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A STUDY OF THE DETERMINANTS AFFECTING ADOPTION OF BIG DATA USING INTEGRATED TECHNOLOGY ACCEPTANCE MODEL (TAM) AND DIFFUSION OF INNOVATION (DOI) IN MALAYSIA

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Abstract: *Large private companies had shown interest in adopting big data technologies. The review of literature and report from international industry analyst were being analyzed on the trends of utilization in development of big data regionally and globally. It seeks to provide understanding of the benefit and challenges for addressing key determinants in the adoption of big data by private companies in Malaysia. This study explores on the adoption of big data in Malaysia. The objective of this study was to bridge the gap by examining the key determinants affecting the adoption of big data in Malaysia by applying the integrated Technology Acceptance Model and Diffusion of Innovation approach and to establish a model for the adoption of big data by private companies in Malaysia. This study help establish the model which are helpful in examining these determinants. The model being proposed clarifies the structural relationships of the seven constructs which consists of perceived usefulness, perceived benefit, predictive analytics accuracy, perceived ease-of-use, perceived risk, training and adoption of big data which were analysed through method of statistical analysis with SPSS and Structural Equation Modeling using AMOS were utilized to obtain an appropriate model of adoption to explain the relationship between key determinants and adoption of big data in the proposed conceptual framework. Furthermore, this study employs on survey method through questionnaire survey in the data collection stage The final result finding will help to extend the better understanding of adoption of big data by private companies in Malaysia and will help to expand the contribution to literature review and contribute to the new knowledge on theory based on the integrated TAM (Technology Acceptance Model) and DOI (Diffusion of Innovation) for adoption of big data.*

Keywords: *Big data, Technology Acceptance Model, Diffusion of Innovation, Adoption of big data, Structural equation modeling*

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1. INTRODUCTION

Most businesses in the organization will need to look into the gain of a competitive edge in order to be more flexible, efficient and innovative. Many organizations begin to consider how to use and develop big data to make a profit (Qin, 2012). Many businesses is ready to deploy big data (Manyika *et al.*, 2011). The emergence of large reference data sets and massively growing raw data streams caused data-intensive computing to become big data (Bell *et al.*, 2009). Big data is referred as data involves in great volume, unstructured format and produced with great velocity (Garlasu *et al.*, 2013). Big data was denoted as huge datasets in sizes for any common software tool to capture, manage and process within an permissible elapsed time (Chen *et al.*, 2013). Gartner stated 'big data are high volume, high velocity, and or high variety information that require new types of processing to allow enhanced decision making, insight findings and process optimization' (Gartner, 2012). Technological transformation had driven millions of people producing incredible amount of data through the rise of use of such devices. Specifically, remote sensors continuously generate much heterogeneous data which are either unstructured or structured which is known as big data (Che, Safran, & Peng, 2013). Currently, the upsurge of the quantity of data growth rate being collected is astounding. Information Technology (IT) and Information System (IS) researchers and practitioners had faced with major challenges since the rate of growth is rapidly surpassing the ability to design suitable systems to manage the data efficiently and analyzing it to obtain significant purpose for decision making (Gupta & Chaudari, 2015). The necessity for businesses to use big data for business benefit is very true, thus for those businesses do not include big data as a strategy will be on disadvantage (Hopkins, 2010). Although the trend of big data is growing rapidly globally, the prospect and advantages of big data help on major businesses, there is still often gap in the adoption of big data. Slower adoption rate of big data had been reported in the United States (IDC, 2014), Europe (BDVA, 2015), Asia-Pacific (EIU, 2013) and overall growth slowed year-over-year from 60% in 2013 to 40% in 2014 (Wikibon, 2015) had shown that broad adoption of big data has not yet really materialized, therefore, there is a need to study on companies adoption of big data in Malaysia. Despite of the findings on the benefits of big data, there is still limitation exists which hinder the adoption of big data by companies in Malaysia (Hanchard & Ramdas, 2014). Most of previous researches concentrated on technology (Bakshi, 2012; Elgaral & Haddara, 2014; Hashem *et al.*, 2014; Dargam *et al.*, 2015) and operational (Mohanty *et al.*, 2013; Hallman *et al.*, 2014; Trifunovic *et al.*, 2015) aspect in the area of adoption of big data technology. Other previous researchers that poses challenges to practitioners and academics based on factors influencing adoption of big data (Ho, 2008; Chen *et al.*, 2012; Chiang *et al.*, 2012; Esteves & Curto, 2013; Kim *et al.*, 2013; Chong *et al.*, 2015).

In this regard, research is conducted on the employees of private companies in Malaysia to attain the answer on this research questions essential to predict the potential prospect on the adoption of big data in Malaysia

- What are the determinants affecting the adoption of big data using integrated TAM and DOI approach by companies in Malaysia?
- Which determinant are the most important in the adoption of big data using the integrated TAM and DOI approach by companies in Malaysia?
- What is the model for the adoption of big data using the integrated TAM and DOI approach by companies in Malaysia?

The primary objective for this study is to answer the research questions by empirical research and examine technological innovation diffusion and adoption of big data in Malaysia. This will enable management and companies to gain valuable insights for the adoption of big data.

2. THEORETICAL BACKGROUND

This section will discuss on the theoretical background on this research study. It includes the definition and evolution of big data as in Section 2.1. In addition, an overview of Information System theory is being discussed on Integrated (TAM) and (DOI) with related works in order to identify the research direction and methodology.

2.1. Big data

Big data refer to large sets of data in which size with common software tools unable for database to store, capture, analyze and manage (Manyika *et al.*, 2011). Harper believes big data has beneficial advantages at the level for the worldwide economy (Harper, 2013). Big data will be the main competition for enterprises, thus introduce new competition attracting employees that have big data critical skills and talents. Big data could generate $300 billion possible annual worth to US health care, and €250 billion to European public administration (Manyika et. al., 2011). Average data growth was estimated yearly by 59% (Pettey & Goasduff, 2011), this figure in percentages will increase tremendously in a few years which contributed to the collection of data at unprecedented rate. IBM affirmed the quantity of structured and unstructured data is nearly 80% at average of organization (Savvas, 2011). The trend is called "big data" acknowledged as one of the biggest IT trend in the year of 2012 (Pettey, 2012). Big data is defined recently as a large and complex digital dataset (Pope, Halford, Tinati & Weal, 2014). Big data analysis now drives nearly every aspect of society, including mobile services, retail, manufacturing, financial services, life sciences, and physical sciences (Jagadish, 2014). Big data will be an important factor to society and business in near future. It was believed that "big data" will be the latest phenomenon in the predictable future and this meaning revealed relativity of big data (Gupta & Chaudhari, 2015). Demchenko stated five key characteristics or 5V's defined big data which are Volume, Velocity, Variety, Veracity and Value (Demchenko, 2013).

