerton & Homer, 2019) who found a strong correlation between the variables.

All latent variables except HT were insignificant towards BI at 95% confidence level as shown by their p-values and t-statistics. This was so despite prior findings (Venkatesh et al., 2003; Venkatesh et al., 2012; Groß, 2015; Abrahão et al., 2016; Shneor & Munimb, 2019; Roy, 2017). The study results, however, confirm previous research findings (Liu & Tai, 2016; Barua, Alam & Hu, 2018; Chao, 2019; Tarhini, Alalwan, Shammout & Al-Badi, 2019; Khurana & Jain, 2019; Gharaibeh, Gharaibeh, Gharaibeh & Bdour, 2020). The following significant paths were established, HT -> BI and BI -> UB with significant p-values and t-statistics.

Our findings found that HM has an insignificant negative impact on BI. The finding is inconsistent with prior studies (Azizi, Roozbahani & Khatony, 2020; Hu, Laxman & Lee, 2020; Faqih & Jaradat, 2021) while consistent with findings by Ain et al. (2016) and Raza et al. (2022). The findings on SI are in line with those by Alotumi

(2022), and Kumar and Bervell (2019) who found insignificant influence of SI on BI. PV has insignificant negative influence on BI consistent with prior findings (Strzelecki, 2023; Nikolopoulou et al., 2020; Osei, Kwateng & Boateng, 2022). However, this was inconsistent with findings by Farooq, Salam, Jaafar, Fayolle, Ayupp, Radovic-Markovic and Sajid (2017), and Azizi et al. (2020). Furthermore, our findings regarding FC were in line with those of prior studies (Strzelecki, 2023; Alotumi, 2022; Kumar & Bervell, 2019; Dajani & Abu Hegleh, 2019). This was contrary to findings by Faqih and Jaradat (2021) and Yu et al. (2021).

Significance of paths, $Q^2$, and $R^2$ were used to assess the path analysis model's goodness of fit as denoted in Table 7. Predictive relevance was established for constructs in line with prior studies (Falk & Miller, 1992; Briones-Penalver, Bernal-Conesa & Nieves-Nieto, 2018; Maune & Themalil, 2022).

Perhaps the most important finding for eLearning adoption and use in higher education by students relates to the IPMA that identifies significant areas of focus (Maune & Themalil, 2022). These are the areas of focus that generates on targeted constructs within the PLS-SEM path analysis diagram. In this study "Habit" (HT) (0.302) had the greatest absolute importance on UB outside BI (0.668) (Figure 3 and Table 8). The same was "Perceived Risk" (PR) (72.155) that showed the greatest performance than any other indicators in the study (Table 8 and Figure 3). Ceteris paribus, a unit rise in HT performance will result in a 0.302 rise in UB (Table 8 and Figure 3).

**Table 8. Importance-Performance Analysis**

| Construct | Performance | Total effect |
|---|---|---|
| BI | 35.763 | 0.668 |
| EE | 37.750 | 0.153 |
| FC | 49.750 | 0.064 |
| HM | 38.961 | 0.043 |
| HT | 44.244 | 0.302 |
| PE | 35.349 | 0.115 |
| PR | 72.155 | -0.039 |
| PV | 48.170 | -0.080 |
| SE | 65.341 | -0.060 |
| SI | 46.613 | 0.041 |
| SN | 64.692 | 0.026 |
| TT | 43.345 | 0.071 |
| UB | 40.614 | - |

## 4. Conclusion and Implications

### 4.1. Conclusion

This study examines eLearning platforms adoption and use by students in Zimbabwe universities using a PLS-SEM algorithm to analyze the data. A path model in Figure 1 was evaluated to establish significant relationships between indicators. This path model was a modification of the UTAUT2 that incorporated other latent variables selected from other theories of technology adoption and use (Maune, 2023). This study confirmed the significant influence of “Habit” on BI on the adoption and use of eLearning platforms by university students in Zimbabwe. The adoption and use of eLearning platforms is still in its infancy stages in Zimbabwe with different universities at different level of adoption and use. Therefore, there is need for more research studies to be carried out in the field. This study can be useful in providing the basis or foundation for further future studies.

### 4.2. Implications for Research

This study examines eLearning platforms adoption and use by students in Zimbabwe universities using a PLS-SEM algorithm to analyze the data. A path model in Figure 1 was evaluated to establish significant relationships between indicators. This path model was a modification of the UTAUT2 that incorporated other latent variables selected from other theories of technology adoption and use. The application and replication of the path analysis model is critical for ODeL experts and other practitioners in higher education given how technological developments are impacting higher education. The role of technology has become more important than ever before, especially with the impact of AI. The findings of this study are critical to the development of higher education in developing countries in general and Zimbabwe in particular. Further future researches with be guided by the findings of this study.

