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FACTORS INFLUENCING BEHAVIOURAL INTENTION OF ACADEMICS IN USING MOODLE: AN APPLICATION OF THE UTAUT MODEL

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ABSTRACT

The study examines factors influencing the behavioural intention and actual usage of Moodle among academics at the University of KwaZulu-Natal (UKZN), South Africa. The study is anchored on the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The research design utilised in this study is quantitative in nature, guided by the survey method where data are collected from 89 academic staff. Data collected are analysed using the Partial Least Squares Structural Equation Modelling (PLS-SEM) technique. The analysis reveals that performance expectancy and social influence are the most relevant determinants of behavioural intention, while facilitating conditions significantly determines actual use. Behavioural intention is also a significant predictor of actual use where higher intentions to use Moodle led to higher usage. Notably, effort expectancy does not impact behavioural intention to use Moodle. Neither gender, age, nor experience, when considered as moderating variables, shows a significant effect on the relationships between constructs. Consequently, the applicability remains consistent across different user groups. The results of this study indicate that interventions aimed at increasing Moodle usage at UKZN, and similar institutions should focus on increasing the perceived usefulness of Moodle, capitalising on positive peer influence, and providing strong support systems. The study also contributes to the validation of the UTAUT model in the South African higher education setting and offers leads that can inform the design and implementation of e-learning strategies for developing countries and the setting of Learning Management Systems (LMS) platforms to maximise educational results.

KEYWORDS

CITATION

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Introduction.

In the last two decades, e-learning in higher education has grown stronger with technological development and increased need to foster flexible and inclusive models of education that could answer the needs and challenges of the 21st century (Bitar & Davidovich, 2024). In South Africa, the integration of e-learning platforms within Learning Management Systems (LMS), such as Moodle, has become an integral part of bridging education gaps and increasing access to higher education (Badaru & Adu, 2022). Moodle being an open-source LMS and its availability allowed many South African institutions to offer blended learning at a very reduced cost (Mpungose, 2020).

Like many other universities, the University of KwaZulu-Natal (UKZN) uses Moodle to facilitate effective teaching and learning among its academics. This is part of the national drive for integrating Information and Communication Technologies into education, facilitated by governmental policies and initiatives in promoting digital literacy and e-learning (Mawonde & Togo, 2019). For Moodle to be effectively utilised, academics must be both motivated and equipped to adopt and integrate this online technology into their teaching practices. Identification of factors influencing behavioural intention is, therefore, crucial to the success of such e-learning initiatives within UKZN and other similarly higher learning institutions.

Furthermore, the emergence of the COVID-19 pandemic in early 2020 created an urgent need to accelerate the implementation of e-learning in South Africa and beyond. The immediate impact of the pandemic was the closure of campuses, necessitating a sudden shift to online learning. This shift compelled UKZN and its designated platforms, such as Moodle, to adapt quickly to ensure academic continuity (UNESCO, 2020). Although Moodle proved to be user-friendly and capable of accommodating most curriculum needs, the shift to online learning highlighted significant challenges related to digital preparedness, infrastructure, and ICT skills among both students and academics. (Van de Heyde & Siebrits, 2019). These challenges also necessitated understanding the adoption process and exploring factors that are necessary for successful use.

Therefore, the Unified Theory of Acceptance and Use of Technology (UTAUT) model, an integrated and complete framework that analyses the various factors affecting the adoption and use of technology, is adopted in this study to address these challenges. Venkatesh et al. (2003) conceptualised the UTAUT model with identification of four key constructs, performance expectancy, effort expectancy, social influence and facilitating conditions. In the context of Moodle's application at UKZN, these constructs are of particular importance because they help to define the way in which the academics perceive and use the Moodle platform. Previous research has identified perceived ease of use, perceived usefulness, and the availability of institutional support as the primary factors influencing the decision to use or avoid technology. (Mpungose, 2020; Maphala & Adigun, 2021). UTAUT's robustness and significance to higher education environments where technology adoption is influenced by individual and organisational factors justified its selection for this study. Most other models do not account for institutional support and peer influence, which both play a significant role in UKZN's circumstance, in relation to Moodle adoption. Several previous studies have shown that perceived ease of use, perceived usefulness and access to institutional resources are significant predictors of technology acceptance by academics (Venkatesh et al., 2003; Graf-Vlachy et al., 2018). This study utilises the UTAUT model to identify and understand which key factors motivate academics in their behavioural intentions towards Moodle to provide insights to enrich e-learning strategies in South Africa's higher education sector.

