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BIG DATA ANALYTICS ADOPTION VIA LENSES OF TECHNOLOGY ACCEPTANCE MODEL: EMPIRICAL STUDY OF HIGHER EDUCATION

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Abstract. The goal of this study was to establish a model to quantify the adoption of big data in relation to education and to translate the adoption of big data in literature into the educational context. This study hypothesizes that encouraging situations, perceived risk, perceived usefulness, perceived ease of use influence the attitude of the students towards use and the intention to use behavior, in turn impacting the adoption of big data in education, this research used the Technology Acceptance Methodology (TAM) model. Through analyzing 282 university students, the present thesis followed quantitative data collection along with analysis procedures. Therefore, the responses of students were grouped into seven testing constructs and evaluated to understand their adoption influence. Accordingly, data were subsequently quantitatively analysed utilising Structure Equation Modelling (SEM). The findings revealed that facilitating conditions, perceived risk, perceived usefulness, perceived ease of use were important determinants of the attitude of students towards use and behavioral intention to use big data, and 71.2% of acceptance was also significant for the attitude of students towards use and behavioral intention to use big data.

Keywords: Big Data Adoption; Technology Acceptance Model (TAM); Empirical Study

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JEL Classifications: I21, I25

1. Introduction

Nowadays, humanity develops data about our behaviors at an exponential growth rate. This knowledge covers, for instance, our mobile phones and their location, all online sales, the Internet of Things, social networks, wearables, etc. A major competitive advantage (Matthews et al., 2022) is gained by universities who are able to turn this data into real-time customer information and knowledge. Usage data allows universities and colleges to understand why their students buy their products, the best times for deals, and how to improve learning. Big data companies

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(Ogbuke et al., 2022) can manage large volumes of data and become market leaders, almost in real time. Big data adoption, implementation, and management also requires university students to develop new skills and knowledge. The task of such big data adoption is increasingly becoming important as data infuses and manages digital evolution. Presented that universities are at an early stage of using big data adoption, it is timely and important to review factors that influence big data adoption technologies at universities. A research by Gartner (Ranjan, & Foropon, 2021) shows that more than three-quarters of organisations are anticipating or engaging in big data, recognizing the important and relevant characteristics that affect the organizational adaptation of this technology. Reviews from 200 (approximately) journal papers along with many conference proceedings related to the adoption of big data so far indicate that less analysis is conducted on features that affect adoption (Georgiadis & Poels, 2022). In addition, considering the lack of analysis into the deciding factor of the adoption report on big data adoption (Iftikhar et al., 2022). The current research therefore intends to establish a model proposing an acceptable view of the departure for future studies on the implementation of big data adoption. In this context, investigation is being performed on certain variables that are likely to influence universities' acceptance of big data adoption technologies, such as TAM variables with adoption factors. The cause of these errors is unknown, aside from being badly examined (Batko & Ślęzak, 2022). There is also a need for more intentional and systematic analysis to determine the speed of organisations to change big data. Sustainable growth and sustainable competitive advantage are becoming more dependent on the ability of every institution to use big data, innovations and the sharing of knowledge management (Ead et al., 2021; Karnan, 2022). However, not as much literature has been found about how different variables impact the acceptance of big data or the present problems that emerged during the implementation of the adoption of big data. There was also a shortage of a detailed structure in this respect, including a lack of references about how to develop and use certain institutional frameworks (Batko& Ślęzak, 2022). In addition, as shown in (Gusc et al., 2022), the existing systems are primarily technical-oriented. In comparison, recent research on the adoption of big data have focused primarily on technological features (for example, technical algorithms or machine learning) in addition to model development (Park & Kim, 2021). There have been several studies focused on the theoretical analysis performed on the fields of big data adoption, but there is a study deficiency that explores the relation between the adoptions of TAM variables. As a result, seven variables have been examined in the latest research on the acceptance of big data by students in educational institutions.

2. Theoretical Model and Hypotheses Development

In education, Big Data has transformed technology and learning in general. Different complementary and conflicting models for the adoption of studies have been developed by adoption research, primarily related to the adoption of the information system (IS), including information technology (IT). TAM by (Davis, 1989) is the most dominant theoretical contribution to the adoption study and is generally used by academics to analyze technology adoption. In the current research, seven influences on the acceptance of big data were analyzed as follows: Facilitating Conditions (FC), Perceived Risk (PR), Perceived Usefulness (PU), Perceived Ease of Use (PEU) Students' Attitude toward Use (AT) Behavioural Intention to Use (BIU), And Big Data Adoption in Education (BDA), see Figure 1.

