Received February 19, 2019, accepted March 5, 2019, date of publication March 25, 2019, date of current version April 18, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2906668

Big Data Adoption and Knowledge Management Sharing: An Empirical Investigation on Their Adoption and Sustainability as a Purpose of Education

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This work was supported in part by the Research Management Centre (RMC), Universiti Teknologi Malaysia (UTM), under Grant PY/2018/02903: Q.J130000.21A2.04E40, and in part by the Deanship of Scientific Research at King Saud University under Grant RGP-1435-003.

ABSTRACT The aim of this paper to develop a model to measure sustainability for education and incorporate the literature big data adoption and knowledge management sharing in the educational environment. This paper hypothesizes that perceived usefulness, perceived ease of use, perceived risk, and behavioral intention to use big data should influence adoption of big data, while age diversity, cultural diversity, and motivators should impact knowledge management sharing. Therefore, knowledge management sharing influences behavior intention to use technologies and big data adoption would be positively associated with sustainability for education. This paper employed a version of TAM and motivation theory as the research framework and adopted quantitative data collection and analysis methods by surveying 214 university students who were chosen through stratified random sampling. Student's responses were sorted into the 11 study constructs and analyzed to explain their implication of sustainability on education. The data were then quantitatively analyzed using structural equation modeling (SEM). The results showed that perceived usefulness, perceived ease of use, perceived risk, and behavioral intention to use big data were significant determinants of big data adoption, while age diversity, cultural diversity, and motivators were significant determinants of knowledge management sharing. The knowledge management sharing, behavior intention to use technologies, and big data adoption succeeded in explaining 66.7% of sustainability on education. The findings and implications of this paper are provided.

INDEX TERMS Big data adoption, knowledge management sharing, motivators, technology acceptance model (TAM).

I. INTRODUCTION

At present, sources of power being shifted from finance, capital and land to knowledge and information [1]. On this regard, exploring big data is extremely significant. Practice has revealed questionable accomplishment from big data application. Organizations usually do not receive appropriate benefit from the usage of big data. The cause of this failure is unclear and yet not well-investigated [2]. Hence, there needs a more deliberate and systematic study for assessing readiness of organizations to implement big data. A sustainable advantage and development are now becoming increasingly dependent on organization's capability to cope up big data, as well as knowledge management sharing [3].

The associate editor coordinating the review of this manuscript and approving it for publication was Yulei Wu.

As data drives the digital revolution, role of Big Data turns out to be increasingly important. Provided that universities inside Malaysia are at initial stage of using Big Data, learning factors that affect implementation of Big Data techniques in Malaysia is timely and critical. A study by Gartner [4] suggest approximately three-quarter organizations are planning to invest on Big Data, considering the aspects that effect adoption of Big Data technology by organizations is crucial. So far, reviews on 200 (approx.) conference proceedings journal articles on the topic of Big Data demonstrate that only few researches are done on factors effecting adoption [5], [6]. Furthermore, given scarcity of the research onto determinants of implementation in Big Data literature [5], [6]. Thus, this research aims to develop a model offering suitable idea of departure for the future exploration on adoption of Big Data. Of researches that exist on subject [7]–[9], some had specifically studied technological component. Furthermore, despite strong progress in Malaysia technology education for managing, accessing and analyzing Big Data. In this regard, research is conducted on factors which are inclined to affect Big Data technology adoption by universities in Malaysia for example knowledge management sharing factors with adoption factors. Understanding what inspires members of any organization or team to share skills or knowledge is important to improve knowledge sharing [10]; though, findings in this knowledge management fields are indecisive regarding promoters sharing knowledge. According to Elias and Ghaziri [11] describes knowledge as an abstraction at higher level that presents in person minds, noting that knowledge is broader, richer and problematic to catch than information or data. Some definitions on knowledge management are already suggested by several researchers. According to Nonaka and Konno [12] knowledge management can be defined like 'a technique for improving and simplifying the procedure of creating, sharing, distributing, and considering company knowledge'. While Knowledge sharing is most crucial procedure of knowledge management, Gupta and Govindarajan [13] defined knowledge sharing is like a technique of identification, transmission inflow and outflow of knowledge in term of "activities of transferring or disseminating knowledge from one person, group, or organization to another." Moreover, Srivastava *et al.* [14] demarcated the knowledge sharing concept including facts sharing, suggestions, ideas and expertise opinion with others.

Learners need specific knowledge and training on questions and problems of sustainability, training for teachers about sustainability is a crucial part of these processes and should consider their different educations and backgrounds, also the matter of sustainability of education should be a significant part of formal learning as well as training process, as they introduce it to peers [15]. Generally, understanding various dimensions of sustainability have demonstrated to be challenge for learners [16]. Many learners might not feel competent for including sustainability matters in learning [17]. Hence, studying in-service subject learners' skills and knowledge to implement sustainability as a purpose of education is a significant subject of research. Usually universities keep role for the knowledge development, offering many undergraduate and postgraduate subjects, for example architecture, law, engineering, sciences, economics and management. Because of these backgrounds and disciplines, diverse approaches are needed to be measured to add main features of sustainability with university curricula following coherent way. An interdisciplinary and multidisciplinary approach is needed too, since sustainability includes several scientific and technical areas [18], [19]. There remains lack of comprehensive framework on this respect and lack of explanations on how to use and build such frameworks in organization [2]. Moreover, as stated in [20], the prevailing framework is primarily technical focused. There are no maturity frameworks which address big data adoption related to temporal dimension as well as their implementation on organization's development issues. A point to note is that past research on big data has focused primarily on the technical attributes (such as machine learning or technical algorithms) and development of system [21]. However, not much research is found on how different factors effect big data adoption or the challenges encountered during implementation. In this research eight factors will be examined the big data adoption for sustainability of education. From the theoretical area, there are many researches, which have been conducted on the fields of big data adoption and intention of use, But there are a lack of research that examine the relationship between knowledge management sharing and big data adoption. thus, this research to investigation an empirical on big data adoption for sustainability of education, there are no research which has been empirically conducted that exploit these variables empirically to improve the successful adoption of big data by government's in education organizations.