Following the guidelines set by the UTAUT, this study focused on the academics of UKZN, in order to survey specific factors upon which their behavioural intention for the use of Moodle is dependent. The results of this study are expected to provide understanding into Moodle adoption in developing countries and highlight strategies that will amplify its use in higher education. Hence, the following specific objectives are achieved in this study.

(i) To investigate the impact of performance expectancy on academics' intention at UKZN to adopt and effectively use Moodle.

(ii) To evaluate the impact of effort expectancy on the behavioural intention of academics at UKZN to adopt and utilize Moodle.

(iii) To examine the role of social influence on the behavioural intention of academics at UKZN to adopt and utilize Moodle.

(iv) To evaluate the effect of facilitating conditions on the behavioural intention and actual use of Moodle by academics at UKZN.

(v) To examine the influence of behavioural intention on actual use of Moodle by academics at UKZN.

(vi) To analyse the moderating effect of gender, age, and experience on the relationship between these factors (performance expectancy, effort expectancy, social influence, facilitating conditions) and the behavioural intention to use Moodle

Literature Review
Theoretical Framework: Overview of the UTAUT Model

Venkatesh et al. (2003) developed the UTAUT model to conceptualise factors determining technology adoption and use. Other models considered while developing the UTAUT model include other several models such as the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), the Theory of Planned Behaviour (TPB), etc. The UTAUT model assumes that behavioural intention to use technology and actual use depend on four key constructs, including performance expectancy, effort expectancy, social influence and facilitating conditions. Factors including gender, age, experience, and voluntariness of use moderates these constructs and modify the strength and direction of relationships with the intention to use the technology. Performance expectancy is defined 'as the extent to which an individual believes that using a system will help them attain and improve performance' (Venkatesh et al., 2003, p. 447). Effort expectancy is the 'degree of ease associated with using a system' (Venkatesh et al., 2003, p. 450). Social influence is 'the extent to which an individual perceives that important social groups believe such an individual should use the new system' (Venkatesh et al., 2003, p. 451). Facilitating conditions means the 'degree to which an individual believes that organisational and technical infrastructure exists to support using a system' (Venkatesh et al., 2003, p. 453). Behavioural intention means a 'person's subjective probability that they will perform the behaviour in question' (Venkatesh et al., 2003, p. 456).

Although TAM, TPB and several other models have been of great value in identifying the issues that influence technology acceptance, none of these models can offer the comprehensive structure of UTAUT around peer influences consideration (Scherer et al., 2019). For example, TAM focuses only on perceived usefulness and ease of use, disregarding the fact that social and institutional pressures exist in academic environments that can play an important role. These external factors are included in the UTAUT model providing a systematic framework to explain technology adoption in environments where peer influence and organisational support are critical to implementation (Teo, 2011). In the context of this study, the UTAUT model offers a good rigorous foundation for testing various factors that affect the academic's behavioural intention towards using Moodle at UKZN. This research uses the UTAUT model to assess Moodle adoption with the purpose of determining the specific factors that influence its adoption with the view of offering recommendations that may increase the adoption of e-learning in higher learning institutions in South Africa.

Moodle Adoption in Higher Education

The acronym Moodle stands for Modular Object-Oriented Dynamic Learning Environment, and it is one of the most popular LMS in higher education across the globe (Hwang, 2009). It was developed in 2002 by computer scientist Martin Dougiamas as a digital environment for creation of online courses and learning content (Costa et al., 2012). Since then, Moodle has evolved through many versions to add more functions, user-friendly interfaces, and more enhanced capabilities. This journey has been characterised by functional enhancement and crucial correction to facilitate the adaptation to demand of changing educational practice (Hwang & Jeong, 2023). This rich feature made it a system of preference for many higher learning institutions in Africa because it supports both face-to-face and online learning modalities (Mpungose, 2019). The adaptation of Moodle by universities in South Africa has been an ideal approach to address the expanding demand for university education is accommodated, to solve the problem of overcrowded classrooms and lack of adequate physical infrastructure to support university education and to promote educational continuity during the outbreak of the COVID-19 pandemic (Mpungose, 2019). The flexibility of the platform, allowing students to learn anytime any place has however made it more rewarding especially in areas where geographical and socio-economic factors may impose constraints on learning (Qwabe & Khumalo, 2020). However, the adoption of Moodle by academics has not been without challenges. Literature has it that while institutions formally adopt Moodle, its use by academics tends to be low because of factors such as poor information and communication technology skills, academics' resistance to change, and lack of adequate support from the higher institutional level (Makhaya & Ogange, 2019).

