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CRITICAL DETERMINANTS FOR LEARNING ANALYTICS ADOPTION IN HIGHER EDUCATION

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ABSTRACT

The purpose of this paper is to present an empirical investigation of the critical determinants for the adoption of learning analytics in higher education. A conceptual model was proposed to understand better the adoption of learning analytics in higher education by teaching staff. Structural equation modelling is used for testing and validating the proposed conceptual model based on the survey data collected from Australia, South Africa, and Zimbabwe. Five study hypotheses were statistically significant, while two were statically insignificant. A positive relationship was revealed between user preparedness, technology preparedness, perceived usefulness, and social influence with behavioural intentions to adopt learning analytics in higher education. Hypotheses between user preparedness and perceived usefulness as well as user preparedness and learning analytics adoption were rejected. This study contributes to the learning analytics adoption research by proposing and validating a research model for the adoption of learning analytics in higher education.

KEYWORDS

Learning Analytics, Data Analytics, Organisational Preparedness, Behavioural Intentions, LMS.

1. INTRODUCTION

Learning analytics refers to using formal analysis techniques, such as machine learning and statistical techniques, to create information that improves decision-making in higher education (El Alfy, Gómez, & Dani, 2019). The adoption of learning analytics in higher education is becoming increasingly popular across the world, demonstrated not only in their rapid growth but also in the wealth of literature resulting from the active research in this area (Başaran & Daganni, 2020; El Alfy et al., 2019; Ngqulu, 2018). The popularity of learning analytics is owing to their potential benefits to active learning, improved teaching and learning approaches, implementation of early interventions for supporting student learning, better student retention, and improved student throughput (El Alfy et al., 2019; Fan et al., 2021).

The remarkable potential of learning analytics mainly is supporting student learning but has not been fully utilised. Most higher education institutions, particularly in developing countries, have not used learning analytics (Ngqulu, 2018). Those who have adopted learning analytics in higher education are still the entry-level adoptees (Başaran & Daganni, 2020; Clark, Liu, & Isaias, 2020). To effectively assist higher education institutions worldwide in their quest for learning analytics, understanding the critical determinants for university lecturers' adoption of learning analytics is significant (De Laet et al., 2020).

Few studies investigate the adoption of learning analytics (Ngqulu, 2018; Tsai, Kovanović, & Gašević, 2021). For example, Clark et al. (2020) explored the critical success factors for implementing learning analytics. Ngqulu (2018) investigated the critical determinants for adopting learning analytics in South Africa. The few studies that explored the critical determinants for learning analytics focus on limited samples, particularly from one institution with campuses in one country. This study explores the critical determinants for the adoption of learning analytics in higher education. A comprehensive review of the related studies is conducted. This leads to developing a conceptual model for exploring the criteria determinants for the adoption of learning analytics. The model is tested and validated using structural equation modelling on the survey data collected, leading to identifying the critical determinants for learning analytics. This study contributes to existing electronic learning research by enriching the understanding of the critical determinants for the adoption of learning analytics.

2. LITERATURE REVIEW

The rapid advancement of Learning analytics is continuously defining the significant areas of higher education (El Alfy et al., 2019). The increased acceptance and use of online learning for various reasons, including COVID-19 contact restrictions and firmer beliefs in the promises of online learning, has led to the generation of substantial amounts of data (Gibson & de Freitas, 2016). Learning analytics, and the application of data analytics in higher education institutions, have led to various benefits, including detecting at-risk students, tracking students' progress, predicting specific learning needs for an individual student, and revealing possible causes of students' academic achievement (Clark et al., 2020; El Alfy et al., 2019). Learning analytics obtains their data from Learning management systems (LMS) such as Moodle, Canvas, and Blackboard (Xin & Singh, 2021).

The LMS is developed to administer, track, report, and deliver educational courses and content. The software applications are accessible on a range of internet-enabled devices, including personal computers, laptops, iPads, Tablets, and smartphones (Xin & Singh, 2021). The high proliferation of LMS in higher education has led to the creation of massive datasets; however, obtaining relevant and accurate data from these data sets using applicable data analytics techniques has become more critical for lecturers to monitor and support students' learning (De Laet et al., 2020; Xin & Singh, 2021).