II. THEORETICAL MODEL

Innovation adaptation research, that primarily deal with acceptance of information technology and information systems (i.e IT and IS), has formed variety of complementary and competing models to study adoption. According to Rogers' [22] and Davis' [23] Diffusion of Innovations (DOI) and Technology Acceptance Model (TAM) represent the most powerful theoretical emphasis to innovation adaptation literature, also, being extensively utilized by scholars to explore a variety of technological innovations adoption [24]. A review on IT adoption study shows that the features of innovations mostly belong to IT adoption literatures [24], [25]. Both TAM and DOI share similar premise that adopters assess innovations on the perception of their characteristics, or postulates that innovations having favorable features are likely to be more adopted [22], [23]. In addition, value-oriented aspects including perceived usefulness and relative advantage [22], [23], effort-oriented features for example perceived ease to use and complexity [22], [23], compatibility [22] are repeatedly been observed as major reasons manipulating adoption of inventions [26]. This is considered a significant theoretical contribution to previous Technology Acceptance

Model (TAM) with Innovation Diffusion Theory (IDT) in the educational context [27], [28]. Both of the motivation theory and technology acceptance model are combined in this research to develop a model to measure the sustainability for education through big data adoption and knowledge management sharing.

A. BIG DATA ADOPTION

Big Data are Information asset categorized by high Velocity, Volume and Variety to have Technology or Analytical techniques for its conversion towards Value [29]. Gartner [4] suggests that three-quarters (approximately) of organizations already invested or preparing to invest on Big Data, visualizing the features that impact adoption of Big Data technology is timely and crucial. Regardless of research expansion on Big Data in several sectors, there found limited research in using Big Data at higher education [30]. Big Data application at Higher Education sectors will encourage tutor inquiry, supply prospects to analytically explore teaching activities and discover methods for outlining improved learning contexts [31], offer insights to reflect teacher's teaching practice as well as how it affects the learning outcomes [32]. According to Hameed *et al.* [24] DOI, TAM, and Technology-Organization-Environment (TOE) by [22], [23]; are the most significant and commonly utilized theoretical perception framework on IT invention adoption. These are extensively implemented by scholars to study the adoption of varieties of innovations, as well as organizational level approval of this Big Data [7]–[9]. In literature studies on Big Data's privacy and security concerns, a study by Salleh and Janczewski [5] presented how these security concerns affect Big Data adaption by various organizations. By describing technology of Big Data like an IT invention, TAM, DOI, and TOE frameworks has become related to Big Data adaption [33]. Therefore, empirical back-up for constructive influence of IT experts on IT adaption across the range of inventions has been observed, including the context of the adoption of Big Data [9].

1) PERCEIVED USEFULNESS (PU)

PU is the extent where any individual trusts that using specific system would develop his or her performance of job [23], [34]. Tan and Teo clarified on perceived usefulness as an imperative determinant in explaining the adoption of technology innovations [35]. An individual's keenness to manage specific systems are already said to be perceived usefulness [36]. User behavior is clarified by usefulness and ease of using perceptions on technology and social media [37]–[39].

2) PERCEIVED EASE OF USE (PEU)

PEU had been stated as the degree at which persons believe that utilizing specific technology should be effort free or less effort [23]. Similarly, perceived ease of use was described as how well for a user in handling system and easiness of attaining the systems to accomplish what is necessary, mental effort needed interaction with system, and easiness of using that system [40]. Empirically, PEOU was found to be a predictor for technology acceptance [34], [41]. Some researchers in the past have not discovered significant evidence whether this construct of TAM would keep effect on perceived ease of use on technology [35], [42].

3) PERCEIVED RISK (PR)

New technology should consider risk as an important factor primarily due to the uncertainty of the adoption resulting to impact on financial. Cunningham segregate perceived risks into two determinants which is consequence and uncertainty whereby uncertainty refer customers' subjective probability of anything happens or not, whereas, consequences are hazard of results next to decision-making [43]. Bauer in his seminal work defined perceived risk as a concoction of uncertainty and momentousness of outcome engaged [44]. Featherman and Pavlou stated that perceived risk is often described as feeling of doubt concerning potential negative outcomes of utilizing a product or service [45]. Perceived Risk (PR) is the particular decision by people make on the uniqueness and significance of a risk before applying use of the system. Literature review found that it was a factor to be considered for the acceptance of technology adoption [22], [34], [46] Luo, Zhang and Shim stressed the importance of multi-faceted perception of risk when deliberating a construct for adoption on technology innovation [47]. Big Data come with risk, several key risks developed by McKinsey Global Institute were considered for this study [48].

4) BEHAVIOURAL INTENTION TO USE (BIU)

BIU is the eagerness to use or continuation of using technology, also, the factors that determine usage of technology [49]. Moreover, in this research, big data adoption is the important element in constructing models for technology utilization [23], [41] According to Venkatesh and Bala [41] these said models and philosophies are from philosophies of TRA which consider big data use as the role of attitude concerning specific behavioral and particular norms that was later prolonged to add perceived control, hence TPB. Similarly, perceived ease to use and perceived usefulness reflect a vital user's post-adoption confidence that results in improved levels of user gratification and persistence plan [50]. Behavioral intention to use E-learning was found to the highly influenced by the factor named as perceived usefulness [51].