Furthermore, studies have demonstrated that even when Moodle is used, it is rarely used to full capacity, this is because most academics simply use it as storage for course materials rather than an interactive learning tool. This put limitations benefits Moodle have for enhancing student learning experiences (Bervell & Umar, 2017). According to Mthethwa-Kunene and Maphosa (2020), some higher learning institutions have continued to address these challenges through intervention programmes such as organising workshops and seminars, and peer monitoring, which could help academics integrate Moodle into their teaching practice to maximise the impact in learning outcomes in higher education.

Factors Influencing Moodle Adoption in Higher Education

The adoption of Learning Management Systems (LMS) such as Moodle by academics in higher institutions is determined by several key factors that can be easily explained with the aid of the UTAUT model. Performance expectancy refers to the degree to which academics believe that the use of Moodle will enhance their teaching effectiveness (Venkatesh et al., 2003). Studies indicated that if Moodle is seen as a worthy resource that will help educators enhance how teaching content is delivered and how students can be engaged, then more educators are likely to incorporate Moodle into their teaching activities (Pérez-Pérez et al., 2019; Lavidas et al., 2023). This belief is usually the most salient of all UTAUT model's factors that encourages the adoption of Moodle because it ties the use of Moodle to potential results such as improved job performance and educational results (Teo, 2011). Effort expectancy, which relates to the perceived ease of use of Moodle—should be a major determinant in the acceptance of the technology (Venkatesh et al., 2003). Studies have shown that effort expectancy can influence technology adoption, if there is adequate training and support to overcome usability challenges, which therefore does not make ease of use a barrier to adoption (Bervell & Umar, 2017; Mtebe & Raisamo, 2014). These findings insinuate that with sufficient institutional support, the ease of use factor becomes less important as a determinant of behavioural intention.

A major driver of technology adoption and use is social influence. Venkatesh et al (2003) define it as 'the degree to which an individual believes that important others expect him or her to use the new technology.' When peers and institutional leaders strongly encourage use of technology, it is most likely that academics feel forced to do the same. The opportunity that peer pressure and leadership support offers could promote the adoption rate of Moodle among the academics (Makhaya & Ogange, 2019; Ifenthaler & Schweinbenz, 2013). Previous studies have proved that when peers and leadership promote technology adoption, academics feel a greater sense of obligation to use it (Graf-Vlachy et al., 2018; VanDerSchaaf et al., 2021).

Facilitating conditions also play a very important role in effective technology adoption. This construct refers to technical support systems, infrastructure, and resources available to ensure effective use of technology (Venkatesh et al., 2003). Regular training along with technical support, hardware and software availability to the academics will ensure to use Moodle effectively for academic purposes (Anderson & Dron, 2011). Earlier studies showed that the availability of facilitating conditions act as a major determinant in technology use behaviour among academics (Moonsamy & Govender, 2018; Ali & Warraich, 2023). Behavioural intention is one of the important determinants of use of technology such as Moodle. According to Venkatesh et al. (2003), it measures the degree to which an individual is willing to use technology. Past research has found that perceived usefulness, ease of use, social influence and facilitating conditions also influence behavioural intention. For example, Davis et al. (2022) revealed that there was a high influence of perceived helpfulness, ease of use, social influence, Internet connectivity and technical support on academic's behavioural intention to use technology system for academic purpose. Lavidas et al. (2023) also showed that academics fully adopted Moodle because of increased perceived usefulness, ease of use, subjective norms and self-efficacy offered by the platform. Jambulingam (2013) maintained that performance expectancy, affordability, and pedagogy determined academics' perception in using Moodle in the learning environments.