Data analytics analyses raw data to provide valuable insights to assist users in planning and implementing suitable interventions (Gutiérrez et al., 2020; Xin & Singh, 2021). There are four classifications of data analytics that can be implemented into LMS: descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics (Xin & Singh, 2021).

Descriptive analytics provides measured metrics and the activities in a certain period (Xin & Singh, 2021). In learning analytics, descriptive analytics enable lecturers to understand student performance patterns better and identify potential risk issues (Xin & Singh, 2021). Diagnostic analytics provide deeper insights that explain the causes of a problem under scrutiny. Diagnostic analytics are narrow and more specific than descriptive analytics (Xin & Singh, 2021).

Predictive analytics is more complex than descriptive and diagnostic analytics. They are driven by machine and deep learning algorithms for delivering a forecast of what is likely to happen. They employ descriptive and diagnostic analytics results to detect clusters and exceptions and predict future trends (Gutiérrez et al., 2020; Xin & Singh, 2021). Prescriptive analytics utilises machine learning and algorithms to prescribe a possible action that can be taken to eliminate a future problem (Xin & Singh, 2021).

The major LMS provides built-in data analytics features, which are primarily descriptive. Higher education systems that lack preparedness to adopt learning analytics often rely on built-in reporting tools based on log data. Low costs characterise these learning analytics systems, and their features and services are limited compared to data analytics plug-ins (De Laet et al., 2020; Xin & Singh, 2021). Third-party developers develop LMS plug-in learning analytics dashboards that emphasise diagnostic and prescriptive analytics to understand the cause of events and figure out solutions to improve learning outcomes. These applications are more costly than built-in. However, they are more effective and useful (De Laet et al., 2020; Xin & Singh, 2021).

Başaran and Daganni (2020) reported that learning analytics is a new technology. As a result, higher education institutions lack the capacity for staff with relevant skills. Additionally, they lack capacity in terms of technology infrastructure. This study provides insights into some of the causes of the low adoption rate s of learning analytics in higher education. Clark et al. (2020) conducted a study exploring the critical success factors for adopting learning analytics in higher education. The study results reveal five aspects of successful implementation and adoption of learning analytics, including strategy and policy at the organisational level, information technological readiness, performance and impact evaluation, people's skills and expertise and data quality. This study is valuable for highlighting critical factors for the implementation, acceptance, and use of learning analytics.

3. THEORETICAL FOUNDATION AND HYPOTHESES DEVELOPMENT

Learning analytics are developed through the implementation of data analytics for facilitating effective learning and teaching (Nguyen, Gardner, & Sheridan, 2020). With the rapid development of information and communications technology (ICT) and the growing adoption of online learning, learning analytics is becoming increasingly popular in higher education due to the potential benefits of learning analytics to higher education institutions (Fan et al., 2021; Tsai et al., 2021).

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Many factors influence the acceptance and use of learning analytics in higher education (Tsai et al., 2021). Several studies reveal numerous theories for better understanding technology adoption, including learning analytics in higher education (Clark et al., 2020; De Laet et al., 2020; Fan et al., 2021; Jivet et al., 2020; Tsai et al., 2021). The most common theories include the technology acceptance model, task technology fit theory, theory of reasoned action, diffusion of innovation, organisation preparedness model, technology–organisation–environment framework, and Unified Theory of Acceptance and Use of Technology (Bere, 2018; Bere & Rambe, 2016; Clark et al., 2020; De Laet et al., 2020; Misra, Satpathy, & Mohanty, 2007; Tsai et al., 2021).

Due to the dynamic nature of online learning and the changing environment of higher education, the use of a single theory to investigate the critical determinants for the adoption of learning analytics in higher education is often subject to criticism due to the limitations of individual theories (Deng, Duan, & Luo, 2019). This study integrates the technology acceptance model and the organisation preparedness model. The organisation preparedness model argues that adopting a particular digital technology is much influenced by the constructs of user and technology preparedness. The technology acceptance model has been integrated to strengthen the model to understand better the user's opinions on the impact of learning analytics in higher education.

