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Big data analytics: does organizational factor matters impact technology acceptance?

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Abstract

Ever since the emergence of big data concept, researchers have started applying the concept to various fields and tried to assess the level of acceptance of it with renown models like technology acceptance model (TAM) and it variations. In this regard, this paper tries to look at the factors that associated with the usage of big data analytics, by synchronizing TAM with organizational learning capabilities (OLC) framework. These models are applied on the construct, intended usage of big data and also the mediation effect of the OLC constructs is assessed. The data for the study is collected from the students pertaining to information technology disciplines at University of Liverpool, online programme. Though, invitation to participate e-mails are sent to 1035 students, only 359 members responded back with filled questionnaires. This study uses structural equation modelling and multivariate regression using ordinary least squares estimation to test the proposed hypotheses using the latest statistical software R. It is proved from the analysis that compared to other models, model 4 (which is constructed by using the constructs of OLC and TAM frameworks) is able to explain 44% variation in the usage pattern of big data. In addition to this, the mediation test performed revealed that the interaction between OLC dimensions and TAM dimensions on intended usage of big data has no mediation effect. Thus, this work provided inputs to the research community to look into the relation between the constructs of OLC framework and the selection of big data technology.

Keywords: Big data, Technology acceptance model (TAM), Organizational learning capabilities (OLC), Structural equation model (SEM), Mediation effect

Introduction

Background

The emerging trends in recent years are "Big Data" and "Big Data Analytics" which have become popular globally. They facilitate the analysis of the entire data in real time by developing and using machine-to-machine algorithms for predictive modelling and to arrive at decisions based on such models [1]. According to McKinsey [2] "Big Data" is considered as the datasets that challenge the ability of typical applications and technologies in managing and analysing the data. Big data also challenges the human imagination. For example, while some might consider a few dozen terabytes as big data, in reality it is not. Surely, it is a large dataset but can still be managed and stored in a local network attached storage (NAS) or storage area network (SAN) using array of disks. By and large, it can be perceived that big data is petabytes in size requiring a complex distributed computing and storage grid coupled with sophisticated applications and tools to manage it.

From the perspective of process, big data refers to the infrastructure and technologies that the companies use to collect, store and analyse various types of data [3–5]. Given the fact that big data is extremely complex to design, build, implement and manage, it is paramount to investigate the motivations behind big data adoptions and the human capabilities that are necessary for such endeavour. This study, rely on the technology acceptance model (TAM) which is has a solid background on the theory of reasoned action (TRA) which states that an individual's behaviour also called as behavioural intention (BI) which is a predecessor for performing any task or using any system for that action. In other words, an intention of using a system relates with actual usage. However, though TAM can explain a significant portion of system adoption, the framework does not account for human capabilities. To put simple, an intention must be coupled with practical knowledge in order to transform into action. A research by Fairchild and Mackinnon [6] revealed that organizational learning capability (OLC) is pivotal factor for adoption of system and technological solutions. In fact, many researchers identified learning capabilities as the most important component for innovation and adoption of new processes as well as technologies.

The components of TAM are being analyzed with those of OLC in order to establish a prospective solution for the enterprises and management of big data. The components include impact of perceived ease of use and perceived ease of usefulness on the intended usage of big data. The other attributes of OLC are managerial commitment, system perspective, openness and experimentation and transfer and integration. These parameters have an impact of technology acceptance model. They also have a positive impact on the big data.

It is being explored in all dimensions of business, government and health care that due to collection and storage, there is growth of voluminous data [7, 8]. According to Davis [9], the 'Technology Acceptance Model' emphasizes that the success of a system is determined by user acceptance of the system, measured by perceived usefulness (PU), perceived ease of use (PEOU) and attitudes towards usage (ATU) [10].

Melville et al. [11] define the concept of organisational learning as the ability that firms have to assimilate and diffuse new knowledge across the entire firm for developing superior performance. Generally, firms that foster a learning environment and develop new capabilities can achieve and sustain the competition [12, 13]. This study is an explanatory research and attempts to connect existing knowledge to understand the relationship among existing theories [14, 15]. To do so, it aims to test a set of hypotheses using quantitative research approach with the help of mathematical modelling and statistical analysis [16, 17]. To test the hypothesis of this study, a cross-sectional survey is a suitable research method as it enables the collection of large amount of data from a sizable population in an economical way [18]. The review and methodology adopted is explained below in detail.