Research Method

The study used quantitative research design and the survey research method to examine factors that influence UKZN academics' behavioural intention to use Moodle for teaching purposes. Using a survey design was appropriate for establishing relationships between variables through a standardised questionnaire. In this study the academic staff of all the four colleges at UKZN, totalling 847 members, were targeted. Since the target population is involved in teaching activities, they are considered the most suitable population for studying factors that motivate the use of Moodle.

To determine the sample size, a priori power analysis was carried out to achieve 80% statistical power based on the recommendation of Hair et al. (2022). Based on the analysis, it was discovered that a minimum of 150 respondents was needed to detect significant effects across different path coefficient levels. As seen in Table 1, the minimum sample size necessary for several levels of minimum path coefficients for specific significance levels are given and the required minimum sample size for robust statistical analysis within PLS-SEM were found to be 150, which reached the minimum necessary level for this study.

Table 1. Minimum Sample Sizes for Different Levels of Minimum Path Coefficients and a Power of 80%.

Minimum path coefficient	Significance level		
	1%	5%	10%
0.05-0.1	1,004	619	451
0.11-0.2	251	**150**	113
0.21-0.3	112	69	51
0.31-0.4	63	39	29
0.41-0.5	41	25	19

Source: (Hair et al. 2022).

To ensure representation, the total sample was proportionally distributed across the colleges of UKZN according to their population size (see Table 2). Particularly for accessing hard to reach populations, snowball sampling (also known as chain referral sampling) was selected since it is difficult to directly access academics because of their busy schedule (Cooper & Schindler, 2014). Snowball sampling, practical in this case, does have its limitations, which include biases toward more interconnected respondents and inability to generalise to the whole population (Atkinson & Flint, 2001). Given these limitations, the study was able to address them by providing proportional representation across UKZN's four colleges to address sampling bias and improve the validity of the sample.

The data collection process began as some initial respondents who were accessible were asked to refer other academics to meet the study's criteria. With this technique, data was collected from a representative sample of the academic staff across UKZN.

Table 2. Proportional Sampling of Respondents from UKZN Colleges

College	Population	% Population	Sample Size per College
College of Agriculture, Engineering and Science	241	28.5%	43
College of Health Sciences	213	25.1%	38
College of Humanities	256	30.2%	45
College of Law and Management Studies	137	16.2%	24
Total	**847**	**100%**	**150**

Source: Author's Computation (2024).

The online questionnaire used in this study was a structured instrument used to assess the UTAUT constructs. Key constructs of the model included: 1) performance expectancy, 2) effort expectancy, 3) social influence, 4) facilitating conditions, 5) behavioural intention and 6) usage behaviour.

A set of indicators adapted from Venkatesh et al. (2003) and Al-Qeisi and Hegazy (2015) with minor modifications to suit the context of Moodle usage at UKZN were used to measure each construct. Respondents rated these statements on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) for easy completion as suggested by Babakus and Boller (1992). Table 3 presented some samples of these statements.

Table 3. Operationalisation of UTAUT Constructs

	Item	Reference	Measurement	Item sample
Performance Expectancy (PE)	4	Venkatesh et al. (2003)	Ordinal: Five-point Likert-type option's choice	I would find the University's Moodle helpful in my job
Effort Expectancy (EE)	4	Venkatesh et al. (2003)	Ordinal: Five-point Likert-type option's choice	My interaction with the University's Moodle would be clear and understandable
Social Influence (SI)	4	Venkatesh et al. (2003)	Ordinal: Five-point Likert-type option's choice	People who are important to me think that I should use the University's Moodle

Facilitating Conditions (FC)	4	Venkatesh et al. (2003)	Ordinal: Five-point Likert-type option's choice	I have the resources necessary to use the University's Moodle
Behavioural Intention (BI)	4	Venkatesh et al. (2003)	Ordinal: Five-point Likert-type option's choice	I intend to use the University's Moodle in my future learning activities
Usage Behaviour (UB)	4	Al-Qeisi and Hegazy (2015)	Ordinal: Five-point Likert-type option's choice	I consider myself a regular user of the University's Moodle

To ensure reliability and validity of the survey statement, the questionnaire was pre-tested using a pilot study of 30 students from the University of South Africa. Using this testing feedback, statements for the survey were slightly modified, to ensure survey statements in the final draft are clear to erase any misinterpretation by respondents. The collected data were analysed using the PLS-SEM method with the support of SmartPLS software version 4.0.8.5. It is favourable to use PLS-SEM because the model is complex, involving moderating variables (Hair et al., 2017). The measurement model (construct validity and reliability) and structural model (constructs relationships) were assessed using PLS-SEM. Descriptive statistics (frequency distribution and percentage) were also computed to summarise demographic characteristics of respondents.