B. KNOWLEDGE MANAGEMENT SHARING

It is the construction and transmission of knowledge having a goal to turn individual knowledge to organizational knowledge. Thus, Knowledge sharing is interacting understanding or knowledge with an expectation to gain more understanding or insight [52]. Knowledge management relies on motivators for sharing knowledge [53]. To progress in knowledge sharing, it is essential to understand what motivates team members of any organization or team to share skill or knowledge [53], [54]. Knowledge management deals with practices

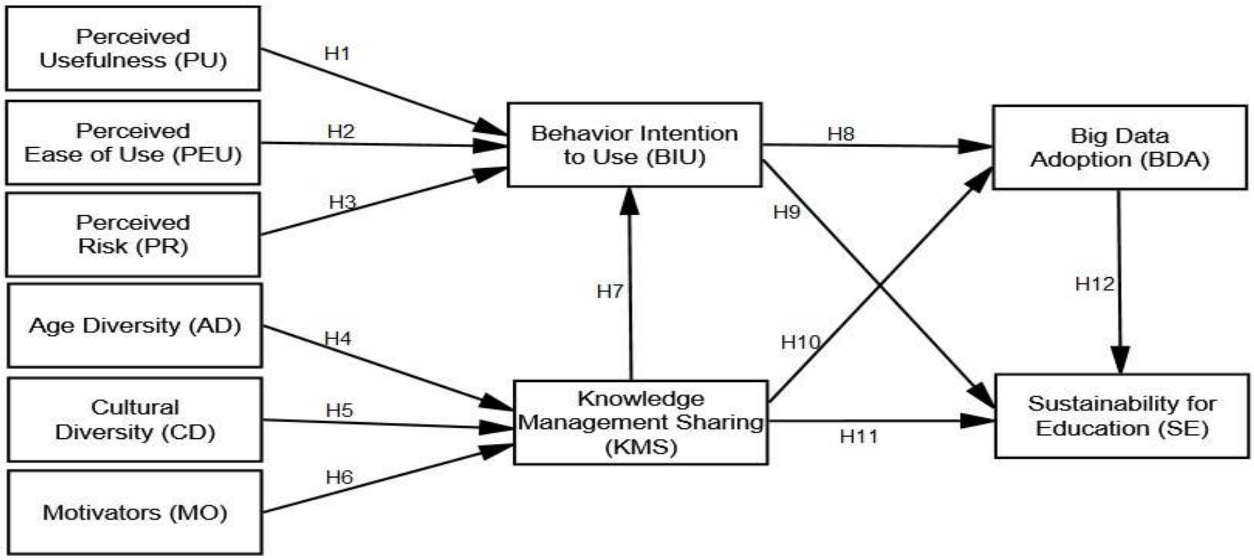

FIGURE 1. Research model and hypotheses.

and processes which enable creation, acquisition, sharing and capturing of knowledge [55]. Though, it is previously being stated big data analytics is a significant segment of knowledge management sharing [56].

1) AGE DIVERSITY (AD)

AD turned to a challenge for institutions or organizations in the developed countries. Due to increased prosperity, lesser birth rates and upgrading health systems, the ratio of persons over 60 years has augmented [57]. Similarly, ageism and age prejudices are increased in western societies too [58] pointing stereotypical beliefs regarding competence of particular age cohorts supplying a fertile base for myths on age diversity effects. Henceforth, knowledge regarding consequences of age diversity for team results are important to managers for estimation of rewards and risks of age diversity. Previous research investigating relationship amongst team outcomes and age diversity exposed inconsistent consequences [59]. Therefore, it is not clear whether age diversity has a negative or positive effect at team outcomes or even it is related at all or not. Even past meta-analysis could not solve mixed findings [60] since these studies included various diversity attributes for example age, ethnicity and gender in diversity indices like demographic diversity and examined relationship amongst accumulated team outcomes and these indices [61]. Age diversity arouses social classification processes among team members, it inhibits expansion of task related perspectives and information [62]. Age diversity teams comprise team member who has gathered diverse organizational, task, or lifetime skills [63], giving more variation at task-relevant perceptions and task-solving abilities [64]. The integration and exchange of deviating perspectives and knowledge should lead towards more innovative and creative solutions [65]. Revelation to deviating perspectives should forward to critical debates about task accomplishment, hence stimulating creativity, problem solving and reflective thinking [66].

2) CULTURAL DIVERSITY (CD)

CD is termed as the difference amongst groups with obvious cultural backgrounds, diverse worldviews as well as views that affect communications [67]. There are several findings on culture influences on knowledge management. Several literatures showed no data that cultural diversification have impact on knowledge managing practices [13], [68]. Similarly, Simonin [69] also observed no evidence where cultural distinctions made effect on uncertainty of knowledge sharing. In contrast, there are several studies which showed impacts onto knowledge management sharing [70]. According to Finestone and Snyman [71] cultural diversity creates barriers at knowledge sharing. In the same way, [72] evaluated cultural influences on behavioral knowledge sharing in teams. It came out that distinct team member's cultural backgrounds are because of ethnicities, national culture, gender, and functions produce a framework of cultural complicacy, which may influence sharing of knowledge in negative way. Another study shows cultural differences rise difficulties of transporting explicit knowledge where increase is lesser for those related with tacit knowledge sharing management [73]. In addition, other studies found no connection between knowledge sharing and cultural diversity [74].

3) MOTIVATORS (MO)

Fullwood *et al.* [75] found that motivators for educators in United Kingdom, sharing knowledge are one of the extrinsic motivations for promotion. Nevertheless, from a survey involving medical professionals of Kuwait, most respondents stated that they haven't receive monetary rewards for knowledge sharing and their major motivation to share was a wish to help and learn from others [76]. These finding recommends that other features for example industry or cultural context may mediate the relationship among knowledge and rewards sharing. The study displays that demotivators and motivators effect this sharing. Demotivators and motivators like industry, culture, and age have been observed to effect sharing of knowledge [53]. These authors also identified extrinsic and intrinsic demotivators and motivators to share skill or knowledge. Demographic features for example age; education and gender have been detected to be both demotivators and motivators to sharing of knowledge. However, another study observed in Saudi Arabia, companies having these characteristics keep insignificant effect on the knowledge-sharing attitude [77]. But, in other survey, two major motivators for the improved sharing of knowledge were stated improving performance and effective communication channels (Rahman, 2011). Besides extrinsic and intrinsic motivators, social factors are found to effect sharing of knowledge [78]. Tan and Ramayah [79] observed intrinsic motivators for enjoyment and commitment in serving others positively impacted knowledge sharing amongst academics of Malaysia.

