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Factors Affecting the Acceptance of Big Data Technology in Teaching among Higher Education Educators: An Empirical Investigation Using the UTAUT Model

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Abstract

The era of big data has arrived along with rapid growth in the development of computer and communication technologies. This advancement of new technologies has brought about a new era of education. Personalized learning analysis and intelligent decision support based on big data technology have greatly improved education quality, optimized education management, and provided important support for realizing education modernization. Despite higher education institutions' growing interest in big data, research on the use of big data technology by teachers in higher education contexts is limited. Therefore, the purpose of this study was to examine the factors influencing higher education educators' intentions to use big data technology in teaching using the UTAUT model and to determine if there were statistical differences in higher education educators' intentions to use big data technologies in teaching based on age, gender, and teaching experience. Using simple random sampling technique, survey data were collected from 193 higher education educators in China's Yunnan Province using an online survey and analysed using structural equation modelling. The findings suggested that performance expectancy and facilitating conditions positively impact educators' behavioural intentions to use big data technology. However, in this study, the effects of effort expectancy and social influence on behavioural intention were not found to be statistically significant. Furthermore, the findings revealed that there were no significant differences in higher education educators' behavioural intentions to use big data technology in teaching based on gender, age, or teaching experience. Based on the findings, this study provides recommendations for university administrators and policy makers to motivate educators' behavioural intentions to use big data technology in teaching so that intentions eventually translate into actual usage behaviour. Future research can add models such as the PC utilization model, combine qualitative research such as interviews, and further expand the target population to other regions to compare the intention to use, level of use, and influencing factors of educators in different regions to make the findings more comprehensive.

Keywords: Big Data Technology, Higher Education, Individual Differences, Intention Behaviour, UTAUT Model

Introduction

The emergence of cutting-edge technologies has significantly altered the world (Chae, 2019). Big data and cloud computing, for example, are quickly expanding technologies that are becoming increasingly prevalent in a variety of social and economic domains. These technologies are also changing people's behaviour and thinking processes. Every moment, people generate massive amounts of data by using technological devices (ur Rehman et al., 2019). Big data is thus defined by Beyer and Laney (2012) as a high-volume, high-variety, and high-speed data set that involves new advanced methods for analysis and processing to support and enhance decision-making mechanisms and optimize processes. Big data, according to Osman (2019), comprises huge data sets that are tough to control, process, or examine in conventional ways. Big data mainly consists of three main characteristics, namely volume (size), variety (format, source, and type) and velocity (frequency and speed) (Xu & Duan, 2019). The arrival of the big data era portends a new technological revolution. As big data becomes more widely available, new opportunities are being created for observing, comprehending, and assessing activities taking place in different contexts. Thus, big data can be used to drive decisions and actions aimed at improving various aspects of society. Almost every industry has felt the impact of the big data era, and education is no different.

In the field of education, a large amount of data are generated through teaching and learning activities and online courses (e.g., massive open online courses [MOOCs]), including students' physiological data, personal records, activities and learning logs, and their learning performance and outcomes (Oi et al., 2017). Big data technology aims to utilize the power of these large amounts of data in real time or in other ways (Daniel, 2019). On April 10, 2012, The United States Department of Education's Office of Educational Technology published "Improving Pedagogy through Educational Data Mining and Learning Analytics: A Brief Introduction," pointing out that the use of big data technology in education mainly includes learning analytics and educational data mining (Bienkowski et al., 2012). Learning analytics applies technologies ranging from the fields of information science, social science, psychology, statistics, machine learning, and data mining, which serve to analyse data collected from education management and service processes (Bienkowski et al., 2012). Educational data mining, however, applies techniques and development methods of machine learning, statistics, and data mining to analyse the data collected during teaching and learning, and through data modelling, finds the correlations between the learning outcomes of learners and variables such as learning content, learning resources and teaching behaviour to predict the future learning trends of learners (Bienkowski et al., 2012). In contrast to traditional educational methods, the use of learning analytics and educational data mining helps to gain valuable knowledge, facilitates personalized education and improves teaching, learning and assessment (West, 2012).