Analysis and Results

A total of 89 respondents successfully completed the online questionnaire, achieving a response rate of 68%. According to Breakwell et al. (2012), a response rate above 40% is appropriate to generalise in survey research. Hence, the demographic profile of these respondents by gender, age, qualifications, academic rank, years of experience, and college affiliation were summarised in Table 4.

Table 4. Demographic Profile of Respondents at UKZN

Demographic Characteristic	Category	Frequency (n=89)	Percentage (%)
Gender	Male	55	61.8%
	Female	34	38.2%
Age	25-35 years	22	24.7%
	36-46 years	44	49.4%
	47-57 years	18	20.2%
	58-68 years	5	5.6%
Qualification	Bachelor's degree	4	4.5%
	Master's degree	58	65.2%
	Ph.D.	27	30.3%
Academic Rank	Professor	3	3.4%
	Associate Professor	9	10.1%
	Senior Lecturer	19	21.3%
	Lecturer	35	39.3%
	Assistant Lecturer	23	25.8%
Years of Experience	0-2 years	17	19.1%
	2-5 years	37	41.6%
	5-10 years	29	32.6%
	Above 10 years	6	6.7%
College Affiliation	College of Humanities	21	23.6%
	College of Health Sciences	19	21.3%
	College of Agricultural Engineering & Science	35	39.3%
	College of Law and Management Studies	14	15.7%

Source: Author's Computation (2024).

The demographic features of the respondents were summarised in Table 4 and showed that the sample consisted of more males (61.8%) than females (38.2%) and were in the 36-to-46-year age range (49.4%). Most of them had master's degrees (65.2%) with many of them being lecturers (39.3%). Most of the respondents had 2-5 years of work experience (41.6%), and the biggest group of them came from the College of Agricultural Engineering and Science (39.3%). This socio-demographic information is used to explain the respondents' points of view regarding factors that can be associated with Moodle adoption and use in UKZN. The high proportion of lecturers and those with moderate experience levels may mean that they are conversant with using Moodle and this may positively influence their behavioural intention to adopt the platform.

Reflective Measurement Model

To test the reliability of the constructs used in the research, the measurement model was estimated. This assessment included estimating Composite Reliability (CR), Cronbach's Alpha, Average Variance Extracted (AVE) and Standardised Factor Loadings (SFL).

Table 5. PLS-SEM Assessment Results of Reflective Measurement Models for UKZN Sample

Constructs/Items	UKZN (n = 89)	CR	AVE
Behavioural Intention (BI)		0.886	0.723
BI1	0.805		
BI2	0.888		
BI3	0.855		
BI4	0.545	Deleted	
Effort Expectancy (EE)		0.884	0.657
EE1	0.841		
EE2	0.844		
EE3	0.795		
EE4	0.759		
Facilitating Conditions (FC)		0.798	0.569
FC1	0.729		
FC2	0.804		
FC3	0.532	Deleted	
FC4	0.729		
Performance Expectancy (PE)		0.845	0.578
PE1	0.797		
PE2	0.810		
PE3	0.668		
PE4	0.758		
Social Influence (SI)		0.845	0.580
SI1	0.792		
SI2	0.802		
SI3	0.828		
SI4	0.605		
User Behaviour (UB)		0.858	0.753
UB1	0.008	Deleted	
UB2	0.080	Deleted	
UB3	0.925		
UB4	0.805		

Source: Author's Computation (2024).

The measurement model results presented in Table 5 showed that all constructs had high reliability and validity coefficients. The CR values for all the constructs were above 0.7 recommended by Nunnally and Bernstein (1994), ranging from 0.798 to 0.886 thus, indicating a good internal consistency. AVE values span from 0.569 to 0.753, surpassing the 0.5 benchmark, thus affirming adequate convergent validity as per Fornell and Larcker (1981). The SFL are mostly above 0.7, indicating solid item reliability, following the guidelines

suggested by Hair et al. (2010). However, items, such as PE3 (0.668) and SI4 were retained despite slightly lower loadings because they contributed significantly to their respective constructs, as recommended by Hair et al. (2017). Items with very low loadings, such as BI4 (0.545), FC3 (0.532), UB1 (0.008), and UB2 (0.080), were deleted to enhance the model's overall validity. This selective retention ensures that the constructs remain well-measured and robust for subsequent analysis, consistent with the standards for structural equation modelling. Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT), ensuring that each construct is distinct from the others. As shown in Table 6, all HTMT values were below the threshold of 0.85, confirming discriminant validity (Henseler, Ringle, & Sarstedt, 2015).