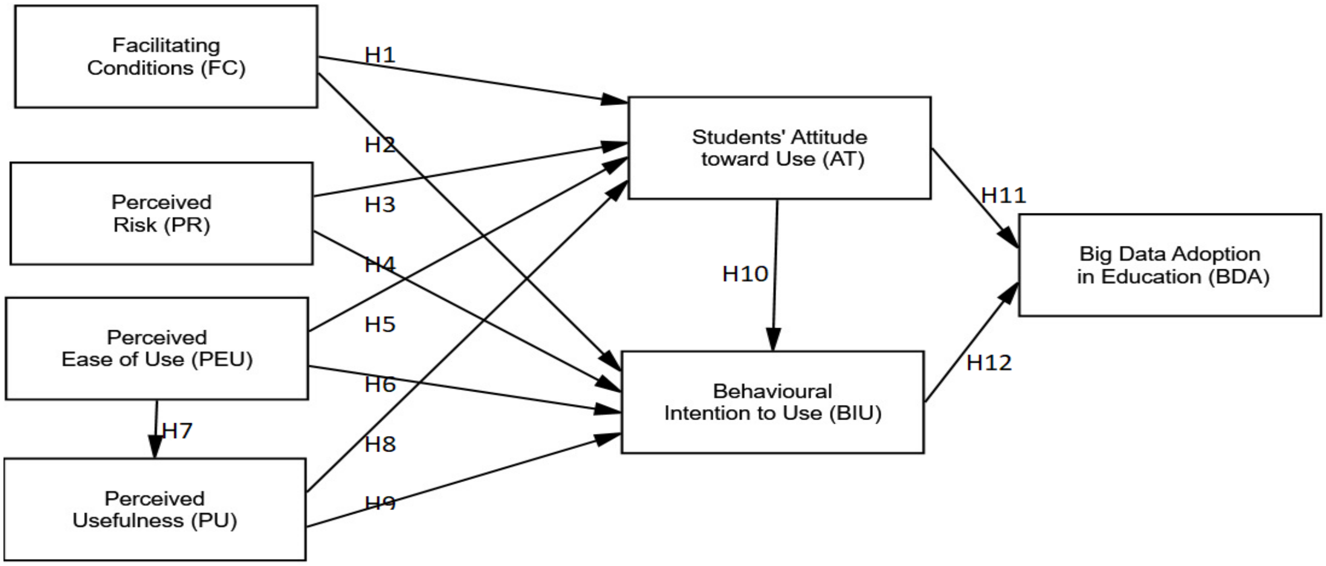

Figure 1. Research Model and Hypotheses
Source: Authors

2.1 Facilitating conditions (FC)
FC are favorable since the tools required to use a new approach and manage it subsequently are easy to access (Venkatesh et al., 2003). (Venkatesh et al., 2012) observed in later studies using TAM that this construct has an important effect on the behavioral motivation to use a new technology. This beneficial effect on behavioral intent has also been supported by more recent findings (Cabrera-Sánchez et al., 2021; Kaur & Arora, 2022). The use of new technology has a positive influence on conditions of relaxation. This beneficial effect on behavioral intent has also been confirmed by more recent findings (Cabrera-Sánchez et al., 2021; Kaur & Arora, 2022). The use of new technology has a positive influence on conditions of relaxation. Numerous subsequent works (Al-Rahmi et al., 2022; Chauhan & Jaiswal, 2016) also affirm this relationship. Therefore, this research use this factor (FC) to measure to students' attitude toward use and behavioural intention to use big data in education. The following hypotheses were suggested based on the discussion above:
H1: FC is positively associated with AT.
H2: FC is positively associated with BIU.

2.2 Perceived Risk (PR)
The current strategy must take risk as a critical consideration into account, mostly due to the complexity of the adoption big data in learning impacts. Cunningham distinguishes expected risk by two variables that determine the future and ambiguity by which uncertainty corresponds to the arbitrary probability of something not happening by students, whereas consequence is risk of effects following final verdict (Jain & Raman, 2022), Bauer defined perceived risk as a concoction of uncertainty and the significance of the consequences (Osakwe et al., 2022). Featherman and Pavlou noted that the perceived risk is sometimes referred to as a sense of suspicion as to the potential detrimental effects of the use of a service or product (Liu & Tao, 2022). Perceived risk is the choice that individuals decide regarding the magnitude and uniqueness of a risk prior to the system's usage. Previous study has found that the recognition of technological adoption has been taken into consideration (Shank et al., 2021; Zhang et al., 2021; Chen et al., 2022). Luo, Zhang and Shim stressed the relevance of multi-faceted risk perception when contemplating a technology implementation framework (Shahid et al., 2022). The implementation of big data is risky and various significant threats found by the McKinsey Global Institute have been taken into account in this study (Di Vaio et al., 2022). Therefore, this research use this factor (PR) to

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measure to students' attitude toward use and behavioural intention to use big data in education. The following hypotheses were suggested based on the discussion above:
H3: PR is positively associated with AT.
H4: PR is positively associated with BIU.