The technology acceptance model is the most widely used theory for investigating the acceptance and use of technology (Bere & Rambe, 2016). It states that technology adoption is influenced by the behavioural intention of users, which is determined by the attitude of users towards the use of technology. Additionally, the perceptions of users with regards to technology usefulness and ease of use are crucial factors in exploring the determinants for adopting a specific technology. Figure 1 presents the conceptual model for the study.

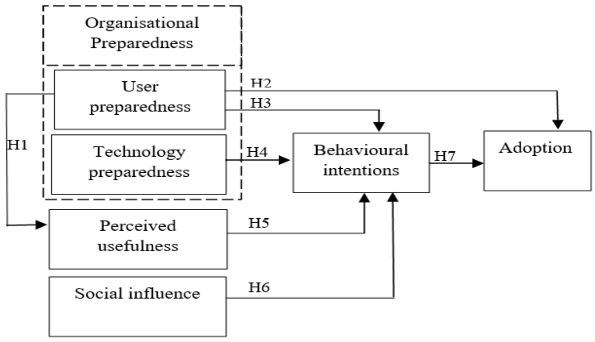


Figure 1. A conceptual model for the adoption of learning analytics

Organisational preparedness

Organisational preparedness refers to the ability of higher education institutions to successfully adopt, use and benefit from learning analytics (Ogunyemi & Johnston, 2012). The preparedness of users and technology are crucial contributors to organisational preparedness.

User preparedness

User preparedness describes how higher education staff and students are ready to productively adopt, use and benefit from specific learning analytics. User preparedness in learning analytics can be demonstrated through a display of various aspects, including tactical users showing abilities to undertake risks involving learning analytics and operational users exhibiting skills to understand the use of learning analytics for learning and teaching in higher education (Misra, Satpathy, & Mohanty, 2004; Misra et al., 2007). The following hypotheses have been developed about user preparedness:

H1: User preparedness positively is positively related to an individual's perceived usefulness of learning analytics.

H2: User preparedness positively influences the adoption of learning analytics

H3: User preparedness positively influences an individual's behavioural intentions to adopt learning analytics

Technology preparedness

Technology preparedness refers to a higher education institution's approach to managing learning analytics (Misra et al., 2007). Learning analytics involves various components, including big data, data storage, computer networks, learning analytics applications, and expertise. Higher education institutions should develop a plan for better aligning their learning analytics technology with existing information systems. The following aspects demonstrated a technology preparedness for a higher education institution (i) a standard technology and component plan to acquire learning analytics hardware and software technologies, (ii) capabilities to utilise learning analytics fully, and (iii) competence to successfully manage and assess the impact of learning analytics projects (Misra et al., 2004, 2007). The following hypothesis has been developed in relation to Technology preparedness:

H4: Technology preparedness positively influences an individual's behavioural intentions to adopt learning analytics

Perceived usefulness

Perceived usefulness refers to the degree to which individuals believe that using learning analytics would enhance their job learning and teaching performance (Bere & Rambe, 2016; Davis, Bagozzi, & Warshaw, 1989; Mafunda, Bere, & Swart, 2016). According to Davis (1989), perceived usefulness is a crucial determinant for influencing user attitude toward adopting a particular technology. The benefits of adopting learning analytics in higher education affect perceived usefulness among students and higher education staff. The following hypothesis has been developed in relation to perceived usefulness:

H5: Perceived usefulness positively influences an individual's behavioural intentions to adopt learning analytics

Social influence

Social influence states that an individual's emotions, opinions, or behaviours to accept and use learning analytics are influenced by others (Bere, 2018). The decision of higher education staff members, such as lecturers, could be influenced by their colleagues and managers. Prior researchers suggest that social influence as a variable has a significant effect on a person's intention to adopt a specific digital technology owing to attained satisfaction through conformity and identification (Amofa, 2014). The following hypothesis has been developed in relation to social influence:

H6: Social influence positively influences an individual's behavioural intentions to adopt learning analytics