This indicates that the constructs in the study measure different concepts.

Table 6. Table: HTMT Ratios for Discriminant Validity

Constructs	BI	EE	FC	PE	SI	UB
BI	1.000					
EE	0.720	1.000				
FC	0.630	0.710	1.000			
PE	0.620	0.700	0.690	1.000		
SI	0.530	0.640	0.580	0.600	1.000	
UB	0.580	0.620	0.570	0.550	0.620	1.000

Note: All HTMT values < 0.85 indicate strong discriminant validity.
Source: Author's Computation (2024).

Structural Model

The structural model was assessed to evaluate the hypotheses related to the factors influencing academics' behavioural intention and user's behaviour towards Moodle at UKZN. The analysis used the standardised path coefficients (β) to measure the strength of the relationships between the constructs, as presented in Table 7.

Table 7. Structural Model Path Coefficients and Moderating Effects

Hypothesised Paths	Path Coefficient (β)	Standard Deviation	T-statistics	P-values
PE -> BI	0.802	0.045	17.822	0.001
EE -> BI	0.117	0.067	1.746	0.081
SI -> BI	0.134	0.067	2.007	0.045
FC -> UB	0.287	0.065	4.415	0.001
BI -> UB	0.455	0.070	6.511	0.001
Gender x PE -> BI	-0.347	0.184	1.887	0.060
Age x PE -> BI	-0.136	0.120	1.133	0.258
Experience x SI -> BI	-0.156	0.102	1.529	0.127
Experience x FC -> UB	0.027	0.134	0.202	0.840
R² (BI)	0.595			
R² (UB)	0.391			

Source: Author's Computation (2024).

The results in Table 7 indicate that PE significantly influenced behavioural intention with a path coefficient (β) of 0.285 (t-statistic = 3.268, p < 0.001), supporting the hypothesis that PE is a strong predictor of BI at UKZN. This finding aligns with the notion that when academics perceive Moodle as useful and believe it enhances their teaching effectiveness, they are most   likely going to adopt it.

SI also demonstrated a significant impact on behavioural intention, with a path coefficient (β) of 0.391 (t-statistic = 3.565, p < 0.001). This suggests that the encouragement and expectations from peers and institutional policies are crucial in shaping academics' intentions to use Moodle.

Contrarily, EE, which measures the perceived ease of use of Moodle, did not significantly influence behavioural intention (β = 0.159, t-statistic = 1.650, p > 0.05). This result might indicate that once adequate support and training are provided, ease of use becomes less of a barrier. Regarding the direct influence on use

behaviour, FC had a significant positive effect on UB with a path coefficient (β) of 0.302 (t-statistic = 3.792, p < 0.001). This highlights the importance of adequate resources and support systems in ensuring Moodle's effective use by academics.