2.3 Perceived Usefulness (PU)
PU is the degree to which any person expects that it will increase her or his job output using a technology (Davis, 1989; Chen et al., 2022). In describing the implementation of technology, Tan and Teo explained the assumed usefulness as an essential determinant (Yeong et al., 2022). The keenness of a person to handle a complex method is considered to be useful (Li, Mao, & Liu, 2022). User efficiency is demonstrated by the usefulness and ease of using technical observations (Bansah & Agyei, 2022). Therefore, this research use this factor (PU) to measure to students' attitude toward use and behavioural intention to use big data in education. The following hypotheses were suggested based on the discussion above:
H5: PU is positively associated with AT.
H6: PU is positively associated with BIU.
H7: PU is positively associated with PEU.

2.4 Perceived Ease of Use (PEU)
PEU is referred to as the degree to which individuals feel that little or no effort should be taken to use any given technology (Davis, 1989). Likewise, PEU was defined as how well a user is doing what is required for a handling system and how simple it is to receive the system, mental work needed to connect with the systems, and ease of using the systems (Al-Rahmi et al., 2021; Alyoussef et al., 2019). Empirically, it has been found that perceived ease of use is an indicator of adoption of technology (Chen et al., 2022; Venkatesh & Bala, 2008; Mitra et al., 2022). In the past, some scholars have not provided significant data as to whether the TAM construct would have an effect on the perceived ease of use of technology (Yeong et al., 2022). Therefore, this research use this factor (PEU) to measure to students' attitude toward use and behavioural intention to use big data in education. The following hypotheses were suggested based on the discussion above:
H8: PEU is positively associated with AT.
H9: PEU is positively associated with BIU.

2.5 Students' Attitude toward Use (AT)
In this analysis, attitude is defined as any actions relevant to big data adaption by the students. It has been hypothesized that the mentality is closely associated with the intent of utilizing actions. Without a pre-defined target, the big data revolution has developed a data management mentality, embracing a bottom-up, inductive approach to big data analysis, exploration and research (D'Hauwers & Walravens, 2022; Chatterjee et al., 2022; Brossard et al., 2022). Attitude towards, which is defined as the attitude of students to big data adaptation, has been included based on the TAM. The Attitude towards mentality is expected in this study to have a statistically significant correlation with the behavioral purpose of reacting to big data. Therefore, this research use this factor (AT) to measure to students' behavioural intention to use and big data adeption in education. The following hypotheses were suggested based on the discussion above:
H10: AT is positively associated with BIU.
H11: AT is positively associated with BDA.

2.6 Behavioural Intention to Use (BIU)
BIU is the the eagerness to use and continue using technology, which defines the use of technology. In addition, in this exploration, the adoption of big data is an important factor in the models of building technology utilization (Davis, 1989; Venkatesh et al., 2003). The theories listed are from TAM theories that have seen the adoption of big data as a result of attitude towards particular behavior and basic rules that were later extended to add perceived influence BIU (Venkatesh & Bala, 2008). In the same way, the perceived ease of use and perceived

utility reflect the trust of the critical students after adoption, resulting in higher levels of student satisfaction and a strategy for persistence (Cheng et al., 2022). Therefore, this research use this factor (BIU) to measure to big data adeption in education. The following hypothesis were suggested based on the discussion above:
H12: BIU is positively associated with BDA.