2.2. Adoption and related technologies

Fundamentally, information systems (IS) theory represents the acceptance of user and utilize on the technology called the Technology Acceptance Model (TAM) (Davis, 1986). He further suggested perceived usefulness and perceived ease-of-use are important determinants in the TAM (Davis, 1989). The representation proposes that when users are suggested with a fresh technology, their decision were influenced by a few determinants and when they will benefit by it, particularly, perceived ease-of-use (PEOU) defined as the degree to which a person accepts that by using a certain system would be free from exertion (Davis, 1989). Since 1950s, the other theory considered in this study which is Diffusion of Innovation Theory (DOI) was utilized to depict the innovation-decision process. DOI progressively advances until the most excellent innovation-decision method was established by Rogers (Rogers 1962, 1983, 1995; Rogers & Shoemaker 1971). DOI theory described the innovation of technology proposed through specific approaches, among the members via the social system. In this research study, it refers to the integration of these two theories, TAM and DOI to examine the determinants affecting the adoption of big data by private companies in Malaysia.

2.3. Perceived usefulness

Perceived usefulness (PU) is the degree to which an individual believes that using a particular system would improve his or her job performance (Davis, 1993; Al-Gahtani, 2001; Mathwick *et al.*, 2001; Zhou *et al.*, 2010; Esteves & Curto, 2013). Tan and Teo clarified on perceived usefulness as an imperative determinant in explaining the adoption of technology innovations (Tan & Teo, 2000). A person's keenness to manage with a specific system is already regarded as perceived usefulness (Bhattacherjee, 2002). User behavior is clarified by usefulness and ease of use perceptions on the technology (Adams *et al.*, 1992). In addition, Gong and Xu defined that perceived usefulness is user's "subjective probability that using a specific application system will increase his or her expectations" (Gong & Xu, 2004).

H1: There is a positive relationship of perceived usefulness (PU) and adoption of big data (ABD)

2.4. Perceived benefit

The fundamental principle is that the better perceived benefit of an innovation, the higher the increase in rate for the adoption as in diffusion of innovation theory (DOI) (Rogers, 1995). Perceived benefit (PB) was determined as the most important determinant for predicting the technology innovation adoption (Moore & Benbasat, 1991; Thong, 1999; Tan & Teo, 2000; Kendall *et al.*, 2001; Esteves & Curto, 2013 and Kim, Lee & Seo, 2013). Clemons stated that for company or organisation in making decision on the adoption will always be concluded through the perception of favourable benefit from an innovation to produce political and economic authenticity to the decision for adoption (Clemons, 1991). Big Data comes with benefits and this study references are being done based on several key benefit developed by McKinsey (McKinsey, 2011).

H2: There is a positive relationship of perceived benefit (PB) and adoption of big data (ABD)

2.5. Predictive analytics accuracy

Predictive analytics covers a range of techniques statistically from data mining, date modeling and machine learning examining historical and current up-to-date facts to develop unknown and future predictions of events (Nyce, 2007; Eckerson, 2007). Mayer-Schonberger and Cukier stated big data is concerning predictions through using math to massive quantities of data to infer probabilities (Mayer-Schonberger & Cukier, 2013). Companies are relying on data to run businesses, and are using analytics in a predictive way to enable them to be more proactive in their decision making and less reactive (Dumbill, 2012). As system grows more accurate in its predictions, it also grows the base of data upon which it makes its predictions, therefore, the process of linking variables with predictive analytics accuracy creates more data and provides a ready example of how big data is becoming (Philbin, 2013). Previous studies focused on characteristics of innovation and information such as accuracy, usefulness, message relevance, comprehensiveness (Chau, 1996; Cheung *et al.*, 2008). Rick Swedloff affirmed in the insurance sector in which insurers do not disregard the assurance of algorithms propelling big data to offer better predictive analytics accuracy comparing the traditional statistical analysis since the power of big data prediction might permit insurers to uncover identified personal information on policy holders without consent. (Swedloff, 2014).

H3: There is a positive relationship of predictive analytics accuracy (PAA) and adoption of Big Data (ABD)

2.6. Perceived ease of use

Perceived ease of use (PEOU) had been defined as the extent to which a person believes that using a certain technology will be free of effort (Davis, 1989). Similarly, perceived ease of use was described as how well for a user in handling the system and ease of getting the system to do what is required, mental effort required to interact with the system, and ease of use of the system (Ndubisi *et al.*, 2003). Empirically, PEOU was found to be a predictor for technology acceptance (Venkatesh & Davis, 1996; Jackson *et al.*, 1997; Agarwal & Prasad, 1999; Hu *et al.*, 1999; Venkatesh & Davis, 2000; Venkatesh & Brown, 2001; Esteves & Curto, 2013; Chang *et al.*, 2015; Rajan & Baral, 2015). Some researchers in the past have not discovered significant evidence whether the construct in TAM would have effect on the perceived ease of use on technology (Keil *et al.*, 1995; Straub *et al.*, 1997; Teo *et al.*, 1999; Lederer *et al.*, 2000).