Behavioural intention itself strongly predicted use behaviour with a path coefficient (β) of 0.436 (t-statistic = 4.526, p < 0.001), confirming that when academics intend to use Moodle, it significantly translates into actual usage. The R² values indicate that the model explains 59.5% of the variance in BI and 39.1% of the variance in UB, demonstrating the model's moderate explanatory power, as shown in Figure 1. The analysis further explored the moderating effects of gender, age, and experience on these relationships. However, none of the moderating variables significantly altered the relationships between the core constructs and either BI or UB, indicating consistent effects across different demographic groups at UKZN.
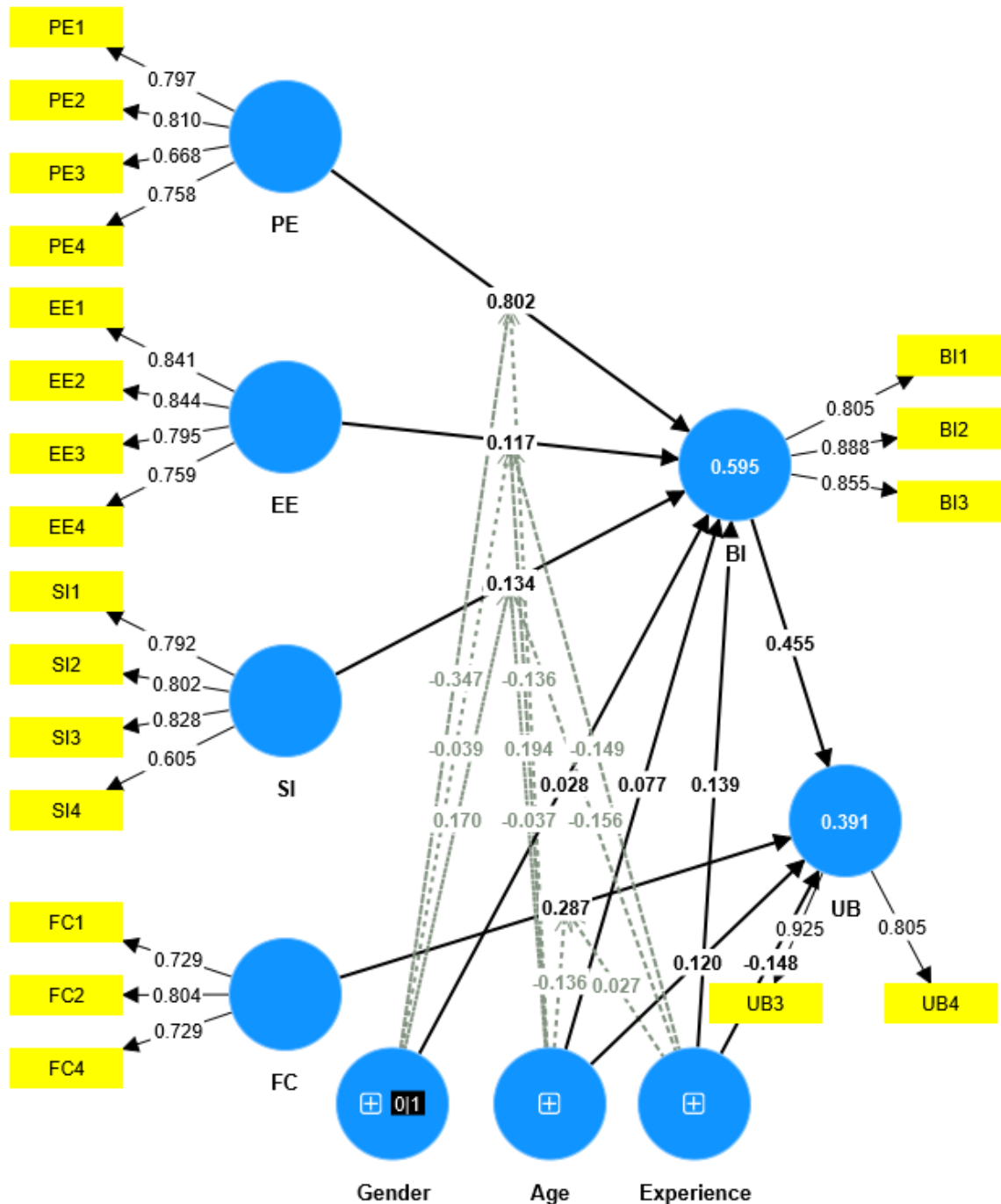

Fig. 1. PLS-SEM Structural Model Results with Moderating Effects for Moodle Adoption at UKZN.

Discussion

The study aims to examine factors influencing the behavioural intention and actual usage of Moodle among academics at the University of KwaZulu-Natal (UKZN) using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The study specifically focused on key constructs such as PE, EE, SI, and FC to understand their impact on BI and UB within the South African higher education context.

The results showed that PE is the strongest predictor of BI for the use of Moodle, with a path coefficient (β) of 0.802. The result implied that academics perceive Moodle as an effective way to improve their teaching, prompting them to create, adopt, and use it. This matches previous findings such as Venkatesh et al. (2003) and Dwivedi et al. (2019) who affirmed that perceived usefulness of any technology determines its adoption. The strong influence of PE demonstrated the need to make Moodle's benefits visible to the academic staff to fully adopt it.