Teachers can use data mining technology to analyse and mine students' learning behaviour data to discern the implied associations. They can further accurately predict students' learning paths and their development trends, and provide them with more targeted course resources, learning content, and learning feedback and suggestions to promote their personalized development (Xu et al., 2019). Natek and Zwilling (2014) classified students through the use of decision tree algorithms, and finally obtained the digital link characteristics and personal information characteristics of different categories of learners, providing a guide for higher education professors to effectively identify issues related to student success. With the help of big data technology, educators can receive immediate and objective feedback to evaluate their course structure as well as their teaching effectiveness and assessment procedures. They can monitor the learning process according to the learners' levels of knowledge and ability to identify their weaknesses and risks of failure early and respond in a timely manner (Linan & Perez, 2015). Song et al (2017) examined student learning patterns and guided course improvement based on data extracted from forum tools integrated in massive open online courses (MOOCs). They proposed a big data-driven approach called Topic-oriented learning assistance (TOLA) based on big data and cyber-physical system. For online learning evolution, TOLA can help to guide course improvement and identify students' learning patterns. Agaoglu (2016) used an artificial neural network, decision tree, discriminant analysis, and supporting vector algorithms to analyse the experimental data set from a questionnaire for student evaluation of the course, and further predicted the teaching effects of teachers, ultimately helping them to improve their performance.

Big data technology has had a significant impact on the field of education. Education quality has greatly improved, teaching effectiveness has increased, educational management has improved, and personalised learning analysis and intelligent decision support have become indispensable tools for accomplishing education modernisation (Drigas & Leliopoulos, 2014). Sun (2021) claimed that the gradual integration of big data into the education field has greatly triggered reforms and innovations, including developments in education management decision-making, which have significantly enhanced the transformation of education and teaching from traditional empirical decision-making to new data-driven decision-making and advanced the education field to become more data-smart. According to Yaqoob et al (2016), incorporation, adoption, and application of technology in the decision-making core of institutions can assist organisations and managers in taking more effective measures to integrate big data with education.

However, while big data provides opportunities for education, it also presents different challenges (Hanapiyah et al., 2018). Since the application of big data in education in China is still in its early stages of development (Zhang et al., 2020), educators in higher education lack awareness and comprehension of big data technologies in teaching, and they usually use it incorrectly and insufficiently. Thus, increasing teachers' intentions to use big data technology in teaching and improving the use of big data technology in teaching are critical for the in-depth use of big data in education. It is worth mentioning that, currently, research on big data in education in China focuses on basic theories (e.g., the concepts, connotation characteristics, application value and prospects, opportunities, and challenges of educational big data) and educational applications and innovations supported by big data technology, especially ideological and political education for undergraduate students (Jiang et al., 2019), but basically does not involve the intention of using big data technology in practice. Furthermore, previous big data research has primarily focused on technical attributes (such as machine learning or technical algorithms) with little consideration given to the intention to use big data technologies in practice (Kwon et al., 2019). In addition, although a few studies have focused on the intentions of adopting big data techniques in organizations (Brünink, 2016; Demoulin & Coussement, 2020; Verma et al., 2018; Sahid et al., 2021; Queiroz & Pereira, 2019; Cabrera-Sanchez & Villarejo-Ramos, 2019), identifying the factors that influence educators' intentions to use big data technology in teaching needs more research.

Based on Venkatesh et al.'s (2003) unified theory of acceptance and use of technology (UTAUT), this research seeks to determine what may drive higher education educators to use big data technology in their teaching. Thus, the factors impacting the intention to use big data technology in teaching among higher education instructors in Yunnan could be identified. This study also seeks to provide a reference for universities and colleges in adopting big data technology to help colleges better prepare for big data technology adoption and encourage the growth of big data education in colleges and universities. Furthermore, this study seeks to determine whether gender, age, and teaching experience influence educators' acceptance of big data technologies in Yunnan Province.