H4: There is a positive relationship of Perceived ease of use (PEOU) and adoption of big data (ABD)

2.7. Perceived risk

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 risk into two determinants which is uncertainty and consequence whereby uncertainty refer to consumers' subjective probability of something occurs or not, whereas, consequence is the hazard of the results after decision-making (Cunningham, 1966). Bauer in his seminal work defined perceived risk as a concoction of uncertainty and seriousness of outcome involved (Bauer, 1967). Featherman and Pavlou stated that perceived risk is often described as feeling of doubt concerning potential negative outcomes of utilizing a product or service (Featherman & Pavlou, 2003). 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 (Rogers, 1995; Kim & Prabhakar, 2000; Heart, 2010; Esteves & Curto, 2013). Luo, Zhang and Shim stressed the importance of multi-faceted perception of risk when deliberating a construct for adoption on technology innovation (Luo, Zhang & Shim, 2010). Big Data come with risk, several key risks developed by McKinsey Global Institute were considered for this study. (Manyika *et al.*, 2011).

H5: There is a negative relationship between perceived risk (PR) and adoption of big data (ABD)

2.8. Moderator variables

The use of moderators is importance to consider on key determinants for dynamic effects, therefore enable the improvement of quality for adopting on the research models suggested by (Venkatesh *et al.*, 2003). Means of moderator analyses can help to model and test for the possibility cause for heterogeneity. (Hair, 2011). Two constructs relationship can be affected positively or negatively due to the variables known as moderators (Benlian, Hess & Buxmann, 2000; Venkatesh, *et al.*, 2003). This research concentrated on adoption of big data by companies, thus it hypothesized on new moderators to deal with the hypotheses of the study. This study applied survey based research for the adoption of big data by the private companies in Malaysia. Related literature was referred hence one relevant determinant for moderator variable had been identified which is training (T). Respondent's level of training was considered to understand the possible basis for modeling and heterogeneity of relevant moderator variables.

2.9. Training

Organisation needs to provide training program to encourage employees' to use innovation more effectively (Talukder, 2012). The sufficiency of training provided to computer specialists and users of the company will have affirmative effect through the perceived usefulness and perceived ease of use impacting on the adoption of big data system directly (Igbaria *et al.*, 1997). Walker (2005) contended Information Communication Technology (ICT) training is a main determinant considered by organizations to facilitate ICT users on understanding on most efficient way to adopt ICT. Barba-Sánchez, Martínez-Ruiz and Jiménez-Zarco (2007) outlines the challenges of utilizing ICT potential is the minimal level of knowledge on the benefits or no precise training on ICTs (such as methodology and application levels). There are other studies done on availability of training influences usage or adoption of IS or IT (Igbaria *et al.*, 1995; Igbaria *et al.*, 1997; Al-Gahtani and King, 1999; Al-Gahtani, 2004; Gallivan et al, 2005; Galbraith, 2014). Imperatively, organization needs to realize the importance of training and treat it as a strategic objective for achieving long term organizational success (Gallivan *et al.*, 2005; Swartz, 2006; HBR, 2014; Chong, Man & Rho, 2015). Training had long been recognized as a necessity for effective adoption and usage of IS/IT by organization (Davis & Bostrom, 1983; Gallivan *et al.*, 2005). Research conducted on Malaysian SMEs in adoption of ICT revealed that 130 out of 180 companies never conduct a formal ICT training for their employees', hence this companies produced incompetence or poor in skillset employees in the ICT which deterred the adoption of ICT (Fishbein & Ajzen, 2005).

H6a: The relationship between perceived ease of use (PEOU) and adoption of big data (ABD) is moderated by training (T). The positive relationship between perceived ease of use (PEOU) and adoption of big data (ABD) will be higher when training (T) is at high level.

H6b: The relationship between perceived risk (PR) and adoption of big data is moderated by training (T). The negative relationship between perceived risk (PR) and adoption of big data (ABD) will be higher when training (T) is at low level.

3. RESEARCH METHODOLOGY

Research methodology is described as composition series of guidelines or events contributing to the validity and reliability of research findings as discussed in sub-section 3.0 (Mingers, 2001; Tabachnick & Fidell, 2001). The proposed hypothesis of the study is being constructed in sub-section 3.2. As part of the research design three types are considered empirically which include: (1) exploratory, (2) descriptive, and (3) casual or explanatory design (Cooper & Schindler, 2001). This three types or research design will help to explain and confirm determinant that influence and interact with it. (Douris, 2002). Subsequently, a brief discussion on data collection methods and survey instrument were described. Finally, in sub-section 3.3 this research model will develop the measurement model. Fundamentally, technology acceptance theories combination of TAM and DOI are based on the development and testing of hypotheses regarding the influences of theoretical constructs on each other (Venkatesh *et al.*, 2003). A typical approach resolving such systems is *Structural Equations Modeling* (SEM) described as "a comprehensive statistical approach to testing hypotheses about relations among observed and latent variables" (Hoyle, 1995). Structural Equation Modeling (SEM) is a multivariate method integrating characteristic of factor analysis and multiple regressions statistically to assess the sequence of consistent dependent relationships concurrently (Schumacker & Lomax 1996; Hair *et al.*, 2006). Structural relationships are being measured along with the unobserved constructs based on pertinent past theories and research, outcomes of the SEM method is a suitable solution for examining the proposed hypotheses and structural model for this study. In SEM procedure, it is possible for the simultaneous examination and explanation of the pattern of a series of inter-related dependence relationships among a set of latent (unobserved) constructs (Reisinger & Turner, 1999). Foundation of the SEM method considered as a combination from confirmatory factor analysis, path analysis and the assessment of mix models which have attributes of both of these analysis steps (Kline, 1998). Element of path analysis in the model highlights the structural associations between constructs combined in the proposed model, while the factor analysis features concentrated on validity, reliability and the degree of the quality of items in signifying the measure (Dillon *et al.*, 1987). Maximum likelihood (ML) method was utilized in SEM for estimating the model assessment and steps (Bentler, 1983; Anderson & Gerbing, 1988; Mueller, 1996; Byrne, 1998), follows on the two stage testing processes (Sethi & King, 1994; Hair *et al.*, 1998; Anderson & Gerbing, 1998).

3.1. Proposed model

In this research, an empirical research is presented to examine the determinants affecting the adoption of big data. The study proposed two set of questionnaires and were disseminates randomly based on stratified random sampling to the employees of private companies in Malaysia. The sample size of this study is 311. The proposed study examines the effects of six determinants including perceived usefulness, perceived benefit, predictive analytics accuracy, perceived ease of use, perceived risk and training on adoption of big data. Figure 1 shows details of our proposed model of study.