2.7 Big Data Adoption (BDA)
According to Singh et al. (2022) Big Data Adoption is an intelligence source characterized by such high speed, scale, and diversity that needs specific analytical methods and technologies to turn them into meaning. An analysis by (Ranjan, & Foropon, 2021) reveals that three-quarters (approximately) organisations have either invested or are preparing to invest in big data, and it is timely and critical to find reasons that influence organizational acceptance of big data adoption. There are limited types of literature on big data adoption in higher education systems (Kumar & Kumar, 2022), spite of the exponential development of study on big data adoption in other fields. The effect on the Higher Education system of big data implementation technologies would promote teacher inquiry, provide opportunities to methodically analyze training exercises, devise methods to find better learning frameworks (Rolf et al., 2022) and provide insights for teachers to represent their teaching strategies as well as how they influence learning outputs (McDowall et al., 2021). These are extensively utilized by scholars for adopting variation of technology, together with organizational big data adoption (Wu et al., 2022; Park et al., 2022; Kornelia & Andrzej, 2022; Gvishiani et al., 2022).

3. Research Methodology

The research was conducted on both postgraduate and undergraduate students in relation to the sampling and population to assess the adoption of big data for learning. Items in the TAM theory questionnaire were tested by students on the basis of the 5-point Likert scale. Students who received the surveys manually have been asked to complete their information and include their views on the adoption of big data for learning. For data analysis, which was extracted from the questionnaires, the Statistical Package for Social Sciences (SPSS) was used. Specifically,' SEM- Amos' was used as the key data analysis method. This technique of using SEM-Amos has taken effect through two major phases: evaluation of construct validity, convergent validity, discriminant validity of measurements; and structural model analysis. Both of these steps have been adopted by the recommendations (Hair et al., 2012).

3.1 Sample Characteristics and Data Collection
311 questionnaires were manually deployed, but only 299 were sent back to the students, representing 96.1 percent of them. Since 3 incomplete surveys were excluded, 296 were analysed using SPSS. 2 further surveys were excluded: 5 were incomplete details and 7 were outliners. Once this omission was completed, the total number of eligible surveys was 282. According to (Hair et al., 2012), this exclusion stage has highlighted that this method is important since the presence of outliers may be a justification for imprecise results. From the demographic data of the respondents: 123 (43.6 %) are male, 159 (56.4 %) are female, 21 (7.4 %) are in the 25-29 age group, 241 (85.5 %) are in the 30-35 age range, 20 (7.1 %) are above 36 years of age. 36 (12.8 %) of respondents were from social science, 94 (33.3 %) of respondents were from engineering, and 152 (53.9 %) of respondents were from science and technology, in contrast to the demographic variables of specialization, see Table 1.

Table 1. Demographic Data of the Respondents

Factor		Number	%
Gender	Male	123	43.6
	Female	159	56.4
Age	25-29	21	7.4
	30-35	241	85.5
	above 36	20	7.1
Specialization	social science	36	12.8
	engineering	94	33.3
	science and technology	152	53.9

Source: Authors

3.2 Measurement Instruments

To satisfy the goal of maintaining content validity, objects in the constructs have been adapted. There are mainly two aspects of the survey. The first section is about the demographic data of the age, gender, level of education. The second section includes the questionnaire used in this analysis. Four elements from (Habibi et al., 2020) have been modified from previous studies promoting condition, perceived risk was adapted four from (Jain & Raman, 2022; Shahid et al.,2022), perceived usefulness was adapted five items from (Davis, 1989), perceived ease of use was adapted five items from (Davis, 1989), students' attitude towards use was adapted four items from (Venkatesh & Bala, 2008), behavioural intention to use was adapted four items from (Venkatesh & Bala, 2008), and big data adoption in education was adapted five items from (Al-Rahmi et al., 2022; Saravanan et al., 2022).

4. Result and Analysis

The Alpha reliability coefficient outcome of Alpha value was 0.910 TAM hypothesis that influenced the acceptance of big data. The Discriminant Validity Assessment (DV) was evaluated using three criteria, namely: Index between variables that must be below 0.80 (Hair et al., 2012), the average variance extracted (AVE) value of each construct that requires to be equal to or greater than 0.50 and the square value (AVE) of each construct that needs to be greater than the factor-correlated inter-construction correlations (IC) (Fornell & Larcker, 1981). In comparison, the results of the factor loading (FL) crematory factor analysis (CFA) have to be 0.70 or more, although the results of the Cronbach Alpha (CA) have been agreed to be 0.70 (Hair et al., 2012). Researchers have also added that composite (CR) reliability must be 0.70.