C. SUSTAINABILITY AS A PURPOSE OF EDUCATION

Sustainability is extensively perceived as domain of the environmental instructors: ''promoters of sustainability at higher education system have tendency to originate from fields of the environmental education, facilities management and studies'' [80]. The word sustainability presents opportunity for regeneration of old schooling systems based on competitive values or principles and based on predatory views of world. ''Education for sustainability means educating for the emergence of a different, possible world'' [81]. The perception on sustainability is complicated and it travels beyond sustainable developments [81]. To us, the term sustainability is the vision of living better. It is an active balance among others and environment; sustainability is harmony amongst differences. According to Antunes [82] developing practical-theoretical teaching tools necessary for education for the sustainability is a task of education/pedagogy corresponding to the Earth Pedagogy, in short, the 'pedagogy of sustainability'. Leonardo Boff believes the class of 'sustainability,' is key to ecological cosmovision, may constitute any anchors of new pattern of civilization that seeks to coordinate human beings, improvement and Earth understand as Gaia. According to Haan [83] education for the purpose of sustainability has now converted to a 'new field of action and learning' [83] which comprises building competencies and new skills [84]. Some universities and institutions are encouraged for adapting such teaching materials and even to advance new events based on their economic and social context. As cultural diversity turns it tough for teachers or instructors to accept sustainability concepts, various cultural aspects and perspectives need to be measured in expansion of teaching tools [85]. Maximum postgraduate and graduate courses contain mandatory corse and minimum time is offered to think new courses to teach sustainability. But there remains possibility to insert them straight into curricula [19], [85]. Lifelong learning's are important for sustainable development as it makes possibility to inspire person to involve them in such subjects from child to adult stage. Simple concepts and principles of sustainability are possible to introduce, for instance, by hands-on scientific experiments, demonstrations or just by joining in the public debates [15].

III. RESEARCH METHODOLOGY

Two experts were consulted for the evaluated the questionnaire's content. Prior to data collection, a permit for this purpose was obtained from Universiti Teknologi Malaysia (UTM). Regarding the population and sampling, the study was conducted on undergraduate and postgraduate students to measure the sustainability for education through big data adoption and knowledge management sharing. The items in the questionnaire on Technology Acceptance Model (TAM) and motivation theory were rated by students based on a 5-point Likert scale. The students, who manually received the questionnaires, were asked to fill in their details and provide their perspectives of the sustainability for education through big data adoption and knowledge management. The Statistical Package for the Social Sciences i.e SPSS was applied for data analysis obtained from questionnaires. In particular, Structural Equation Modeling (SEM- Amos) was utilized as major tool of data analysis. The process of using SEM- Amos was of two main stages: assessing the construct validity, the convergent validity, and the discriminant validity of the measurements; and analyzing the structural model. These two steps followed the recommendations by Hair *et al.* [86].

A. SAMPLE CHARACTERISTICS AND DATA COLLECTION

244 questionnaires were manually distributed and only 233 forming 95.5% of them were returned to the researchers. After excluding 6 incomplete questionnaires, 227 were analyzed using SPSS. Additional 4 questionnaires were excluded: 3 were of missing data and 6 were outliners. The total number of the valid questionnaire was 214 after this exclusion. This step of exclusion is considered by [86] who highlighted that this process is important to be carried out since the existence of outliers might be a reason for imprecise outcomes. In terms of the demographic details of the respondents: 75 (35.0%) were males, 139 (65.0%) were females, 15 (7.0%) were in the age range of 25-29, 181 (84.6%) were in the age range of 30-35, 18 (8.4 %%) were above 36 years of age. Regarding the demographic factors of specialization, 20 (9.3%) of the respondents from social science, 61 (28.5) of the respondents from engineering, and 133 (62.1%) of the respondents from science and technology.

B. MEASUREMENT INSTRUMENTS

The items of the constructs were adapted to meet the purpose of ensuring content validity. The survey is mainly of two parts. The first section is on the respondents' demographic details such as age, gender, educational level. The second section contains 25 items adapted from the measurement by

TABLE 1. Summary of goodness fit indices for the measurement model.

Type of measure	Acceptable level of fit	Values
Chi–square (χ2)	≤ 3.5 to 0 when perfect fit and (ρ > .01)	3443.750/1082
Normed Chi–square (χ2)	Value should be greater than1.0 and less than 5.0	3.183
Root-Mean Residual (RMR)	Close to 0 (perfect fit)	.031
Normed Fit Index (NFI)	equal to or bigger than 0.90.	.968
Relative Fit Index (RFI)	equal to or bigger than 0.90.	.956
Incremental Fit Index (IFI)	equal to or bigger than 0.90.	.961
Tucker Lewis Index (TLI)	equal to or bigger than 0.90.	.978
Comparative Fit Index (CFI)	equal to or bigger than 0.90.	.976
Root-Mean Square Error of Approximation (RMSEA)	below 0.10 designates good fit; below 0.05 means very good fit.	.047

Davis [23] and Venkatesh and Bala [41]. The third and final section, which is designed based on knowledge management sharing factors, includes 24 items adapted from the previous studies [87].

IV. RESULT AND ANALYSIS

The result of Cronbach's Alpha reliability coefficient was 0.912 of the TAM and motivation factors which have an influence on big data adoption and knowledge management sharing for sustainability of education. The evaluation of discriminant validity (DV) was conducted through the use of three criteria namely: index among variables which should be below 0.80 [86], the average variance extracted (AVE) value of each construct that needs to be equal to or above 0.50, and square of (AVE) of each construct that has be above, in value, than the inter construct correlations (IC) connected with the factor [88]. Furthermore, crematory factor analysis (CFA) results with factor loading (FL) should be 0.70 or over while the results of Cronbach's Alpha (CA) are agreed to be $\geq$ 0.70 [86]. The researchers also add that composite reliability (CR) should be $\geq$0.70.