3.2. Measures

A measurement model was developed based on the constructs items referred through an initial literature. The development of the item was being assessed

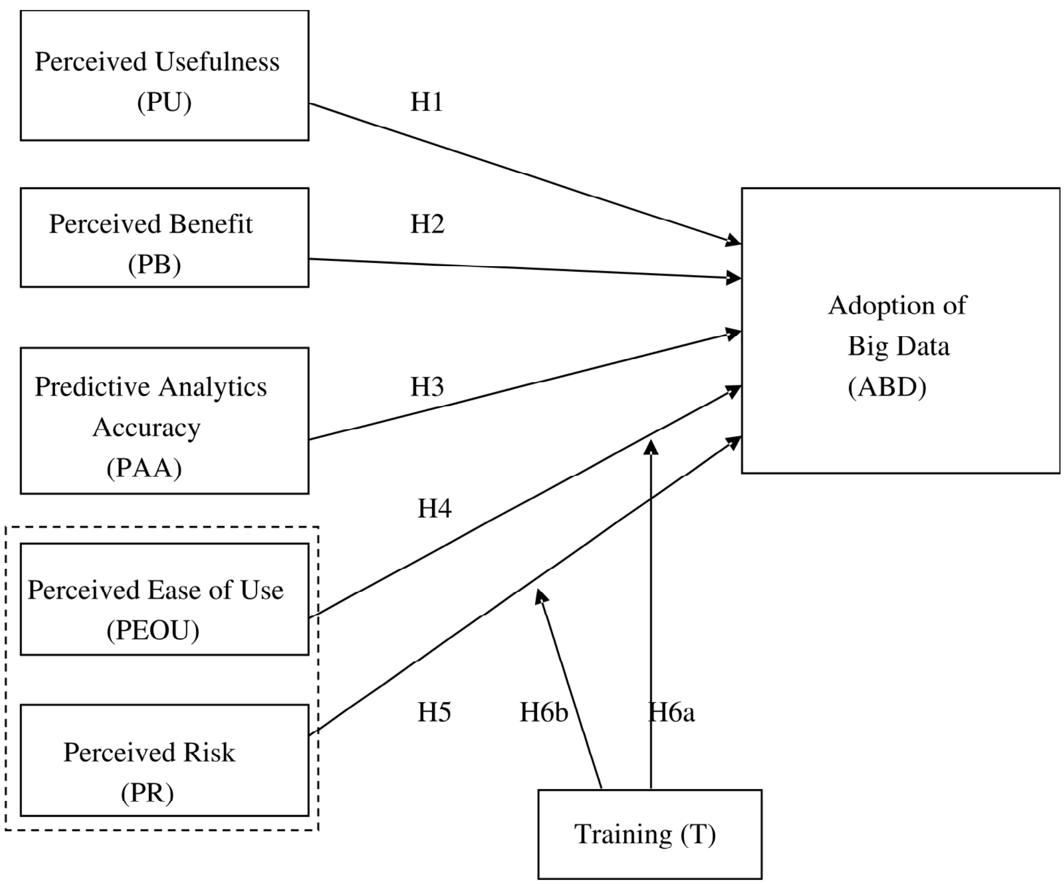

Figure 1: Proposed Model of Study

through its construct under investigation (Straub, 1989; Hinkin, 1998). It was further suggested by Sekaran on the advantages of questionnaire method such as being able to administer questionnaire to individuals concurrently which is inexpensive and time saving comparing to interviewing method which does not depend on require any skillset to administer the questionnaire (Sekaran, 2003). This is to ensure that identification of major indicators described for the structural model. In order to ensure that the methodological challenges are being addressed, the measurement model will be presented by the latent variables in Figure 1. All indicators were transformed into questionnaire items. Since SEM requires scaled date in metrics for analysis, thus we had constructed the items based on five-point Likert scale for the model estimation in SEM (Bortz, 2006; Weiber, 2010).

3.3. Data collection and sample

Disposition of this study is quantitative in nature, thus a survey research method was adopted. The purpose of using survey research is to explore and describe what is, rather than to evaluate why and observed the distribution (or attitude) exists (Cooper & Schindler, 2001). Data are being collected from large number of private companies in Malaysia, face-to-face interview, mailed and hand-delivered questionnaire utilized to handle the personally administered survey questions. The next step will involve a pre-test to assure precision of the survey questions. The measurement model was implemented in a survey-based research method and validated by a pre-test with 40 individuals or employees from private companies in Malaysia. The target population for this study was individuals or employees from the private companies in Malaysia which also involved the senior management in the organization's decision-making process regarding the adoption of big data in companies. The sample included employees comprises of CIOs or VPs, head of department, mid-management level, IT executives, IT engineers and IT analytics users of the companies in Malaysia. Upon completion of the pre-test, it follows by a pilot study being considered as the main survey. Findings of the pilot study exhibited only minor modification was required. Further pre-test was not considered due to minor changes, thus the responses were included in the main survey.

4. FINDINGS

Empirical study of the model for the research is being presented in this section. The method of sampling and collection of data are being described with the implication that was inferred from descriptive data analysis. Furthermore, the model estimation including the hypotheses testing is being described in this section. Finally, the results are discussed with regard to the research question in this study.

4.1. Demographic of the respondent

The results is illustrated in Table 2, it revealed that the majority of respondents were age between 21-30 years at 39.5%. Findings showed that male respondents represented 59.8% of total respondents, while female respondents only 40.2% of total respondents. Racial composition revealed highest composition is from the Chinese (45.3%), follows by Indian (31.2%), Malay (21.5%) and other races (2.0%). Most respondents in this survey was described as equal balance of composition with all the level of education group in which High School (SPM/STPM) (25.7%), Certificate or Diploma (27%), Bachelor's or Degree (23.2%) followed by Post-graduate (Master/ PhD) qualifications (24.1%). Technology department had the highest number of respondents (47.3%), followed by Operation (19.6%) and Sales or Marketing department (18.3%). Five categories of job position level are being surveyed with majority of the respondents are based on executive/engineer/data analytic specialist (43.3 %). However, respondent from mid-management level to top management (CIO or VP) represents (52.4%), while the others only represent (4.2%). Most of the respondent in their current job position for duration for 1-5 year is at 46.9%.