However, contrary to some previous findings, EE did not significantly influence BI ($\beta = 0.117$, $p > 0.05$). This is a divergence from typical UTAUT applications in which ease of use is typically a critical predictor. This result may be associated with high familiarity and training that academics possessed using Moodle. Perceived ease of usage, as suggested by Mtebe and Raisamo (2014), may play less role when training is given to users of technology.

It is shown that SI also significantly influenced BI ($\beta = 0.134$, $p < 0.05$), validating the hypothesis that peer expectations and institutional norms have a decisive impact on the adoption of Moodle. This result aligns with findings from other studies (e.g., Al-Gahtani, 2016), which emphasise the significance of social influences in the process of technology acceptance. Such an effect of SI suggested that soliciting the peer network and establishing a community of practice may be essential ways to increase Moodle adoption among academics.

FC had a significant and strong effect on UB ($\beta = 0.287$). However, this result showed that academics did have access to resources and support systems that made them effectively use Moodle for educational purposes. This result aligns with previous past research of (Venkatesh et al., 2003) and (Scherer et al., 2019) that emphasised the significance of institutional support as a success factor for technology adoption. Continued Moodle use means that academics need access to infrastructure and technical support for the activities. It was found that BI had a significant influence on UB ($\beta = 0.455$, $p < .05$), which signified academics' high intention to use Moodle for academic purposes. The result is in tandem with one of the core tenets of the UTAUT model and previous empirical studies (e.g., Dwivedi et al., 2017; Aziz et al., 2022) that reported a direct association between intention and behaviour in the adoption of technology.

In addition, the study examined the effects of gender, age, and experience as moderators for the relationships between the UTAUT constructs and BI/UB. Notably   , none of these moderating variables moderated their respective relationships. This finding also implies that any strategies that will be implemented to improve Moodle adoption among academics can be applied across board without adjustments based on these moderating variables. This consistency across different demographics accords with the findings of some previous studies (e.g., Venkatesh et al., 2012) but is in contrast with others in which demographic factors had a more important effect (e.g., Morris et al., 2005).

Theoretical and Practical Implications

The study has added to validating and extending on the UTAUT model in the South African higher education context. The results indicate that underlying core constructs of the UTAUT model can be applied to determine factors influencing academics' behavioural intention to use Moodle, however, effort expectancy requires re-evaluation in an environment where users already have experience in using technology. From a practical perspective, the study identified the importance for institutions, such as UKZN, to ensure that Moodle is perceived as useful by users, leveraging social influence, as well as providing strong support systems to maximise users' effective utilisation of Moodle.

This research provides valuable insights that can inform policy and practice not only at UKZN but also at other institutions facing similar challenges in technology adoption. By understanding the factors that drive Moodle adoption, educational institutions can design more effective interventions to promote the integration of e-learning platforms, ultimately enhancing the quality of education delivery.

Conclusions

The study revealed that PE and SI are critical factors influencing BI to use Moodle among academics at UKZN, while FC significantly affects UB. BI was also found to be a strong predictor of UB, indicating that higher intention directly translates to increased usage of Moodle. The study found that the moderating variables—gender, age, and experience—did not significantly impact the relationships between the constructs. The issues addressed in this study can be used to optimise Moodle adoption at UKZN and make it a more effective learning tool for improving education outcomes within higher education. The study also contributed to existing studies by validating the UTAUT model in the context of developing countries, providing insights that would be useful in guiding broader e-learning strategies in similar educational environments.

Recommendation

University administrators should prioritise enhancing Moodle's perceived usefulness and leverage on the social influence of peer network to boost adoption. Ensuring the availability of adequate resources and support is vital for sustaining Moodle usage. Given the consistent impact across different demographic groups, strategies to promote Moodle adoption can be applied broadly without the need for demographic-specific adjustments.

Limitations and Future Research

The study's focus on a single institution may limit the generalizability of the findings. The non-significance of EE and the moderating variables suggest that further research is needed to explore other potential factors influencing Moodle adoption. Future research could also investigate the role of specific training programmes and the impact of different cultural or institutional contexts on technology adoption. Additionally, examining the reasons behind the strong BI-UB relationship could provide deeper insights into the mechanisms driving technology usage.

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