A. MEASUREMENT MODEL ANALYSIS

The current study used AMOS 23 for data analysis. In particular, both SEM and CFA were applied as the major tools of analysis. Uni-dimensionality, convergent validity, reliability, discriminant validity was used to assess measurement model. Hair *et al.* [86] emphasized that goodness-of-fit guiding principle, like normed chi-square, normed fit index (NFI), chi-square/degree of freedom, relative fit index (RFI), Tucker-Lewis coefficient (TLI) comparative fit index (CFI), incremental fit index (IFI), parsimonious goodness of fit index (PGFI), root mean square error of approximation (RMSEA) and root mean-square residual (RMR) are all tools that can are used as the procedures to assess the model estimation. The measure model of sustainability for education through big data, knowledge management sharing and innovation was evaluated by the goodness-of-fit indices and illustrated in Table 1 while Figure 2 illustrates measurement technology acceptance model (TAM) and innovation diffusion theory (IDT) of the sustainability for education through big data, knowledge management sharing and innovation.

B. VALIDITY AND RELIABILITY OF MEASURES MODEL

This type of validity is normally used to determine the size of the difference between a concept and its indicators with other concepts [89]. Based on the analysis in this regard, discriminant validity proved to be positive for all concepts since the values were above 0.50 (cut-off value) with $p = 0.001$ [88]. According to Hair *et al.* [86], correlations of items in any two given constructs should not be greater than square root of average variance shared by them in one construct. The resulting values of composite reliability (CR) and those of Cronbach's Alpha (CA) were around 0.70 and above while the results of average variance extracted (AVE) were around 0.50 and above which indicates that the whole factor loadings (FL) were significant as they meet the conventions of such assessment [86]. The sections below expand more on the findings on the measurement model. The results of validity and reliability as well as those of the AVE, CR and CA all were accepted are also illustrated establishing the discriminant validity. It is observed that all the values of (CR) are ranging between 0.894 and 0.931 which means that they are above the cut-off value of 0.70. The (CA) resulting values are also ranging between 0.837 and 0.939 exceeding the cut-off value of 0.70. The (AVE) are also above 0.50 ranging between 0.570 and 0.683. All of these results are positive and indicating significant (FLs) and they meet the conventional assessment guidelines [86]. See Table 2 and 3.

C. STRUCTURAL MODEL ANALYSIS

The path modeling analysis was used in this study to develop a model to measure the sustainability for education through TAM and IDT factors on their knowledge management sharing, adoption of big data and innovation. Based on the model, the results are presented and compared in the discussion of hypothesis testing. Later, being the second phase, factor analysis (CFA) was done on the structural equation modelling to test the proposed hypotheses as illustrated in Figure 3.

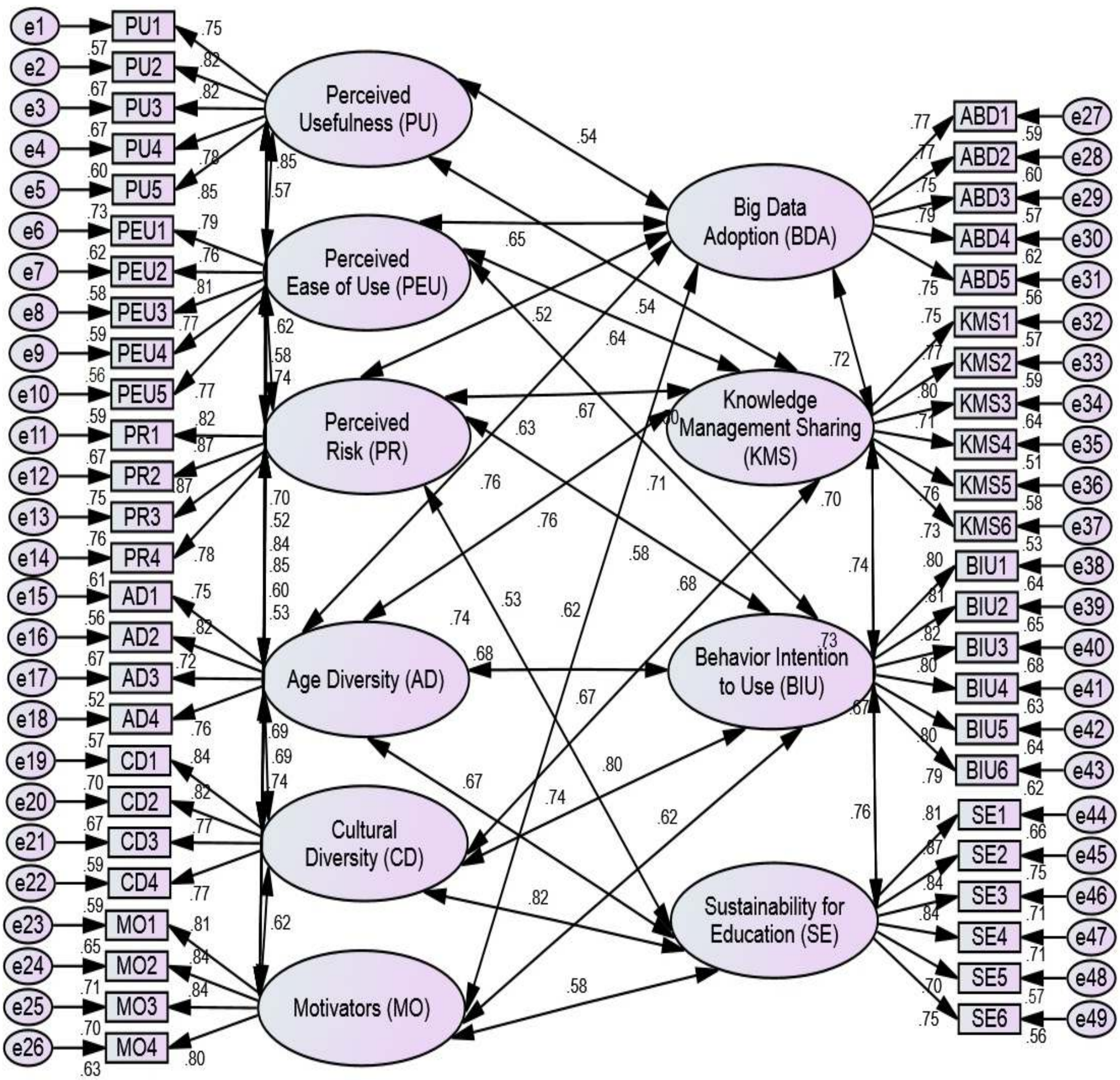

FIGURE 2. Measurement model.