Table 2
Demographic of respondent
Demographic detail of respondent for the main study (N=311)

Variable	*Category*	*Frequency %*
Age (year)		
< 21	19	6.1
21 - 30	123	39.5
31 - 40	102	32.8
41 - 50	45	14.5
51 - 60	14	4.5
>60	8	2.6
Gender		
Male	186	59.8
Female	125	40.2
Race		
Malay	67	21.5
Chinese	141	45.3
Indian	97	31.2
Other races	6	2.0

contd. table 2

Variable	*Category*	*Frequency %*
Education (level)		
High School (SPM/STPM)	80	25.7
Certificate / Diploma	84	27.0
Bachelor's / Degree	72	23.2
Post graduate	75	24.1
(Master or PhD)		
Department		
Technology	147	47.3
Sales/Marketing	57	18.3
Operations	61	19.6
Finance	35	11.3
Top Management	6	1.9
Other	5	1.6
Job Position		
CIO or Vice President (VP)	6	1.9
Head of Department (HOD)	63	20.3
Mid-management (Manager)	94	30.2
Executives/engineers/	135	43.4
Data analytics specialist		
Others	13	4.2
Duration in current		
Job (year)		
< 1	18	5.8
1 – 5	146	46.9
6 – 10	81	26.0
11 –15	53	17.0
>15	13	4.3

4.2. Structural Equation Modeling (SEM)

The increasing attention to the assessment of measurement properties has led this study to adopt an established process in the data analysis with SEM. An eight-stage process was adopted from Koufteros for use in this study (Koufteros, 1999).

4.2.1. Measurement Model

Latent constructs are derived through the measurement model being the element of the entire model. Unobserved variables such as the latent construct denoted by the covariance of two or more observed indicators (Hoyle, 1995). Anderson and

Gerbing suggested that the measurement models based on confirmatory must be assessed and re-specified before structural equation models being tested concurrently (Anderson & Gerbing, 1988). Each construct in the model must be examined separately before analyzing on the overall measurement models.

Table 3
Confirmatory Factor Analysis results for Overall Measurement Model

Constructs and Items	*Standardised factor loadings*	*t-values (critical ratio)*	*Composite Reliability (>0.60)*	*R^2*	*AVE (>0.50)*	*Cronbach Alpha*
Perceived Usefulness			0.975		0.776	0.954
PU1*	0.869			0.756		
PU2	0.889	22.267		0.790		
PU3	0.860	20.828		0.740		
PU4	0.890	22.332		0.793		
PU5	0.897	22.665		0.804		
PU6	0.879	21.758		0.773		
Perceived Benefit			0.972		0.730	0.950
PB1*	0.877			0.770		
PB2#	0.812	18.927		0.660		
PB3	0.830	19.723		0.690		
PB4#	0.850	20.613		0.722		
PB5	0.884	22.368		0.781		
PB6	0.841	20.209		0.707		
PB7	0.884	22.349		0.781		
Predictive Analytics Accuracy			0.975		0.750	0.954
PAA1*	0.860			0.740		
PAA2	0.833	19.256		0.694		
PAA3	0.854	20.154		0.730		
PAA4	0.869	20.834		0.756		
PAA5	0.873	20.991		0.762		
PAA6	0.884	21.533		0.782		
PAA7	0.888	21.704		0.788		
Perceived Ease of Use			0.978		0.793	0.960

contd. table 3

Constructs and Items	*Standardised factor loadings*	*t-values (critical ratio)*	*Composite Reliability (>0.60)*	*R^2*	*AVE (>0.50)*	*Cronbach Alpha*
PEOU1*	0.896			0.803		
PEOU2	0.899	24.597		0.809		
PEOU3	0.878	23.249		0.772		
PEOU4	0.898	24.515		0.806		
PEOU5	0.879	23.295		0.773		
PEOU6	0.893	24.210		0.798		
Perceived Risk			0.980		0.813	0.963
PR1*	0.908			0.825		
PR2#	0.854	22.543		0.729		
PR3	0.905	26.121		0.819		
PR4	0.901	25.749		0.811		
PR5	0.902	25.849		0.813		
PR6	0.937	28.865		0.877		
Adoption of Big Data			0.958		0.713	0.914
ABD1*	0.844			0.712		
ABD2	0.811	21.824		0.658		
ABD3	0.877	19.687		0.768		
ABD4	0.829	17.963		0.687		
ABD5	0.858	18.999		0.736		

Note: * - Fixed parameter in path analysis, # -Item deleted after CFA

The result of the overall model assessment shown in Table 3 indicated that all indicators is within the hypothesized fundamental factors and were significant. Overall t-values were greater than ±2.58 at 0.01 levels which clearly demonstrated the evidence of convergent validity (Anderson & Gerbing, 1988). In assessing model reliability such as individual item reliability, composite reliability and average extracted variance, suggestion from Bagozzi & Yi (1988) was adopted in this study. Further analysis is done on the standardized factor loadings, resulting between 0.811 and 0.937. Relative significance of the observed variables in the constructs was determined by these standardized loadings. Squared Multiple Correlation (*R^2*) value for each individual indicator ranged from 0.658 to 0.877. This implied that the reliability of each individual item in this measurement model satisfied the acceptable threshold level of reliability (0.50) (Bollen, 1989; Steenkamp & van Trijp, 1991). Overall constructs reached composite reliability values which is greater than 0.70, exceeding the recommended value of 0.60 (Bagozzi & Yi, 1988). Reliability assessment on average extracted variance (AVE) met the suggested value of 0.50

(Fornell & Larcker, 1981). The construct variance obtained is greater than the variance accounted for which indicates measurement error (Hair *et al.*, 1998). It is noteworthy that each of the observed variables fulfilled the threshold level of acceptable reliability with Cronbach alpha values which is greater than 0.70. (Nunnally, 1978).