Behavioural intentions

Behavioural intentions refer to motivational factors that determine the need for individuals to adopt learning analytics (Amofa, 2014). Behavioural intention is the most important predictor of an individual's behaviour in adopting learning analytics (Ajzen, 2020; Amofa, 2014). The following hypothesis has been developed in relation to behavioural intentions:

H7: An individual's behavioural intentions are positively related to the adoption of learning analytics

4. RESEARCH DESIGN

This study explores the critical determinants for the adoption of learning analytics in higher education. The study adopted a survey-based approach to achieve its objective of the study. The use of a survey is appropriate in this study because it enables the testing and validation of the proposed model while verifying the critical determinants for adopting learning analytics. Data was collected from higher education lecturers from Australia, South Africa, and Zimbabwe to better understand the critical factors influencing their acceptance and use of learning analytics for supporting student learning.

4.1 Demographic Characteristics

The demographic characteristics of the participants are summarised in section. The result reveals that most respondents are male (56.02%). The participant's age groups range from 30 to over 50 years. Additionally, the sample drawn comprises lecturers from Australia (43.46%), South Africa (31.94%), and Zimbabwe (24.60).

Previous studies that investigated the adoption of digital technologies employed a self-completion questionnaire (Bere, 2019; Bere & Rambe, 2016; Deng et al., 2019; Mafunda et al., 2016). This approach has been reported to be easy to manage and quickly score. This leads to faster data collection. Due to these reasons, this study employed a self-report questionnaire for data collection.

The questionnaire for the study has been developed using existing literature based on the study's objectives. It used a 7-point Likert scale format. The responses options ranged from 1 to 7, representing ''strongly disagree'', ''disagree'', ''partially disagree'', ''Neutral'', ''partially agree'', ''agree'', and ''strongly agree'' respectively. Fifteen participants comprising 8, 4, and 3 from Australia, South Africa, and Zimbabwe were randomly chosen for pilot-testing the questionnaire. Pilot testing enabled the researchers to identify and correct ambiguous statements in the questionnaire. Table 2 below presents the 21-item questionnaire measurement items used as the basis for the questionnaire developed for this study.

5. MAIN SURVEY DESIGN

Previous studies show that a sample of at least 175 participants would be ideal for achieving 95 % confidence (El-Gayar, Moran, & Hawkes, 2011). The questionnaire for the study was administered by a data collection online tool called survey monkey to 263 participants in 2021. A total of 197 questionnaires were returned, but six were discarded due to incomplete competition. As a result, 191 were deemed usable, comprising a response rate of 73 %, surpassing a minimum recommended sample size.

In this study, partial least squares (PLS) were used for the statistical analysis of data. PLS is suitable for this study due to its limited demand for data distribution compared to other statistical software packages used for structural equation modelling (El-Gayar et al., 2011).

The objective of using PLS is to measure the direction and strength of the relationships among model constructs. The PLS statistical analysis method has also been used to compute each item's weights and loading factors about the construct it was proposed to measure (El-Gayar et al., 2011).

Evaluating the measurement model requires assessing the internal consistency for every batch of constructs and their construct validity (Bere & Rambe, 2013). Factor loadings measure the composite reliability (CR) and average variance extracted (AVE) to evaluate internal consistency. The CR and Cronbach's alpha measure the reliability of the constructs, but CR provides a closer approximation (Bere & Rambe, 2013; El-Gayar et al., 2011).

5.1 Results

The mean values for this study ranged from 5.66 to 6.23, as shown in Table 3. Such mean values reveal they show that participants have a positive evaluation of the adoption of learning analytics (Fornell & Larcker, 1981). A factor loading of at least 0.7 is recommended for measured variables (El-Gayar et al., 2011). The factor loadings for this study ranged from 0.763 to 0.958, indicating that the measured variables have good reliability (Bere & Rambe, 2013; Fornell & Larcker, 1981).

The primary indicators for measuring convergent validity are CR and AVE. The recommended CR is 0.7, which covers internal constancy. The CR for this study ranges from 0.854 to 0.943, signifying a good internal consistency for each construct (Bere & Rambe, 2013; El-Gayar et al., 2011; Fornell & Larcker, 1981). AVE indicates the measure of the error-free variance of a set of convergent validity (Fornell & Larcker, 1981). A recommended AVE should be greater than 0.5 (Fornell & Larcker, 1981). In this study, the AVE for individual construct ranges from 0.793 to 0.916.