This paper is structured as follows. It begins with a review of the literature on the variables and relationships of the proposed model. The research methodology is discussed in the third section. The fourth section describes and analyses the results obtained from the sample data. Finally, the conclusions and limitations of the model are addressed.

Theoretical Background and Research Hypotheses

Several previous models have been developed to understand technology acceptance, including the theory of reasoned action (Fishbein & Ajzen, 1975), the technology acceptance model (Davis, 1985), and the theory of planned behaviour (Ajzen, 1991). The Unified Theory of Technology Adoption and Use of Technology (UTAUT) was developed based on the above models and other related models. Venkatesh et al (2003) proposed the UTAUT, which attempts to characterise both user intentions to adopt technology and their subsequent usage behaviour. The UTAUT model's determining variables are (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions. The four variables have a direct influence on the behaviour intention (BI) to use new technologies. While the model is robust, it must be retested and examined in the event of new trends or technological advancements. The UTAUT was developed to justify user behaviour in the adoption of new technologies, especially in the context of organisations. The model has also been extended and applied to a wide range of research areas to explain how individuals accept new technologies. Scholars, however, have called for further research on extending the theoretical validity and empirical applications of the UTAUT model to other situations and users. Utilizing the UTAUT model in different contexts would allow for a more accurate description of big data adoption behaviour. The model's applicability arises from the fact that big data is predominantly technology-driven and user-focused. As a result, the model is well adapted to reflect the nature of big data since it accounts for technological innovation and user behaviour. Thus, this study investigated the factors influencing higher education educators' intentions to use big data technology in teaching using the UTAUT model. In addition to the four key determinants of behavioural intention, the study investigated the influences of gender, age, and teaching experience on the behavioural intentions of Yunnan Province college instructors in adopting big data technology in teaching.

Performance Expectancy

The degree to which an individual believes that employing a given system would increase his or her work performance is referred to as performance expectancy. Performance expectancy is considered to be the direct influencing factor of behavioural intention in UTAUT, and it has been demonstrated that performance expectancy is the most important factor affecting an individual's use intention. In this study, performance expectancy refers to lecturer expectations for improving teaching performance and expanding professional skills through the use of big data technologies. Performance expectancy, as evidenced by the literature, is a significant predictor of behavioural intention regarding the use of educational technologies. Many studies have found a positive relationship between performance expectancy and behavioural intention (e.g., Brünink, 2016; Chauhan & Jaiswal, 2016). Teachers' criteria for evaluating the usefulness of technology are based on their expectations that technology will help them improve results and achieve their objectives. In higher education, big data technology is a new trend. Therefore, the purpose of this study is to examine the impact of performance expectancy on educators' intentions to use big data technology in the education sector. Consistent with prior studies, the following hypothesis was thus proposed for this research

H_1 Performance expectancy positively affects the intention to use big data technology in teaching among higher education educators.

Effort Expectancy

The ease with which users interact with a system is referred to as effort expectancy. It is considered to significantly affect use intention. In this study, effort expectancy refers to the amount of effort, time, and cognition that teachers believe is required to use big data technologies in their jobs. In other words, the effort expectancy variable refers to how easy it is for the teacher to use big data technology in teaching procedures, which determines whether or not the teacher adopts big data technology. Previous research has demonstrated that individuals are unwilling to use a new system or a technology if it is difficult to use (Chauhan & Jaiswal, 2016; Yu, 2012). Based on these findings, it is proposed that effort expectancy is one of the influencing factors of the intention to use big data technology in educational administration and teaching in Yunnan colleges and universities. Thus, the following hypothesis was proposed for this research:

H_2 Effort expectancy positively affects the intention to use big data technology in teaching among higher education educators.