Although the UTAUT2 is an important theory in evaluating relationships between constructs in the use of technology, modifications and expansion of the theory has proved important in different fields with different results realized. This is critical in research since there is no straight solution to a given problem. Researchers should therefore forge ahead with what works since truth is a normative concept – truth is what works.

The proposed path analysis model was evaluated empirically using PLS-SEM to establish critical relationships in eLearning platforms adoption and use in higher education. Using this approach, a cognitive psychological viewpoint to human behaviour in decision making was adopted. The findings of this study show an insignificant relationship among all the constructs except for HT and BI that had significant paths as shown by their p-values and t-statistics. Habit came out as a key determinant in the adoption and use of eLearning platforms by students in universities in Zimbabwe confirming the findings by Strzelecki (2023).

Overall, results showed that behavioural intention has significant influence on use behaviour in the adoption and use of eLearning platforms by students in universities in Zimbabwe. To further authenticate these findings, there is need to analyze this data using different analytical softwares such as AMOS, R and Stata. A bigger sample might be considered in this endeavor. Further modifications maybe required to this framework. This study was critical in addressing the research gap exposed by prior research (Maune, 2023). The study (Maune, 2023) reviewed relevant literature in developing the extended path model that was evaluated by this study. This study provides the starting point in further future researches in the field. Critical dimensions have been identified that will help in future researches. The path model was informed by literature (Maune, 2023).

More so, by expanding the path model, the study hypothesized that social influence, habit, performance expectancy, facilitating conditions, effort expectancy, subjective norm, self-efficacy, hedonic motivation, price value, trust, and perceived risk were key determinants in adopting and using of online learning applications by university students in Zimbabwe. However, more indicators for facilitating conditions and effort expectancy were not supported by data; hence they were omitted in the path analysis model. However, the findings in this study confirm prior research results (Shneor & Munimb, 2019; Chao, 2019; Tarhini, Alalwan, Shammout & Al-Badi, 2019; Khurana & Jain, 2019; Gharaibeh, Gharaibeh, Gharaibeh & Bdour, 2020).

### 4.3. Implications for Practice

Technology has proven to be key in higher education especially during and after COVID-19 pandemic. Globally, technology has become prevalent in higher education especially AI related applications such as ChatGPT. Gill et al. (2024) argue that, “AI applications are becoming crucial for colleges and universities, whether it be for personalized learning, computerized assessment, smart educational systems, or supporting teaching staff. They offer support that results in reduced expenses and enhanced learning results.” However, although use of technology in higher education has become popular, it comes with its own risks and difficulties. To this end, Gill et al. (2024) state that, “there are concerns regarding the potential misuse of [technology], as it could be employed to generate academic tests and assignments for students and provide tailored responses to coursework questions and assessments. As a result, a number of institutions have forbidden students from using [certain technologies] including a ban within an entire country.”

The path analysis model was able to explain and predict various relationships as shown in Figures and Tables above. This has practical implications in recommending factors driving “Behavioural Intention” and “Use Behaviour” in the use of online learning applications by university students. The path analysis model has essential inferences critical for higher education. Maybe, the most essential discovery was that Habit (HT) plays a critical role in the adoption and use of eLearning platforms by students in universities in Zimbabwe.

Furthermore, the IPMA has also proven to be critical in decision-making and in this case, “Habit” (HT) (0.302) had the greatest absolute importance on UB outside BI (0.668) (Figure 3 and Table 8). The same was “Perceived Risk” (PR) (72.155) that showed the greatest performance than any other indicators in the study (Table 8 and Figure 3). IPMA clearly shows critical areas for managerial focus and prioritization. For example, management’s focus should be on the constructs of higher importance and low performance. These constructs have higher chances for improvement. This is critical for management since it is illogical to focus on constructs of low importance as this will have no impact in improving the targeted construct.

### 4.4. Limitations

This study examines eLearning platforms adoption and use by students in Zimbabwe universities using a PLS-SEM algorithm to analyze the data. A path model in Figure 1 was evaluated to establish significant relationships between indicators. Sample size limited this study as a bigger sample could have improved the findings. More universities could have been used in this study but only two were targeted. The study was also limited to students in the Faculty of Commerce and level 2.2 and 4.2. Financial resources also limited the study as this study was self-funded. Given funding, the researcher could have improved on the sample size by targeting students in different faculties and programs. The study was also limited to a single methodology.

Mixed methods will improve the research findings as studies have shown that mixed methods are better than mono-methods. Mixing qualitative and quantitative research methods is critical in dealing with biases associated with using one method. By using mixed methods, the researcher will be able to answer a broader and more complete range of research questions because the researcher is not confined to a single method or approach. The researcher will be able to use the strengths of an additional method to overcome the weaknesses in another method by using both in a research study. Despite all this, the researcher forged ahead with the approach that worked for this study since truth is a “normative concept.”

**Disclosure Statement**

There is no potential or existing conflict of interest in this study.

**Data Availability Statement**

The study used data obtained from a survey which can be provided on request from the author.

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