Table 1. Constructs descriptive statistics and instrument reliability and validity

Construct	Item	Mean	Factor loading	Cronbach's α	Composite reliability	AVE
User preparedness	UP1	6.23	.793	.836	.816	.850
	UP2		.817			
	UP3		.849			
	UP4		.763			
	UP5		.811			
Technology preparedness	TP1	5.87	.924	.911	.791	.916
	TP2		.887			
	TP3		.909			
Perceived usefulness	PU1	5.66	.841	.915	.875	.793
	PU2		.786			
	PU3		.827			
	PU4		.771			
Social influence	SI1	6.12	.958	.860	.901	.824
	SI2		.936			
	SI3		.891			
	SI4		.918			
Behavioural intentions	BI1	6.61	.862	.936	.779	.831
	BI2		.869			
	BI3		.805			
	BI4		.858			
	BI5		.929			

Discriminant validity evaluates the extent to which assessed constructs that should be unrelated are, in reality, unrelated. The notion of discriminant validity is endorsed when the square root of AVE for each construct is greater than the correlation coefficients between the construct and the other constructs (Fornell & Larcker, 1981). The results of this study reveal, as shown in Table 2, existence due to the square roots of AVE being more significant than the correlation coefficients between the construct and the other constructs (El Alfy et al., 2019; Fornell & Larcker, 1981).

Table 2. Discriminant validity calculation

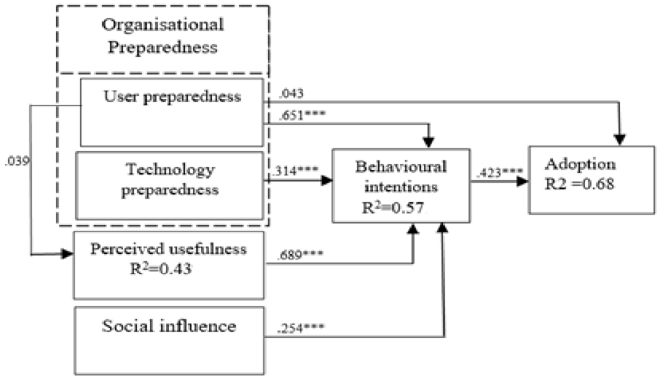
	UP	TP	PU	SI	BI
User preparedness (UP)	**.713**				
Technology preparedness (TP)	.324	**.862**			
Perceived usefulness (PU)	.582	.625	**.796**		
Social influence (SI)	.269	.532	.521	**.865**	
Behavioural intention (BI)	.426	.712	.428	.481	**.924**

Bold values show all the square roots of AVE, which are greater than the correlation coefficients between the construct and the other constructs.

5.2 Modelling Testing

The structural model analysis assesses the path coefficients (β) and R^2 for constructs of the research model. The β values evaluate the relative strength and sign of causal relationships amongst the constructs (Bere & Rambe, 2013; Deng et al., 2019). The R^2 estimates denote predictability for the research model. The combination of β and R^2 values provides the relationship between the structural model and experimental data (Bere & Rambe, 2016). For a path to be statically significant, a minimum β value of 0.05 is recommended (Bere & Rambe, 2016). Figure 3 indicates β and R^2 for this study.

The recommended acceptable β value for a path to be statically significant is at least 0.005. Figure 3 shows that H3, H4, H5, H6, and H7 are statistically significant with β values of 0.651, 0.314, 0.689,0.254, and 0.423 respectively while H1(β = 0.039) and H2(β = 0.043) are statistically insignificant hypotheses.



Note ***p ≤ 0.001

Figure 3. Structural model analysis

In this study, R^2 greater than zero ranges from 0.43 to 0.68. The R^2 correlations show that perceived usefulness explained 43% variance, behavioural intentions explained 57% variance, and adoption explained 68% variance. The R^2 attained in this study reveals that the constructs are significant.