Social Influence

The degree to which a person believes that someone (such as a friend or family member) important to him or her should adopt a new system is referred to as social influence. In this study, social influence refers to the fact that teachers may be encouraged to adopt big data technology by important people around them, such as colleagues and university officials. Previous research has indicated that social influence has a substantial impact on the intention to use a system in the early stages of technology adoption (Al-Gahtani, 2016; Lee & Song, 2013). Thus, this study examined the relationship between social influence and behavioural intention in educators' big data technology adoption and with the assumption that social influence has a positive impact on behaviour intention. Therefore, the the following hypothesis was proposed for this study:

H_3 Social influence positively affects the intention to use big data technology in teaching among higher education educators.

Facilitating Conditions

Facilitating conditions are described as a technology user's perceptions about the resources and support available to develop use behaviour (Venkatesh et al., 2003). In this study, facilitating conditions refer to resources offered by schools such as technical support, technical tools, and related technical knowledge to help educators in using big data technology. Previous research has shown that facilitating conditions have significant effects on the intention to use technology (Radovan & Kristl, 2017; Teo & Noyes, 2012). This study also examined the relationships between facilitating conditions and behavioural intention in big data adoption by teachers with the assumption that facilitating conditions have positive impacts on behaviour intention. Therefore, the following hypothesis was proposed for this research:

H_4 Facilitating conditions positively affect the intention to use big data technology in teaching among higher education educators.

Behavioural Intention

Behavioural intention is defined as the degree to which individuals are willing to employ technology (Teo, 2011). In this study, behavioural intention refers to teacher's behavioural tendency to use big data technology in their future teaching. Figure 1 depicts the proposed research model for this study based on the given hypotheses.

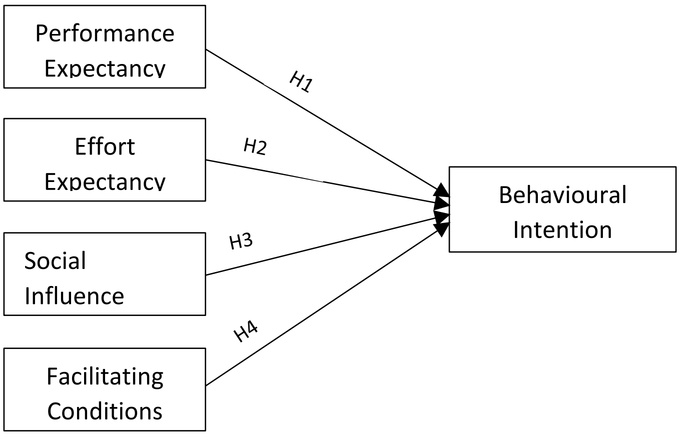

Figure 1: Research Model and Hypotheses

Methodology

Participants

A total of 200 questionnaires were distributed among higher education educators in Yunnan, a province in southwest China, via the Wen Juan Xing (WJX) online survey platform. To ensure data accuracy, data were collected only from the educators teaching in higher education sectors, and each respondent could only take the survey once. The research was designed in a way that ensures respondents' privacy and anonymity. Furthermore, participation in the research study was completely voluntary and optional. After obtaining the data from the sample, it was screened for missing cases and outliers. Outliers are extreme responses that are reported inconsistently within a particular construct. Outliers can impact the outcome of an analysis by skewing the mean and altering the normal distribution. After the screening process, 193 valid responses out of the 200 collected questionnaires were retained for analysis.

Among the participants,121 (62.69%) were males, while 72 (37.31%) were females. The majority of respondents (*n* = 103, 53.37%) reported that they were between the ages of 31 and 40. Diverse academic disciplines were represented by educators (e.g., engineering, science, education and medicine). At the time of the study, 42 (21.76%) of the participants were professors, 67 (34.72%) were associate professors, 31 (16.06%) were assistant professors, 42(23.32%) were lecturers, and eight (4.14%) were teaching assistants. In terms of teaching experience, 72 higher education educators (37.31%) reported that they had been teaching for sixteen years or more, 26 educators (13.47 %) for eleven to fifteen years, 52 educators (26.94 %) for six to ten years, and 43 educators (22.28 %) for five years or less. Furthermore, the majority of respondents (64.25%) had received professional training in integrating big data technology into teaching. Table 1 displays the respondents' demographic information.