4.2.2. Structural Model

Structural model is the model hypothesized the relationships among observed variables and latent constructs that are not indicators of latent constructs (Hoyle, 1995). Normally, this model described as the element of the whole model associating with the constructs and to other constructs by imparting coefficient of the path for each of the hypotheses in the research. A particular composition among latent exogenous and endogenous constructs should be hypothesized, thus the measurement model for these latent constructs should be established in the structural model. (Mueller, 1996; Hair *et al.*, 1998). Maximum likelihood (ML) methods are used for estimation since these techniques permit for the model analysis linking non-zero error covariances and latent constructs across structural equations (Mueller, 1996; Kline, 1998). Generally, if t-value is being estimated greater than 1.96, the value indicated a significant in the two-tailed test at the 0.05 level of significance (Mueller, 1996). The structural model for this study is illustrated in Figure 2 indicating the standard coefficient for each of the hypotheses in this research study.

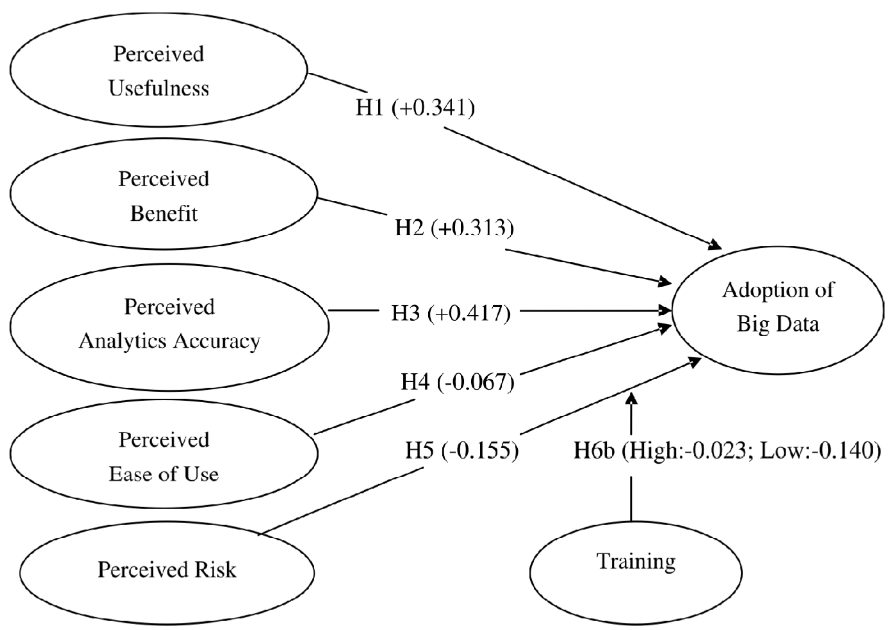

Figure 2: Structural Model

The estimation result of the model consists of t-values and standardised coefficients are presented in Table 4. The t-value related with each of coefficient of path exceeded the critical value of 1.96 at a significance level of 0.05 or exceeded the critical value of 2.58 at a significance level of 2.58 (Mueller, 1996) with the exception of perceived ease of use at 1.355 shown in Table 4. Furthermore, perceived ease of use was not significant, thus it was rejected.

Table 4
Hypothesis and Hypothesized Path

	Hypothesis and Hypothesised path			*Standardized Coefficients*	*t-value*	*Results*
H1	Perceived Usefulness (PU)	→	Adoption of Big Data (ABD)	0.341	5.549***	Supported
H2	Perceived Benefit (PB)	→	Adoption of Big Data (ABD)	0.313	5.549***	Supported
H3	Predictive Analytics Accuracy (PAA)	→	Adoption of Big Data (ABD)	0.417	6.444***	Supported
H4	Perceived Ease of Use (PEOU)	→	Adoption of Big Data (ABD)	-0.067	-1.355#	Rejected
H5	Perceived Risk (PR)	→	Adoption of Big Data (ABD)	-0.155	-3.152**	Supported

Note: *** = Significant at $p < 0.001$;** = Significant at $p < 0.05$; # = In-significant at $p > 0.05$

4.2.3. Moderator (SEM)

Method by Dabholkar and Bagozzi was considered to signify if there is change in the chi-square between the unconstrained and constrained model, resulting in the moderating effect (Dabholkar & Bagozzi, 2002). The chi-square value obtained through unconstrained to the constrained model will signify that moderator variable has differential effect on the causal path tested, therefore confirming on the moderator (Miyaki, 2013).

The moderation effect test for training relating perceived ease of use and adoption of big data is not significant (see Table 4), thus the moderation test was not performed since perceived ease of use was not a significant predictor to the adoption of big data. However, the moderation test was done for hypothesis (H6b) and the result shown the moderation effect for training between perceived risk and adoption of big data is significant as the difference in chi-square value between

Table 5
Moderation effect for Level of Training

Item	*Basic model*	*Constrained*	*Unconst-rained*	*Chi-square difference*	*Critical value at p<0.001*	*Result on Moderation*	*Result on Hypothesis*
Chi-square	511.943	2377.038	1458.518	918.52	16.27	Significant	Supported
DF	339	1020	1017	3			
GFI	0.893	0.807	0.856				
AGFI	0.872	0.770	0.828				
CFI	0.981	0.920	0.974				
RMSEA	0.041	0.046	0.026				
CMIN/DF	1.510	2.330	1.434				
H6b: Training moderates the relationship between Perceived Risk (PR) to Adoption of Big Data (ABD)							Supported

the unconstrained and constrained model is more than 16.27 at p-value less than 0.001 illustrated in Table 5. Hence, the difference in chi-square value is (2377.038 – 1458.518) = 918.52**,** whilst the difference in degrees of freedom is (1020-1017) **=** 3**.** The difference in chi-square value must be higher than the value of the chi-square (critical value) for the test to be significant, with degree of freedom (3) the critical value is 16.27.Hypotheses for moderation test effect was conducted, resulted on the training (T) does moderate the causal effect of perceived risk (PR) on adoption of big data (ABD). Hypothesis (H6b), predicting a moderating effect of training (T) on the relationship between perceived risk (PR) and adoption of big data (ABD), thus this hypotheses was supported. Similarly, analyzing on the path coefficient values between high level of training and low level of training indicates some differences. Based on the result shown in Table 6, low level of training (ß = -0.140***, t = -3.409) was discovered to have higher moderating effect on the path compared to high level of training (ß = -0.023***, t = -3.409). These results imply that the effect of perceived risk (PR) on adoption of big data (ABD) is more pronounced in low level of training compared to high level of training. Since the standardized beta estimate for low level training is significant while the standardized beta estimate for high level training is not significant, this type of moderation is known as full moderation. Additionally, the results imply that if perceived risk (PR) is high, then individual with low level of training (T) influence negative relationship between perceived risk (PR) and adoption of big data (ABD).