4.1 Measurement Model Analysis

For data processing, this analysis employed AMOS 23. Specifically, as primary research methods, It has incorporated both structural equation modelling (SEM) and confirmatory factor analysis (CFA). Therefore, in order to validate the measurement model, (Hair et al., 2012) extended the criteria for goodness-of-fit, Uni-dimensionality, convergent validity, reliability along with discriminant validity such as standardized chi-square, degree of freedom/chi-square (χ2- 3908.523/1219), relative fit index (RFI- .947). The normed fit index (NFI-.959), the comparative fit index (CFI-.978) of the Tucker-Lewis coefficient (TLI-.979), the incremental fit index (IFI-.969), the root mean square approximation error (RMSEA-.047) and the root mean square residual (RMR-.035) are all methods that can be used to test the model estimation method that facilitating conditions, perceived risk, perceived usefulness, perceived ease of use effect the students' attitude toward use and behavioural intention to use, in turn in effect big data adoption in education.

4.2 Reliability and Validity of Measures Model

In this research the method of validity is used to verify the scale of the difference, along with other theories, between a hypothesis and its measures (Bagozzi et al., 1998). Discriminant validity, through review in this context, was positive for both hypotheses, assuming that the values were above 0.50 (cut-off value) at p=0.001

(Fornell & Larcker, 1981). In conformity with (Hair et al., 2012), the correlation of the factors in any two given constructs shall not surpass the square root of the average variance shared by them in one construct. The resulting composite reliability (CR) values, in addition to those of Cronbach's Alpha (CA), remained about 0.70 and above, although the results of the average variance extracted (AVE) remained about 0.50 and higher, the total loading factor (FL) remained relevant as it complied with certain measurement (Hair et al., 2012; Fornell & Larcker, 1981). The following sections comment further on the estimation model's results. In order to assess the validity of the discriminant, the validity and reliability results with which the average variance extracted (AVE), CR and Cronbach's Alpha (CA) were all accepted are also indicated. Both (CR) values have been noted to range from 0.879 to 0.932, which means they are over the cut-off value of 0.70. In comparison, the resulting (CA) values range from 0.842 to 0.919 and reach the cut-off value of 0.70. AVE value of 0.599 to 0.682 is also over 0.50. Both of these outcomes are positive and significant (FLs) and agree with the criteria for traditional evaluation (Hair et al., 2012; Fornell & Larcker, 1981). Refer to table 2 and table 3.

Table 2. Confirmatory Factor Analysis Results

Factors	Items	Factor Laoding	AVE	CR	CA
Perceived Usefulness	PU1	.788	.599	.904	.917
	PU2	.841			
	PU3	.823			
	PU4	.794			
	PU5	.892			
Perceived Ease of Use	PEU1	.881	.611	.882	.907
	PEU2	.846			
	PEU3	.738			
	PEU4	.880			
	PEU5	.798			
Perceived Risk	PR1	.836	.602	.894	.907
	PR2	.812			
	PR3	.875			
	PR4	.846			
Facilitating Conditions	FC1	.807	.682	.932	.842
	FC2	.846			
	FC3	.753			
	FC4	.864			
Students' Attitude toward Use	AT1	.891	.611	.907	.900
	AT2	.846			
	AT3	.794			
	AT4	.866			
Behavior Intention to Use Big Data	BIU1	.810	.611	.911	.919
	BIU2	.863			
	BIU3	.884			
	BIU4	902			
Big Data Adoption	BDA1	.854	.644	.879	.890
	BDA2	.877			
	BDA3	.895			
	BDA4	.865			
	BDA5	.794			

Source: Authors

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Table 3. Validity and reliability for the Model

Factors	Code	PU	PEU	PR	FC	AT	BIU	BDA
Perceived Usefulness	PU	.921						
Perceived Ease of Use	PEU	.341	.901					
Perceived Risk	PR	.370	.435	.836				
Facilitating Conditions	FC	.433	.348	.330	.890			
Attitude toward Use	AT	.324	.456	.412	.400	.870		
Behavior Intention to Use	BIU	.442	.501	.409	.382	.411	.879	
Big Data Adoption	BDA	.394	.345	.323	.467	.349	.402	.902

Source: Authors

4.3 Structural Model Analysis

The path modeling research in the current study was used to construct a model to measure facilitating conditions and perceived risk with TAM model variables on learning adoption of big data. The effects are showed and compared in the hypothesis testing discussion, according to the model. Subsequently, factor analysis (CFA) was conducted on SEM to evaluate the suggested hypotheses as seen path model results in Figure 2 and hypotheses testing in Figure 3 for the second step.

Figure 2 and Figure 3 above indicates that the findings of this study have accepted all hypotheses via path model results and hypotheses testing. In addition, Table 4 below indicates that the key model statistics were fit, demonstrating model validity and hypotheses by showing the values of standard errors and then unstandardized coefficients of structural model testing coefficients.