Table 1
Demographic Information of Respondents

Demographics		**Frequency**	**Percentage (%)**
Gender	Male	121	62.69
	Female	72	37.31
Age	30 years old and below	15	7.77
	31–40 years old	103	53.37
	41–50 years old	53	27.46
	51 years old and above	22	11.40
Academic Rank	Professor	42	21.76
	Associate professor	67	34.72
	Assistant Professor	31	16.06
	Lecturer	45	23.32
	Teaching Assistant	8	4.14
Teaching Experience	Less than or equal to 5	43	22.28
	6-10 years	52	26.94
	11-15 years	26	13.47
	More than or equal to 16	72	37.31
Professional Training	Yes	124	64.25
	No	69	35.75

Instruments

The research instrument was developed using validated scales from the relevant literature to collect data for testing hypotheses. The measures, however, were adapted and modified to fit with the purpose of this study. To achieve the objectives of this research, the researcher employed a questionnaire developed by (Venkatesh et al., 2003). The questionnaire was divided into main three sections. In the first section, the participants were asked to provide demographic information such as gender, age, teaching experience, and experience with big data technology. In the second section, participants were asked to answer questions regarding their knowledge and application of big data. The third section of the questionnaire included 33 items related to the five constructs of this study. The items measuring effort expectancy (6 items), performance expectancy (7 items), facilitating conditions (8 items), social influence (6 items), and behavioural intention (6 items) were adapted from the UTAUT (Venkatesh et al., 2003). Responses to questionnaire items regarding the study's constructs were rated to a five-point Likert scale with anchors ranging from 1 "strongly disagree" to 5 "strongly agree." The researcher used back-to-back translation to translate the English questionnaire into Chinese and then asked language specialists to review its accuracy to ensure consistency between the Chinese and English questionnaires.

Data Analysis and Results

First, the data were examined for violations of the assumptions of normality, linearity, homoscedasticity, and multi-collinearity. There were no major concerns about the data obtained. Second, descriptive statistics (i.e., means and standard deviations) were obtained to provide basic information about the scales.

Following that, a principal component analysis was used to determine whether the factor analysis for the measurements was empirically distinct and conceptually validated. Furthermore, the survey questionnaire reliability and validity were assessed using exploratory factor analysis, which was followed by confirmatory factor analysis (Hair et al., 2020). Finally, to evaluate the study's model fit and test the hypotheses, the analysis of moment structures software AMOS version 24.0 was employed for structural equation modelling (SEM) (Hair et al., 2020; Tabachnick & Fidell, 2019).

Exploratory Factor Analysis (EFA)

Before conducting confirmatory factor analysis (CFA), EFA assesses the dimensions of each scale. Factor loadings are determined using principal component analysis and a varimax rotation. According to the meaning of the item in the scale and the rotation component matrix, the factor loading is greater than 0.5 indicating that it can be used as an important item for analysis (Hair et al., 2010). The results showed that the factor loading for each item in each dimension was greater than 0.5 and each item did not cross-load on other factors. The variance explained by each factor was 27.62% for facilitating conditions, 12.08% for performance expectancy, 9.66% for social influence, 8.60% for behavioural intention, and 5.65% for effort expectancy. The cumulative variance explained 63.64% of the overall variation.

Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis was used to assess how well the data fit the measurement model. The results suggested an adequate model fit (χ^2 = 639.66, χ^2/DF = 1.31, $p < .001$, TLI = 0.94, CFI = 0.95, IFI = 0.95, GFI = 0.84, and RMSEA = 0.041. Convergent validity was tested by using composite reliability (CR) and average variance extracted (AVE) measures. As shown in Table 2, the results for CR and AVE are much higher than the threshold values of 0.70 and 0.50, respectively (Fornell & Larcker, 1981). According to the findings, each item was significantly correlated with its related construct. Furthermore, the results showed that the square root of the AVE values was significantly larger than all other cross-correlations, implying that the discriminant validity was ascertained (see Tables 2 and 3).