TABLE 2. Confirmatory factor analysis results.

Factors	Code	AVE	CR	CA
Perceived Usefulness	PU	.622	.894	.906
Perceived Ease of Use	PEU	.589	.902	.837
Perceived Risk	PR	.570	.834	.893
Age Diversity	AD	.644	.904	.840
Cultural Diversity	CD	.683	.921	.909
Motivators	MO	.655	.913	.939
Behavior Intention to Use Big Data	BIU	.601	.885	.910
Knowledge Management Sharing	KMS	.615	.917	.925
Big Data Adoption	BDA	.641	.931	.889
Sustainability for Education	SE	.616	.911	.902

Figure 3 above illustrates that five hypotheses were accepted and only one was rejected based on the results of this study. Table 3 below indicates that main statistics of models are good, representing model hypotheses and validity testing results through illustrating the values of standard errors and unstandardized coefficients of structural model.

TABLE 3. Validity and reliability for the model.

Factors	PU	PEU	PR	AD	CD	MO	BIU	KMS	BDA	SE
PU	.832									
PEU	.411	.899								
PR	.390	.536	.901							
AD	.427	.430	.333	.888						
CD	.434	.392	.432	.454	.921					
MO	.458	.451	.412	.546	.499	.892				
BIU	.444	.423	.452	.598	.509	.502	.892			
KMS	.345	.495	.455	.432	.437	.532	.549	.909		
BDA	.389	.543	.531	.538	.498	.429	.323	.508	.929	
SE	.409	.456	.509	.481	.501	.489	.429	.499	.501	.911

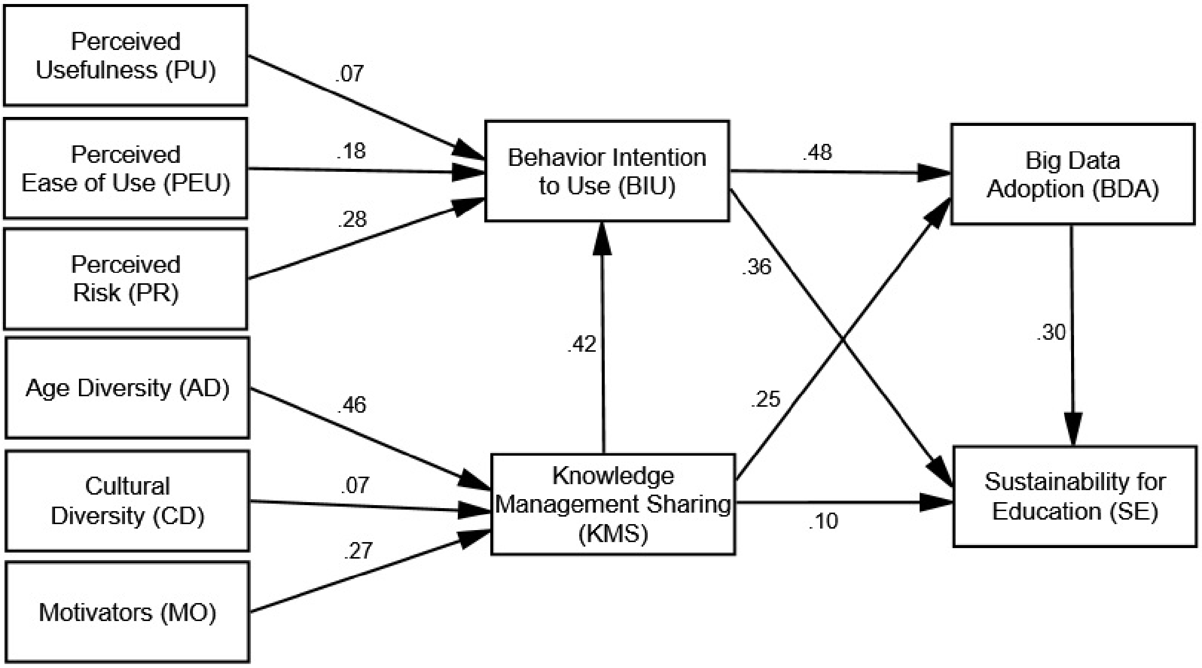

FIGURE 3. Results for the proposed path model (Estimate).

Regarding the first hypothesis, the relationship between perceived usefulness and behavioral intention to utilize big data attained following output ($\beta = 0.071$, t = 2.666, $p < 0.001$). Thus, first hypothesis proved positive, hence, supported. The second proposition is positive too, hence, supported, as the analysis indicates a relationship between perceived ease of use and behavior intention to use big data ($\beta = 0.183$, t = 6.182, $p < 0.001$). The next effect is relationship between perceived risks and behavior intention to use big data ($\beta = 0.276$, t = 7.744, $p < 0.001$). Thus, third hypothesis is positive and supported. The next hypothesis number four is a positive and supported, as the analysis also indicates a relationship between age diversity and knowledge management sharing achieved the following results ($\beta = 0.456$, t = 15.504, $p < 0.001$). Moreover, next hypothesis five is also positive and supported, as a relationship exists between cultural diversity and knowledge management sharing ($\beta = 0.071$, t = 1.943, $p < 0.001$). Nonetheless, based to the relationship between motivators and knowledge management sharing has a positive and significant with ($\beta = 0.273$, t = 6.634, $p < 0.001$) indicating that the 6th hypothesis proposed a positive and significant relationship. Added to the above results, the next hypothesis direct effect the relationship between knowledge management sharing and behavior intention to use big data ($\beta = 0.416$, t = 12.192, $p < 0.001$). Thus, the 7th hypothesis is positive and supported. The relationship between behavior intention to use big data and big data adoption has a positive and significant with ($\beta = 0.477$, t = 8.410, $p < 0.001$) indicating that the 8th hypothesis supported. Moving on to the hypothesis number nine, it proposed a significant relationship between behavior intention to use big data and sustainability for education ($\beta = 0.358$, t = 7.177, $p < 0.001$) indicating that the 9th hypothesis was supported. Also, the direct effect