Research model

Figure 1 shows the theoretical model for this study. The research model adapts and expands the original technology acceptance model (TAM) [9, 19, 20] by incorporating

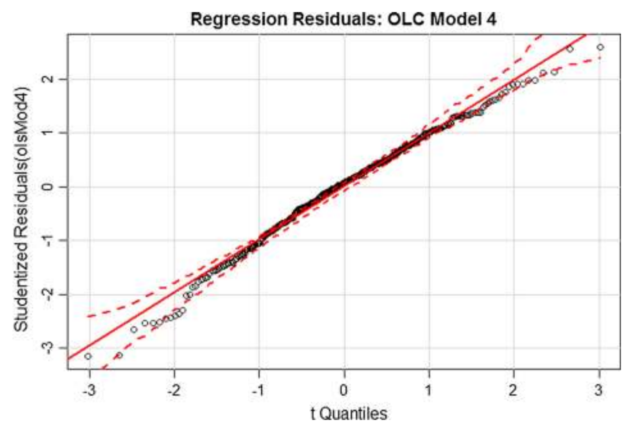

Fig. 1 Model regression with studentized residuals

the dimensions of organisational learning capabilities (OLC) [21]. The dimensions of TAM (perceived ease of use and perceived usefulness) have extensive empirical evidence to support its direct impact over technology use. However, these TAM dimensions do not take the organisational environment that certainly influence system usage into account [22].

TAM

The area of information system management has been studying technology usage and acceptance since early 1970s. But, the early studies noticed that many successfully implemented cases failed as they replicated the same technology in a different scenario. In this regard, Bailey and Pearson [23] suggested that user satisfaction plays a significant role in technology acceptance and identified 39 factors that could influence end-user satisfaction towards technology. But, the user satisfaction model clearly failed to explain the acceptance factors [24, 25].

TAM suggests that system or technology adoption can be explained by user's motivations that are based on perceived system features and capabilities [20, 26]. TAM has its origin in the theory of reasoned action [27] and the theory of planned behaviour [28]. Both theories are from the field of psychology and suggest that behaviour is determined by beliefs and evaluations (attitude towards behaviours) and also normative belief to comply (subjective norms). These theories combined with the studies of Swanson [29] provided ground to determine the beliefs that are sufficient pre-empt the attitude of the end-user towards the adoption of a system.

OLC

The concept of organisational learning has emerged in the field of organisational studies and received increasing attention in the field of information systems and technology management [30, 31]. Some other studies found empirical evidence to support the theory that organisational learning has a direct impact on ERP system's usage and an indirect impact on user satisfaction [22, 32]. Other researchers have also acknowledged the importance of training before implementing a new system or technology [33].

Even though, any technology adoption presents a learning curve, the dimensions of OLC in technology adoption are often overlooked by the literature. There are couple of explanations for neglecting the concept of organisational learning in information system adoption. First and foremost is the overuse of TAM to explain system usage. Second, the lack of consensus and measurement tools for organisational learning [21, 34, 35]. The following section establishes the concept of OLC and its dimensions.

Literature review

Concept of big data

The concept of big data, as stated in the introductory section, refers to massive dataset in terms of volume, velocity and variety that challenges the current technological landscape. The key challenge in big data is not about storing increasingly large volumes of diverse data, but to make sense of unstructured data and turn it into actionable information. According to Hilbert and López [36] big data is capable of delivering important prospects to guide better decisions. Likewise, Daniel [7] proposed a conceptual framework to describe big data in higher education with three components-utilizing the framework as a way to describe, link the data systems in order to organize the available literature, and develop a research design to help frame a set of approaches for investigation [7, 37]. Moreover, Assunco [38] mentions that big data challenges others aspects beyond storage, which are data management, governance and analytics. Organisations today generate a massive volume of data as a result of new technologies and systems that allow them to collect an increasing amount of logs, sensor information, datasets, trackers, etc. Social media is indeed a vast source of big data, as a single user can generate gigabytes of data per month by sharing photos and videos, sending thousands of messages and sharing other user's content. To encounter this scenario, the infrastructural requirement that are needed for big data analytics are: (a) linear scalability; (b) high throughput; (c) fault tolerance and auto recovery; (d) high degree of parallelism; and (e) distributed data processing [39, 40]. To achieve the requirements mentioned above, a combination of technologies throughout the data processing life cycle is necessary as mentioned below in Fig. 2.