Table 2
Reliability and Convergent Validity

Variable	**Loading**	**AVE**	**CR**	α
Performance Expectancy		0.531	0.888	0.887
PE1	0.696			
PE2	0.713			
PE3	0.712			
PE4	0.684			
PE5	0.806			
PE6	0.756			
PE7	0.727			
Effort Expectancy		0.570	0.888	0.888
EE1	0.710			
EE2	0.737			
EE3	0.779			
EE4	0.811			
EE5	0.728			
EE6	0.759			
Social Influence		0.575	0.890	0.889
SI1	0.713			
SI2	0.744			
SI3	0.725			
SI4	0.756			
SI5	0.838			
SI6	0.766			
Facilitating Conditions		0.542	0.904	0.904
FC1	0.741			
FC2	0.823			
FC3	0.747			
FC4	0.705			
FC5	0.673			
FC6	0.746			
FC7	0.743			
FC8	0.701			
Behavioural Intention		0.585	0.894	0.893
BI1	0.727			
BI2	0.736			
BI3	0.854			
BI4	0.796			
BI5	0.755			
BI6	0.710			

Note: AVE = average variance extracted, CR = composite reliability, α= Cronbach’s coefficient alpha.

Table 3
Discriminant Validity

Variable	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Behavioural Intention
Performance Expectancy	**0.729**				
Effort Expectancy	0.253	**0.755**			
Social Influence	0.198	0.197	**0.758**		
Facilitating Conditions	0.406	0.171	0.160	**0.736**	
Behavioural Intention	0.534	0.134	0.182	0.456	**0.765**

Note: Diagonal (in bold) represents the square root of the AVE

Hypothesis Testing Results

After establishing the reliability, convergent validity, and discriminant validity of the constructs, the structural model was evaluated to determine the percentage of variance predicted by the model (R^2). Moreover, the size of the path coefficients as well as the significance of the hypothesised relationships were evaluated. The results of the structural model analysis are shown in Figure 2. The results suggested that the four predictors (performance expectancy, effort expectancy, social influence, and facilitating conditions) explain 35.7% of the variance in intention to use big data technology, indicating that the independent variables explained approximately 36% of the variation in the dependent variable. Moreover, the study examined the size of the proposed relationships among the latent variables. The results revealed that performance expectancy ($\beta = 0.415$, $t = 6.31$, $p < .001$) and facilitating conditions ($\beta = 0.283$, $t = 4.39$, $p < .001$) had positive and significant impacts on behavioural intention. Therefore, H_1 and H_4 were supported. However, the effects of effort expectancy ($\beta = 0.031$, $t = 0.51$, $p > .05$) and social influence ($\beta = 0.062$, $t = 0.99$, $p > .05$) on behavioural intention were statistically insignificant, and therefore, H_2 and H_3 were not supported. Table 4 and Figure 2 show the hypothesis testing results.

Table 4
Results of Hypotheses Testing

Hypotheses		Path coefficient	*t*-value	Results
H_1	PE→ BI	0.415	6.311	Supported
H_2	EE→ BI	0.031	0.510	Not supported
H_3	SI→ BI	0.062	0.994	Not supported
H_4	FC→BI	0.283	4.395	Supported