4.2.4. Goodness-of-Fit for Final Structural Model

Three types of entire model fit measures are normally considered: Absolute Fit Measures (AFM), Incremental Fit Measures (IFM) and Parsimonious Fit Measures (PFM) when analysing the measurement and structural models (Hu & Bentler,

Table 6
Comparison of T-value (CR) and Path Coefficient on Level of Training

	Hypothesis and Hypothesised path		*Level of Training (High)*		*p-value (High)*	*Level of Training (Low)*		*p-value (Low)*	*Comp-arison*
			Est. (ß)	*t-value*		*Est. (ß)*	*t-value*		
H6b	Perceived Risk (PR)	Adoption of Big Data (ABD)	-0.023	-0.523	0.601	-0.140	-3.409		*** High < Low

*** = Significant at $p < 0.001$

1995; Kline, 1998; 2005; Byrne, 2001; Arbuckle, 2003; Hair et. al., 2006; Cunningham, 2008). Subsequently, overall hypothesized model was analyzed utilizing three types of fit indices with all the supported hypotheses (H1, H2, H3 and H5) (see Table 4). The goodness-of-fit findings with the total of 311 samples were reported (see Table 7). All the values met the criteria for AFM, IFI and PFM.

Table 7
Summary of Goodness-of-Fit indices

Goodness-of-Fit-Measures	*Final Structural Model without PEOU*
Absolute Fit Measures	511.943 (df=339, p=0.000)
Chi-square (χ^2) of estimate model	(Bollen-Stine bootstrap p-value is 0.006)
CMIN/DF	1.510
Root mean square residual (RMR)	0.043
Root mean square error of approximation (RMSEA)	0.041
Goodness-of-fit Index (GFI)	0.893
Incremental Fit Measures	
Adjusted Goodness-of-fit Index (AGFI)	0.872
Normed Fit Index (NFI)	0.946
Tucker Lewis Index (TLI)	0.979
Parsimonious Fit Measures	
Parsimony Goodness-of-fit Index (PGFI)	0.746
Parsimony Normed Fit Index (PNFI)	0.848
Comparative Fit Index (CFI)	0.981
Incremental Fit Index (IFI)	0.981

5. DISCUSSION AND CONCLUSION

5.1. Discussion

The result of the finding is explained pertaining to the research questions as mentioned below:

(a) Research Question 1 (RQ1)

What are the determinants affecting the adoption of big data using the integrated TAM and DOI approach by companies in Malaysia?

Findings in this study suggested perceived usefulness and perceived benefit is predicting the adoption of big data which corresponds to previous studies (Manyika *et al.*, 2011; Esteves & Curto, 2013). Predictive analytics accuracy is the most important determinant for predicting the adoption of big data based on this study (Swedloff, 2014). Result recommended that perceived risk is the other important predictor considered for the adoption of big data (Manyika *et al.*, 2011; Esteves & Curto, 2013). Subsequently, training had shown there is moderating effect between perceived risk and adoption of big data which contributes to this study (see Table 5 and Table 6). Generally, the result was supported by the previous findings based on availability of training influences usage or adoption of IS or IT (Nelson & Cheney, 1987; Lepore *et al.*, 1989; Igbaria *et al.*, 1997; Igbaria & Tan, 1997; Al-Gahtani & King, 1999; Al-Gahtani, 2001; Venkatesh *et al.*, 2003; Al-Gahtani, 2004; Gallivan *et al.*, 2005; Benlian, Hess & Buxmann, 2009; Chong, Man & Rho, 2015). Finally, result discovered perceived ease of use had no effect to the adoption of big data by private companies in Malaysia as result found that it was rejected (see Table 4), it was supported by empirical studies whereby perceived ease of use does not significantly contribute to the adoption of technology (Szajna, 1996; Gefen & Keil, 1998, Gefen *et al.*, 2003; Rotchanakitumnuai, 2003; Godoe & Johansen, 2012).

(b) Research Question 2 (RQ2)

Which determinant are the most important in the adoption of big data using the integrated TAM and DOI approach by companies in Malaysia?

Result obtained on the determinant of predictive analytics accuracy (PAA) suggested the most important determinant to influence in adopting big data followed by perceived usefulness (PU), then perceived benefit (PB), finally perceived risk (PR) based on the order of the determinant from highest to lowest, The other determinant which is the perceived ease of use (PEOU) (H4) was rejected (see Table 4), thus it does not contribute significantly to the adoption of big data (ABD). Finally, the other determinant, training (T) does contribute based on the moderating effect between perceived risk (PR) and adoption of big data (ABD).

The low level of training had significant effect on the negative relationship between perceived risk (PR) and adoption of big data (ABD) when perceived risk is high.

(c) Research Question 3 (RQ3)

What is the model for the adoption of big data using the integrated TAM and DOI approach by companies in Malaysia?

From this finding, it can be suggested that predictive analytics accuracy is the most important determinant to be considered for adoption big data in private companies in Malaysia. Therefore, (H3) is accepted (see Table 4). This particular determinant plays significant roles for adopting big data by private companies (Nyce, 2007; Eckerson, 2007; Cheung et al., 2008; Mayer-Schonberger & Cukier, 2013; Swedloff, 2014). The findings also revealed that perceived benefit (H2) and perceived risk (H5) are deemed to be significant determinants for employees' to adopt big data (Kim & Prabhakar, 2000; Esteves & Curto, 2013). The other hypotheses training (H6b) is also accepted as this finding suggested training had significant moderating effect between perceived risk and adoption of big data, thus improving the quality of the research model (Venkatesh *et al.*, 2003). Previous studies finding on information system (IS) related studies showed that perceived usefulness is considered significant predictor, similar to this research for the adoption of big data by private companies (Thong 1999; Tan & Teo, 2000; Esteves & Curto, 2013), thus, H1 is accepted (see Table 4). From the overall findings, all of these hypotheses (H1, H2, H3, H5 and H6b) can be used to answer all the research questions (RQ I, RQ II and RQ III) (see Table 4).