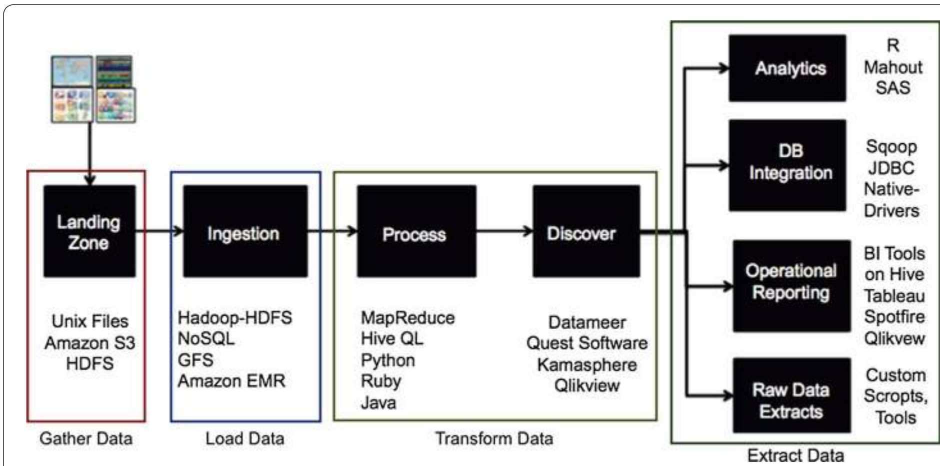

Fig. 2 Big data technology stack Source: Krishnan ([40], p. 41) and Sheikh ([41], p. 190)

Big data is characterized by volume, variety, velocity and value according to Philip Chen and Zhang [42]. Advanced IT devices, social media services and corporate information systems are continuously churning out very large amounts of structured and unstructured data and businesses are increasingly facing challenges in managing and capitalizing to their advantage. Big data analytics is defined as technologies (database and data mining tools) and techniques (analytical methods) that a company can implement to analyse large scale, complex data for various applications intended to augment the performance of the firm in various dimensions. According to a study conducted by Philip Chen and Zhang [42] it is revealed that high-tech data storage, management, analysis capability and visual technologies are all part of big data analytics [43].

Narayanan [5] in his studies found that big data is both an entity and a process. The research also emphasized that as an entity, big data comprises volume of information that usually cannot be processed using traditional database and software techniques. Gleaned from a variety of sources, some of them are internal and some are external. Big data typically includes structured data, which is the organized information obtained from relational databases, spreadsheets and machines. Unstructured data is dynamic information not made available in a fixed place, such as emails, texts and voicemails. Semi-structured data does not reside in fixed fields but uses tags or other markers to capture elements of the data (XML and HTML-tagged texts are examples). As a process, big data refers to the infrastructure and technologies companies use to collect, store and analyze various types of data [5, 44–46].

According to Gorten [47], big data applications are prevalent across many industries as the technology became more accessible and streamlined. For example, it is estimated that US healthcare saves about 450 billion dollars from analysis of the patient dataset, taken from diverse sources, such as insurance companies, hospitals and other health providers and clinical studies. Moreover, big data can also improve operational efficiency for disease treatments and epidemiology control (Gorten 47). Brock and Khan [32] in his study pertaining to big data analysis mentioned that as information has become a highly valued commodity across the world, increase in data collection as well as research on Big and Cloudy data have been gaining popularity.

According to a report by the McKinsey Global Institute [2], big data refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage and analyse' In a study conducted by Krishnamurthy and Desouza [48], it is mentioned that various tools are intended to transform organizational decision making, increase process efficiency, identify future areas for innovation and engage citizens in the policy analysis, design and implementation process.

Components of big data and applications

Assunção et al. [38] in a study mentioned that big data is characterized by a multi-V model. The components of the model include volume, velocity, value and variety. Apart from these, another component veracity is also identified. Volume refers to a massive amount of data. Velocity refers to the rate or speed with which the data is generated and processed. Variety represents the multitude of sources and data types. Finally, Veracity refers to trustworthiness and reliability of data.

It is worth noting that over the past decade, substantial amount of research data has been produced and made publicly available for advancement in the scientific field. Likewise, with the advent of diffusion of the internet, government entities, public companies, statistics bureaus, weather stations, financial institutions and many others have also made a significant contribution to the data that is publicly available for public consumption. In other words, there has never been a time when so much information is easily available. Three V's (volume, velocity and variety).