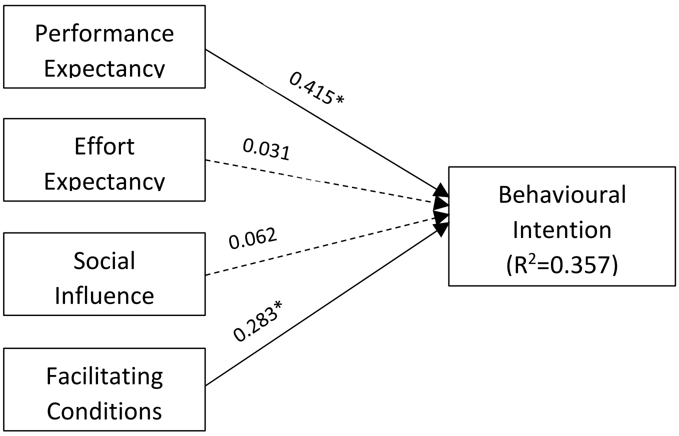

Figure 2: Structural Model with Hypothesis Testing Results
*Significant at $p < 0.001$; Dotted lines indicate non-significant paths

The study also examined the impact of gender, age, and teaching experience on the behavioural intentions of college educators in Yunnan Province to use big data technologies in teaching. The independent samples *t*-test results revealed that there was no significant difference in higher education educators' behavioural intention to use big data technology in teaching based on gender. Furthermore, the one-way ANOVA results revealed that there were no significant differences in educators' behavioural intentions to use big data technology in teaching based on age or teaching experience.

Discussion and Implications

Determinants of Acceptance of Big Data Technology

This study empirically validated the proposed research model, which was based on the UTAUT. The model included the UTAUT model's key predictive variables, which are performance expectancy, effort expectancy, social influence, and facilitating conditions. The empirical results of the research indicated that, of all the determinants, performance expectancy had the greatest influence on behavioural intention to use big data technology among the UTAUT explanatory variables. This significant relationship is consistent with previous research (Radovan & Kristl, 2017; Teo & Noyes, 2012), which concluded that performance expectancy is a key factor influencing teachers' intention to adopt new technologies. Other studies (Brünink, 2016; Sahid et al., 2021; Cabrera-Sanchez & Villarejo-Ramos, 2019) also found positive and significant effects of performance expectancy on the intention to use big data technology. This result implies that if educators believe that using big data technology will benefit their careers, they will be more likely to accept it. As a result, there needs to be an awareness about the usefulness of big data technology in the higher education sector. It is also critical for institutions to increase perceived performance expectancy by emphasising the value-adding properties of big data technology usage. Higher education institutions need to consider highlighting the importance of big data technology in industry as well as the benefits of using it.

Surprisingly, contrary to Venkatesh et al (2003), there was no significant impact of effort expectancy on behavioural intention to use technology in the context of big data acceptance. This finding was consistent with those of Pynoo et al (2011); Radovan and Kristl (2017), who concluded that teachers' intentions to use technology were not influenced by effort expectancy. Similarly, Queiroz and Pereira (2019); Brunink (2016) also found that effort expectancy did not have a significant effect on behavioural intention to use big data technology. According to the findings, effort expectancy was not a predictor of behavioural intention to use big data. This implies that user friendliness is not regarded as an important factor for educators' acceptance of big data. This may be explained by the fact that big data is considered a technology that is pre-determined to be difficult to use, and this does not influence the intention to use it.

Furthermore, the results revealed that social influence was not a predictor of behavioural intention to use big data. This means that the views and opinions of one's social circle have no significant impact on one's behavioural intention to use big data technology. This study's findings was consistent with those of Birch and Irvine (2009); Pynoo et al (2011), and Alshmrany and Wilkinson (2017), who all found that social influence had no effect on teachers' intention to adopt the technology. Queiroz and Pereira (2020) also found that social influence had no effect on behavioural intentions to adopt big data. Given the nature of big data technologies, one explanation could be that utility factors (e.g., performance expectancy) are major determinants of behavioural intention to use the technologies, leaving social influence as a weak explanatory variable.

Moreover, facilitating conditions were found to positively impact the behavioural intention to use big data technology. This finding is consistent with other studies on big data technologies (Alryalat et al., 2013; Paver et al., 2014). Queiroz and Pereira (2019) and Cabrera-Sanchez and Villarejo-Ramos (2019) also found that facilitating conditions can be good predictors of behavioural intentions to use big data. This finding suggests that higher education institutions need to develop supportive environments for integrating big data technology into teaching. Teachers should receive high quality big data acceptance training so that a strong and accessible support function can be built around the use of big data. In addition, a strong feedback system is required so that teachers can offer insightful suggestions on how universities can further enhance the use of big data technology in teaching.