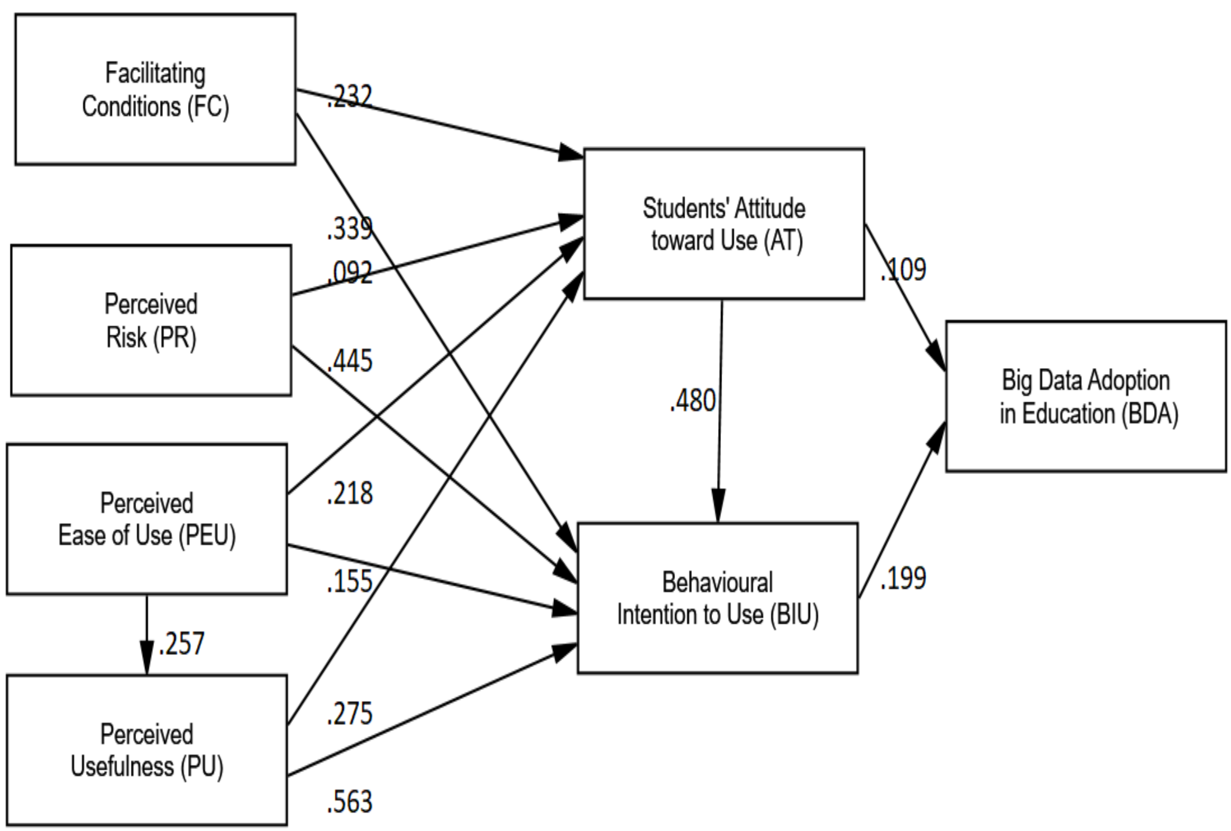

Figure 2. Path Model Results
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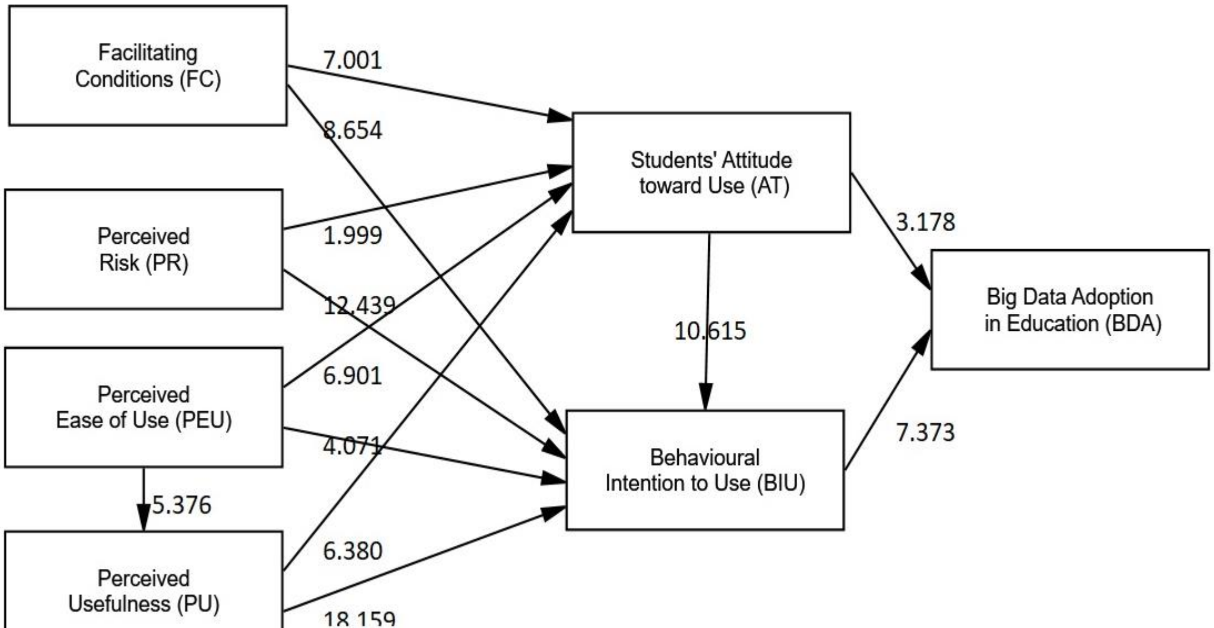

Figure 3. Hypothesis Testing
Source: Authors

Table 4. Structural Model Hypothesis testing results

Hypotheses	items	Relationsh	items	Estimate	S.E	C.R	P	significant
H1	FC	→	AT	.232	.033	7.001	.000	Yes
H2	FC	→	BIU	.339	.039	8.654	.000	Yes
H3	PR	→	AT	.092	.046	1.999	.046	Yes
H4	PR	→	BIU	.455	.037	12.439	.000	Yes
H5	PU	→	AT	.218	.032	6.901	.000	Yes
H6	PU	→	BIU	.155	.038	4.071	.000	Yes
H7	PU	→	PEU	.257	.048	5.376	.000	Yes
H8	PEU	→	AT	.275	.043	6.380	.000	Yes
H9	PEU	→	BIU	.563	.031	18.159	.000	Yes
H10	AT	→	BIU	.480	.045	10.615	.000	Yes
H11	AT	→	BDA	.109	.034	3.178	.001	Yes
H12	BIU	→	BDA	.199	.027	7.373	.000	Yes

Source: Authors

As shown in Table 4, all hypotheses were accepted as all the seven factors were found to be statistically significant. Facilitating Condition-> Students' Attitude toward Use (β=0.232, t=7.001), Facilitating Condition-> Students' Behavior Intention to Use (β=0.339, t=8.654), Perceived Risk-> Students' Attitude toward Use (β=0.092, t=1.999), Perceived Risk-> Students' Behavior Intention to Use (β=0. 455, t=12.439), Perceived Usefulness -> Students' Attitude toward Use (β=0.218, t=6.901), Perceived Usefulness -> Students' Behavior Intention to Use (β=0.155, t=4.071), Perceived Usefulness-> Perceived Ease of Use (β=0.257, t=5.376), Perceived Ease of Use -> Students' Attitude toward Use (β=0.275, t=6.380), Perceived Ease of Use -> Students' Behavior Intention to Use (β=0.563, t=18.159), Students' Attitude toward Use -> Students' Behavior Intention to Use (β=0.480, t=10.615), Students' Attitude toward Use -> Big Data Adoption (β=0.109, t=3.178), and finally, Students' Behavior Intention to Use-> Big Data Adoption (β=0.199, t=7.373). Thus, confirming hypothesis number 12 is positive and supported. The in line with previous findings ((Georgiadis & Poels, 2022; Gvishiani et al., 2022; Fayda-Kinik, 2022; Naderi et al., 2022).