5.2. Implications

5.2.1. Practical

Findings from the result obtained as in Table 2 suggested most Malaysian employees in private companies are male (59.8%), obtained (Certificate/Diploma) and above in education (74.3%). Most of the employees' is in the age of between 21 to 40 years (72.3%), mainly from the Technology department (47.3%). Similarly, more than half of the respondents held a position of mid-management (manager) and head of department (50.5%), finally, the employees in the duration of between 1 to 5 years in their current job is at 46.9%. This information is useful to guide private companies to define their adoption strategies to a targeted segmentation of the employees in the companies. It is an important source for enabling management to plan suitable development program for specific groups to enable them to adopt big data in the companies. Primary concern in making employees adopt new technology is whether they consider that the technology provides benefits for them. In this study, predictive analytics accuracy was discovered as the most significant determinant affecting the adoption of the big data. This determinant enabled big data for business organizations in major improvement in decision support making accurately and intelligently to the management. Predictive analytics accuracy inspired on the decision to adopt big data (Nyce, 2007; Eckerson, 2007). Perceived benefit was discovered to be important means in adopting big data. Empirically, Information systems (IS) research suggested that companies adopting information technology at different times might have definite perceptions on the adoption of a specific technology (Dos Santos & Peffers 1995; Iacovou, Benbasat & Dexter 1995; Dillon & Morris 1996). Perceived benefit is a key determinant to be considered for the adoption of big data as it was further evidenced through past studies (Esteves & Curto, 2013). The non-significance result obtained showed that perceived ease of use is not a predictor to the adoption of big data confirmed by previous literature on IT (Szajna, 1996; Gefen and Keil, 1998; Rotchanakitumnuai, 2003; Gefen & Straub, 2005; Godoe & Johansen, 2012). Other result obtained found perceived risk is statistically significant and negatively influenced the adoption of big data. Past research had clarified in other IS studies that organizations cited such risks as a major deciding factor in their adoption decision for IS related technology such as Enterprise Resources Planning (ERP) (Chau, 1995; Gupta, 2000; Hitt & Wu, 2002; Subashini & Kavitha, 2011; Wu *et al.*, 2011) Finally, the following results obtained show that training moderates between perceived risk and adoption of big data. Thus, it predicted that training will help to reduce the perceived risk in terms accelerating the adoption of big data. Other literatures on IS related study found developmental training is the time management devoted to training the sales force to enhance knowledge (Ahearne, Jelinek & Rapp, 2005), similar to other study in the field of IS (Groza *et al.*, 2012).

5.2.2. Theoretical

This study imparted extension evidence on suitability of using the TAM to measure the adoption of big data. As evidenced from previous TAM studies, one specific behavioral belief (Perceived Usefulness) explained the adoption of big data. The results aligned with the general findings across several studies in information system research (Davis, 1989; Adams *et al.*, 1992; Venkatesh & Davis, 2000). In this study, it was supported by Diffusion of Innovation (DOI) theory of measuring the adoption of innovation technology (Rogers, 1995). This can be seen by the determinants of perceived benefit and perceived risk being the other important determinants that enable the employees on the adoption of big data. The integration of TAM and DOI theory for this study helps to broaden the theoretical knowledge on this field of study as previous study was based on decomposed theory of planned behavior (Esteves & Curto, 2013).

5.3. Limitations

As with any research, the present research findings should be interpreted with some caution based on several limitations. Firstly, generalisability in information system (IS) studies is commonly the challenges found and similarly same as in this study. As this study was conducted on Malaysian employees of private companies, whose adoption decision might be influenced by their technological development, socio-economic status and lifestyle, the generalisability of the findings to other countries may be limited. There should be call for research to address the issue by an examination of the deeper cross-cultural generalisability issues. Secondly, present research was limited to the perspective of private companies in Malaysia, thus the generalisation of findings is restricted by the uniqueness of this specific industry. Similarly, generalisation of the findings beyond private companies such as from the public sector must be cautiously inferred. Thirdly, the research design of this study based on cross-sectional in which all of the constructs incorporated in the hypothesised model were assessed at a single point in time. Hence, no definitive conclusions can be derived relating the causality of relationships between constructs (DeWulf, 1999). Future research based on longitudinal study need to be considered to ensure the improvement of significant contributions to knowledge. Finally, the measures of all the research constructs were collected at the same point in time and via the same instrument, so the potential for common method variance may exist (Straub *et al.*, 1995). Future research will be able to provide a more prohibited experimental handling to prevent respondents from providing consistent responses across entire constructs.

5.4. Conclusions

The development on the adoption of big data is at infancy stage whether the private companies choose (or do not choose) on adopting of big data is beyond being completely understood. Refining the understanding of employees' adoption of big data is needed to better assessed and predict the extreme impact of big data. Findings from this study produced initial evidence that earlier technology acceptance and diffusion research, and the integrated of TAM and DOI can provide underpinning for much desired research on employees' adoption of big data related activities. This study was developed on present knowledge and established a sequence of research propositions that give a more comprehensive understanding of employees' adoption of big data. The research framework is an initial study to include training as a moderating variable through the literature on employees' adoption of innovation DOI and TAM, therefore facilitate on the assimilation of cross disciplinary studies in information system. The research model explicitly considers perceived usefulness, perceived benefit, predictive analytics accuracy, perceived risk and training as key determinants of employees' adoption of big data. This research framework based on the integration of TAM and DOI enhances information system research. This study suggests that the proposed theories through diverse leading researchers can be combined into single framework, so that the awareness and prediction of employees' adoption of big data are broadly grounded than by using only single theory. In conclusion, theoretical framework of this study provides a combination of current research and a catalyst to forthcoming research in the information system research field of study.

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