Roles of Gender, Age and Experience Differences

This study also investigated the influences of gender, age, and teaching experience on Yunnan Province college educators' behavioural intentions to adopt big data technology in teaching to highlight differences in these issues. The results showed that there were no statistically significant differences among college educators in their intentions to use big data technologies based on gender, age, or teaching experience. These results are mainly explained by the fact that the use of big data technology in teaching is in its infancy in Yunnan Province (Zhang et al., 2020), and most teachers of different ages and genders have few differences in experience in using big data technology in education. Al-Shawi and Al-Wabil (2013) proposed a similar argument that age and gender differences do not play critical roles in the use of new technologies, mainly because people have equal access to technological tools, especially in the educational context. Brunink (2016) also found that the differences in the intention to use big data technology between men and women of different age groups may have narrowed so that they are not significant anymore.

The research model, which has several important implications for the higher education sectors as described in this study, has been empirically validated. In conclusion, understanding the variables that affect intention to use big data technologies can encourage and direct educators in Yunnan universities to use the technologies in their teaching. To increase the level of educators' performance expectations and ultimately promote the intention to use big data technology, the university administration can create incentive mechanisms and hold competitions for teaching big data technology. Additionally, universities and colleges should set up technical support platforms to help educators overcome these barriers. Experts in technical support platforms can do their best to help educators solve problems in using big data technology in teaching and thus further promote the continued use of big data technology by educators.

Limitations and Future Research Directions

It is important to address the limitations of the present study. First, this study focused on educators' intentions to use big data technology in their teaching. However, the intention to use big data technology is only an indicator for the actual behaviour of using big data technology, which may or may not necessarily turn into actual big data technology usage in the future. Future research could look into how the intent to use big data technology in education relates to actual usage behaviour.

Second, the purpose of this study was to look into higher education educators' intentions to use big data technology in their teaching in Yunnan Province. Therefore, future research should broaden its scope to include higher education in other parts of China.

Third, this study used an online questionnaire collection platform to collect data and used a quantitative research method. Thus, it is recommended that future studies include experimental designs as well as qualitative methods such as observations and interviews to provide a deeper understanding of the factors that influence higher education educators' intentions and actual usage behaviours in using big data technology in teaching through various forms of data.

Lastly, for this research, four influencing factors were selected, namely performance expectancy, effort expectancy, social influence, and facilitating conditions, which were obtained from the UTAUT model. However, educators from various subject areas and regions may be influenced differently by the use of big data technology depending on the specific requirements of the subject they teach and the surrounding environment. Consequently, future research could include other models such as the Model of PC Utilization, TAM, etc., based on UTAUT, to account for a greater number of potential influencing factors.

Conclusion

The UTAUT model has been widely used in all major fields, and the education field is no exception. To understand the factors that influence intention to use big data technology in teaching among higher education educators in Yunnan, this study examined the four independent variables (performance expectancy, effort expectancy, social influence, and facilitating conditions) of the model as well as the dependent variable (behavioural intention). The study also examined other variables, namely gender, age, and teaching experience, to understand the statistical differences in educators' intentions to adopt big data technology in teaching. From the study, it is clear that performance expectancy and facilitating conditions were the main factors that influenced educators' intentions to use big data technology. The results of this study also found no significant influences from gender, age, and teaching experience differences on educators' intentions to use big data technology. This research is significant in that it suggests productive directions for university educators, university policy makers, and administrators to facilitate educators' adoption of big data technology in teaching to further achieve universities' teaching goals. Based on this, it is hoped that all parties will propose improvements to make the adoption of big data technology more beneficial and enjoyable for all educators in the future.

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