4.4 Discussion and Implications

The purpose of this research was to cultivate a novel about how to explore the variables affecting the adoption of big data by facilitating conditions and perceived risk with TAM model. According to the proposed model, the relationships between the seven creative characteristics with the facilitating conditions, perceived risk, perceived usefulness, perceived ease of use, attitude of students towards use, behavioral intention to use, and adoption of big data in education were examined. Big data adoption is at an early stage, but is steadily improving as significant investments are made in the implementation of novel technology and techniques (Moturi et al., 2022). Big data adoption is observed by organisations around the world in popular media and academic journals. For sharing information, the use of big data characterizes both potential and challenge. It is foreseeable that the implementation of big data would sweep away the sharing of information and knowledge, consigning it to a drawer of institutional history (Al-Rahmi et al., 2021b; Sayaf et al., 2022). Alternatively, the adoption of big data could lead information management back to the dark eras, with a strong focus on correlation and technology and the recorded heightened risk of failures (Sayaf et al., 2021). Big data adoption, on the other hand, is struggling with many similar dilemmas and challenges posed for years by the sharing of information and knwoledge, the foregrounding of technology over human sociology and the phenomenological perspective of knowledge. One problem with sharing knowledge and information is that it has been and continues to be a highly dis-integrated area. This study could also provide possibilities for the implementation of big data adaptation by university students. In General, the results validated and explores the factors of (TAM) to investigate facilitating conditions, perceived Risk, perceived usefulness, perceived ease of use, students' attitude toward use, behavioural intention to use, in turn, affect big data adoption in education, this is our research findings support students' attitude toward use and behavioural intention to use big data. Results concurred with the previous investigation indicate that facilitating conditions, perceived risk, perceived usefulness, perceived ease of use, attitude of students towards use, behavioral intention to use had significant positive effects on learning adoption of big data ((Georgiadis & Poels, 2022; Venkatesh et al., 2012; Zhang et al., 2021; Chen et al., 2022; Di Vaio et al., 2022; Kornelia & Andrzej, 2022; Gvishiani et al., 2022; Al-Rahmi et al., 2021c; Alhussain et al., 2020). In addition to transactional data used by many organisations, there are also significant treasure troves of mature, less structured adoption of big data knowledge that can be used for valuable information (Al-Rahmi et al., 2021c; Behera et al., 2022). Twitter, Facebook, Google+, Linked, are used these days for online activities by top college students. In addition, users are familiar with Flickr where their photographs can be uploaded, semantria.com to manage perception mining or sentiment analysis, ebay.com to buy or sell goods, and crowd sourcing functions by Amazon.com, these are forms of big data application (Al-Maatouk et al., 2020; Al-Rahmi et al., 2020a). Data is also available from instruments, cameras, websites, telephony, social networks, medical records and e-commerce. In addition, the internet and web-based social networking adoption of big data has increased rapidly in simplicity and speed, and social networking platforms today allow public exchange of information, engagement, and collaborative learning (Alamri et al., 2020a; Alamri et al., 2020b). The use of Big Data adoption to provide teaching materials to facilitate students' adoption of technology must be demonstrated by the faculty. Furthermore, the findings would indicate that faculty should explain how technologies can assist students and help them study Big Data adoption or achieve other learning goals. A positive behavioural intention to adopt big data is gained by students who believe they can benefit from the adoption of big data. Similarly, this analysis provides two methodological bits of knowledge. The first empirical effects of students' attitude to use, behavioral intention to use conditions that facilitate, perceived risk, perceived usefulness, perceived ease of use. The second observational evidence of students' attitude toward use, behavioural intention to use that can influence big data adoption in learning. This research has provided outstanding results, it has certain limitations, the limitations being that one university was limited by the sample size of the research. As a result, the findings do not disclose the success of colleges, military, or school lecturers from non-governmental institutions. Other limitations are that only questionnaires were included in this study. In the study, no qualitative data are examined, and the research is focused on only the expectations of students, which may differ with the perception of teachers. Also, the analysis does not consider

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variations within fields of analysis. Future studies, however, are recommended to adopt surveys in different countries, with various views and reflect these constraints further.

5. Conclusion and Future Research

The findings of our study endorse students' attitude to use and behavioral intent to use through facilitating conditions, perceived risk, perceived usefulness, and perceived ease of use for big data education adoption. The results also confirmed the use of the TAM model in researching students' attitude towards use and their behavioural intention to use big data. As a result, overall outcomes may have been enhanced by a plan that integrates conditions of facilitation and perceived risk with the TAM model. Given the importance of the behavioural intention of students to use big data, future research would have to consider developing guidelines for teachers on the Big Data adoption initiative for educational programs in different fields. Future research in this field on the use of big data adoption in educational institutions must also be considered by teachers and other higher education leaders. Although this study indicates that students may find it quite positive, limitations and facilitators should be examined. Exploring and evaluating perspectives from and with other countries would also enrich the findings achieved in the current study and build a larger perspective on how higher education adoption of Big Data is perceived.

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