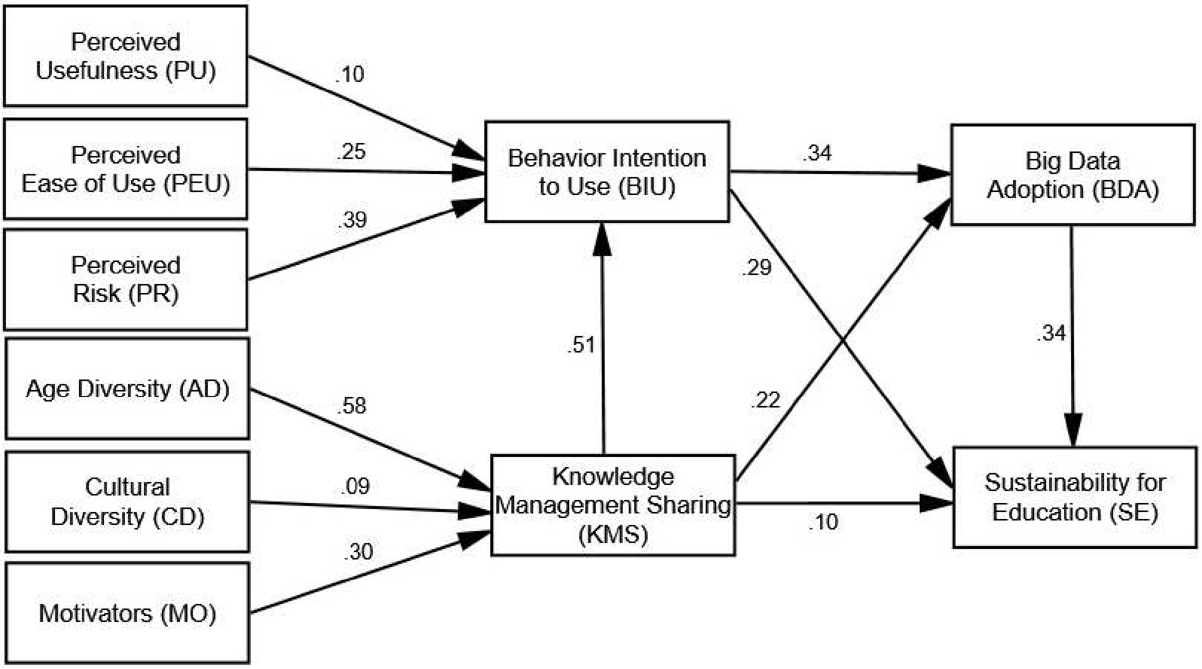

FIGURE 4. **Results for the proposed hypothesis testing model (T. Value).**

it's a positive and significant relationship between knowledge management sharing and big data adoption has a positive and significant with ($\beta = 0.246$, $t = 4.364$, $p < 0.001$). Thus, 10th hypothesis was accepted. The next hypothesis direct effect is knowledge management sharing has a positive and significant with sustainability for education ($\beta = 0.100$, $t = 2.081$, $p < 0.001$) indicating that the 11th hypothesis was supported. Finally, the results also confirm that big data adoption related to sustainability for education achieved the following results ($\beta = 0.304$, $t = 9.428$, $p < 0.001$). Thus, confirming hypothesis number 12 is positive and supported. The consistent with previous studies [5], [9], [15], [19], [75], [78], [81], [85].

D. DISCUSSION AND IMPLICATIONS

The purpose of the research was to cultivate a novel on how big data model adoption via merging knowledge management sharing with TAM to discover the features affecting students' behavioral intentions to knowledge management sharing and big data in the institution of higher education. This research was an innovative effort in applying knowledge management sharing into a big data adoption via TAM model. Based on the model proposed, the relationships between twelve innovative characteristics was explored with the perceived usefulness, perceived ease of use, perceived risk, big data adoption, age diversity, cultural diversity, motivators, knowledge management sharing, behavior intention to use big data and sustainability for education. Big data adoption is on its beginning but is growing rapid since substantial invests are made for the realization of novel technologies and techniques [90]. Information on popular media and academic journals point towards big data adaptions received by organizations worldwide. For knowledge management sharing, big data adoption presents both opportunity and threat. Any threat in there is foreseeable that Big Data Adoption shall sweep knowledge management sharing away, consigning it to drawers of organizational history. On the other hand, big data adoption might push knowledge management back to dark ages characterized by solid focus on correlation and technology, and the stated massive incidences of failures [91]. But alternatively, big data adoption is fighting with several same dilemmas and issues which knowledge management sharing has challenged for decades, specially foregrounding of the technologies over phenomenological or human sociological knowledge perspective. The main problem for knowledge management sharing is: it has been remained as highly non-unified field. Perhaps big data adoption offers opportunities to bring unity. There seen obvious synergies among two disciplines, where mutual lessons could be learned. These propositions open several fascinating avenues regarding future research. Some illustrations draw from knowledge management sharing perspective emphasizes new knowledge and innovation rising from the social interactions in teams with the study of Leonard and Sensiper [92]. From the results of statistical analysis, Table 3 shows all hypotheses are supported. Generally, the outcomes confirmed the research model and the hypotheses. The outcomes of this research deliver an insight into the knowledge management sharing; age diversity, cultural diversity and motivators, in turn, affect behavior intention to use big data for sustainability of education. As well, examines the factors of TAM to examine the perceived usefulness, perceived ease of use, perceived

TABLE 4. Hypothesis testing data of structural model.