The path coefficient β of 0.651 for H3 shows that user preparedness positively influences lecturers' behavioural intentions to adopt learning analytics. This finding is consistent with Dondorf, Pyka, Gramlich, Sewilam, and Nacken (2019)'s findings which reveal that for lecturers to develop positive intentions to adopt learning analytics, they should perceive that learning analytics application software is to be easy to use, including visualisations that are easy to access. Ifenthaler (2017) argues that the adoption of learning analytics in higher education is lacking due to the lack of lecturers with appropriate skills for using learning analytics. This finding suggests better learning analytics training programmes for lectures since trained users are highly likely to adopt learning analytics to improve their teaching and learning. Ngqulu (2018) emphasises vital staff development programmes enable high utilisation of learning analytics in higher education.

The path coefficient β of 0.314 for H4 shows that organisational technology preparedness positively influences lecturers' behavioural intentions to adopt learning analytics. This finding is consistent with Misra et al. (2007)'s claim that digital technologies available, including hardware, software, and network infrastructure, influence the lecturer's intentions to use technology. Ifenthaler (2017) argues that the adoption of learning analytics in higher education is deficient due to the lack of suitable learning analytics technology. This finding suggests that higher learning analytics adoption could be achieved with improvements in learning analytics infrastructure in higher education institutions. Dondorf et al. (2019) stated that various higher education institutions rely on built-in learning analytics of learning management systems such as Moodle. This demonstrates the higher education organisational preparedness to provide adequate technologies for learning analytics. The finding of this study suggests that higher investments in learning analytics technologies may improve learning analytics adoption by the lecturers.

The path coefficient β of 0.689 for H5 shows that perceived usefulness positively influences lecturers' behavioural intentions to adopt learning analytics. This finding is consistent with Gibson and de Freitas (2016) finding that lecturers' intentions to adopt learning analytics are driven by these technologies' ability to present insights that help understand what learners know and can do based on their interactions in digital learning spaces. Such understanding enables lecturers to implement suitable interventions for reducing supporting student learning. El Alfy et al. (2019) stated that lecturers' perceived usefulness of learning analytics is based on their ability to analyse various data, including students' test scores, demographics, and students' psychographics and gain insights into students' learning. This leads to a reduced workload for lecturers, resulting in positive intentions to adopt learning analytics.

The path coefficient β of 0.254 for H6 shows that social influence positively influences lecturers' behavioural intentions to adopt learning analytics. Ngqulu (2018) argues that management encourages lecturers to exploit their full potential by using learning analytics. This suggests that lecturers' behavioural intentions to adopt learning analytics are influenced by other people they think are essential in their careers. This finding is inconsistent with Başaran and Daganni (2020) result that reported a weak relationship between social influence and behavioural intentions.

The path coefficient β of 0.423 for H7 shows that behavioural intentions positively influence lecturers to adopt learning analytics. This finding is consistent with Başaran and Daganni (2020)'s finding that reported a strong relationship between behavioural intentions and adoption of learning analytics in higher education. This suggests that the lecturer's decision to adopt learning analytics starts with their positive intentions.

The path coefficient β of 0.039 for H1 shows that user preparedness does not affect the perceived usefulness of lecturers. This suggests that a lecturer's proficiency in learning analytics has no impact on their belief regarding learning analytics usefulness.

The path coefficient β of 0.043 for H2 shows that user preparedness does not affect lecturers' perceived usefulness. This indicates that a lecturer's proficiency in learning analytics has no direct significance in learning analytics adoption.

6. CONCLUSION

This study investigates the critical determinants for the adoption of learning analytics in higher education. A comprehensive review of the related studies is conducted, leading to developing a conceptual model with the integration of the organisational preparedness and technology acceptance model constructs. The model for the study is tested and validated using structural equation modelling on the survey data collected, leading to the identification of the critical determinants for learning analytics adoption in higher education. The study shows that the critical determinants of adopting learning analytics in higher education are user preparedness, technology preparedness, perceived usefulness, social influence, and behavioural intentions. Two hypotheses for the study were statistically insignificant, while five hypotheses were statistically significant.

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