H	Independent	Relationship	Dependent	Estimate	S.E	C.R	P	Result
H1	PU	⟶	BIU	.071	.027	2.666	.008	Supported
H2	PEU	⟶	BIU	.183	.030	6.182	.000	Supported
H3	PR	⟶	BIU	.276	.036	7.744	.000	Supported
H4	AD	⟶	KMS	.456	.029	15.504	.000	Supported
H5	CD	⟶	KMS	.071	.037	1.943	.049	Supported
H6	MO	⟶	KMS	.273	.041	6.634	.000	Supported
H7	KMS	⟶	BIU	.416	.034	12.192	.000	Supported
H8	BIU	⟶	BDA	.477	.057	8.410	.000	Supported
H9	BIU	⟶	SE	.358	.050	7.177	.000	Supported
H10	KMS	⟶	BDA	.246	.056	4.364	.000	Supported
H11	KMS	⟶	SE	.100	.048	2.081	.037	Supported
H12	BDA	⟶	SE	.304	.032	9.428	.000	Supported

risk and behavioral intention to use big data, in turn, affect adoption and sustainability as a purpose of education.

The findings of this research support the knowledge management sharing and behavior intention to use big data for sustainability of education. The findings also showed that perceived usefulness, perceived ease of use, perceived risk and behavioral intention to use big data should influence adoption of big data. Likewise, the findings also showed that age diversity, cultural diversity and motivators had an optimistic important with knowledge management sharing. The use of TAM Model with knowledge management sharing factors in examining behavior intention to use big data for sustainability of education. Therefore, the findings also validated knowledge management sharing and behavior intention to use big data for sustainability of education. The outcomes agreed with prior research revealing that perceived usefulness, perceived ease of use and perceived risk had significant positive effects on behavior intention to use big data [5], [9], [34], [46], [48], [49]. In turn, affect adoption and sustainability as a purpose of education. On the other hand, when the students observed the age diversity, cultural diversity and motivators had significant positive effects on knowledge management sharing [53], [63], [74], [75], [78]. In turn, affect behavior intention to use big data, adoption and sustainability as a purpose of education. As stated by Thuraisingham and Parikh [93] Knowledge management is related to organization that are sharing expertise and their resources and forming intellectual assets so that later they can rise their competitiveness. Knowledge Management finds holds and develops organizational knowledge having an intention to control resources based on knowledge in an organization [94]. Beyond transactional result used by several organizations, there exists a potential treasure trove of non-traditional, less structured data (Big data) which can be mined for obtaining useful information [95]. These days, most of the young people use Facebook, twitter, linked-in, google+ accounts for online activities. As well, people are acquainted with Flickr to upload personal photographs, semantria.com to see sentiment analysis or opinion mining, ebay.com to sell or buy products, and crowd sourcing tasks on Amazon.com. All of these are examples of applications of Big data. Digital news available on Internet is increasing 10 folds in every five years on a scale of Zeta-bytes. Data is available from blogs, RFIDs, cameras, sensors, social networks, e-commerce, telephony and medical records. Conversely, the web and web-based social networking (big data) have significantly expanded in simplicity and speed, and thus social networking sites also allow for the public sharing of information, engagement, and collaborative learning [96], [97].

Faculty should demonstrate the use of the big data and provide instructional materials that would ease student learning of the technology. Moreover, the results recommend that faculty should define how the technology will help students and benefit them study big data or accomplish other learning objectives. Students who perceived that the big data would benefit them acquire a better behavioral intention to use big data for sustainability of education. Likewise, this research provides three empirical pieces of evidence. First empirical evidence of behavior intention to use big data through perceived usefulness, perceived ease of use and perceived risk. Second empirical evidence of knowledge management sharing through age diversity, cultural diversity and motivators, that in turn, affect behavior intention to use big data. The third empirical evidence of knowledge management sharing and behavior intention to use big data that can affect big data adoption for sustainability of education. The substantial theoretical contribution to previous knowledge management sharing with Technology Acceptance Model (TAM) in the educational context [98]–[101]. The three implications based on the result of this research are as follows:

1. To employ that the use of big data for learning, additionally, lecturers and supervisors can support the students by responding to the students' questions, knowledge sharing with ease that will improve learning concert of students and develop the skill of researchers towards research.

2. Universities are encouraged to enrol students to have the know-how of using big data for learning courses rather than forcing them to do so.

3. Technology and resource are significant matters of concern in students' attitude concerning using big data and behavioral intention to use big data adoption for sustainability of education.

V. CONCLUSION AND FUTURE WORK

The findings of this research support the effective behavioral intention to use big data influence big data adoption for sustainability as a purpose of education. The findings also showed that knowledge management sharing influence behavior intention to use big data and big data adoption would be positively associated with sustainability for education. The use of TAM model and knowledge management sharing factors in examining behavior intention to use big data and big data adoption for sustainability of education was also validated by the findings. Therefore, the input of this research to big data adoption and knowledge management sharing for sustainability of education. Consequently, a proposal that combines knowledge management sharing and TAM model could offer better overall results. Considering the importance that students give on behavior intention to use big data for sustainability of education, future work should consider designing guidelines for teachers concerning the proposal of learning activities with the use big data in different fields. Future studies in this area must also take into account the teachers and other higher education stakeholders regarding the use of big data in educational settings. Even though this study shows that the students could be rather positive with it, constraints and facilitators should be studied. Exploring and comparing views from and with other countries could also enrich the results obtained in this study and generate a broader view of how this topic is being dealt with in higher education.

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