Volume

According to Borne [49], from the beginning of written language until 2003, humanity had produced about five exabytes of data. In 2011, the same amount of data is created every 2 days. In 2013, the same amount of data is created every 10 min. This is because today organizations collect data from different sources, such as machine data, application logs, clickstream logs, whether data, emails, contracts, geographic information systems and geospatial data, survey data, reports, spreadsheets, and social media [41, 50]. The ability to compute massive quantity of information is the key feature of big data analytics.

High-volume data impose limits to storage technologies, processing capabilities and database modelling. According to Dumbill [51], huge data imposes an immediate challenge to traditional data storage infrastructure as it calls for scalable systems and distributed querying. Moreover, it also challenges traditional databases that cannot cope with massively parallel processing and unstructured indexation. Computational power is also a critical point for big data analytics. According to Hilbert and López [36], the size of data sets has surpassed the capabilities of computation. In 2007, humanity is able to store about 2.9×1020 bytes and to process about 6.4×1018 instructions per second (p. 60). It is worth mentioning that a general purpose computer needs more than three instructions to process a byte [52–54].

Velocity

Studies show that in 2013, the world created about five exabytes every 10 min. It is reasonable to infer that today five exabytes are probably being created every minute or so. The importance of data's velocity has followed a similar rate to that of volume as the data flow into organizations increases at exponential rates [51, 55]. For example, according to Cukier [56], Wal-Mart generates about 2.5 petabytes per hour (or 5825.42 gigabits per second). The most efficient media for data transfer, i.e., fibre optic cable, can transfer up to 100 gigabits per second (0.043 petabytes per hour) [57, 58]. To put simply, Wal-Mart produces more data than it could transfer to a single data centre.

However, data velocity not only challenges communication networks but also processing capabilities of a constant inflow of data streams [59]. Big data technologies have to process information in real-time (streaming processing). According to Dumbill [51] some level of analysis is necessary during the data inbound in order to keep storages levels practical. This can include on-the-fly data strips, compression or heuristics. For example, the large hadrons collider (LHC) generates more raw data than the CERN computing grid can store; thus data has to be instantly analysed [60]. This problem seems to be straightforward, but real-time analytics challenges traditional parallel and distributed computation [61].

Variety

Traditional information systems rely on very structured data. Inputs have to be accurately entered into the system in order to produce meaningful outputs (lists, reports, forecasts, etc.). Scholars often discuss the dimension of data quality as accuracy, relevancy, completeness and timeliness [62]. Heterogeneous environments frequently need to use data cleaning techniques to solve the "garbage in, garbage out" problem [63]. Variety of data from different sources like sensor data, application logs, clickstream logs, whether data, emails, contracts, geographic data, reports, spreadsheets and social media is difficult to handle. That is, data from different domains are virtually impossible to translate into a structured form [41]. In fact, big data is diverse and unstructured, therefore it requires special tools and techniques that go beyond traditional information system and relational databases solutions.

According to Dumbill [51] and Kambatla et al. [61], data diversity is a common case for big data system and a frequent use of big data analytics is to consider unstructured data and find meaningful information. Even when there is no significant mismatch in the data type, the static nature of relational database schemas is not suitable for a dynamic and exploratory environment ([51], p. 13). Big data solutions need different processing capabilities that are not present in traditional databases to process text, image, video, audio, geo-spatial data, etc. The following Fig. 3 lists the V's mentioned by various authors.

Technology acceptance model (TAM)

Dimensions of TAM

According to Swanson [29], perceived ease of use and perceived usefulness are amongst important elements for users' involvement in system implementation and information perspective. The identification of these two components aligned with the theory of reasoned action supported the research of Davis [20]. People would use a system or technology if it would help them to perform their job better (perceived usefulness) with low effort to use (perceived ease of use) [64]. Perceived usefulness is defined as the "degree to which an individual believes that using a particular system would enhance his job performance", while perceived ease of use is defined as the "degree to which an individual believes that using a particular system would be free of physical and mental effort" [20]. These two factors result in the user's attitude towards using new technology.

Figure 4 shows the relationship between the elements of TAM [9]. In order to measure and weigh each component of the model, David created psychometric scales and refined them overtime. Theses scales would ask users to rank questions like: "Using technology *x* improved my job performance" (to measure the perceived usefulness). "Learning

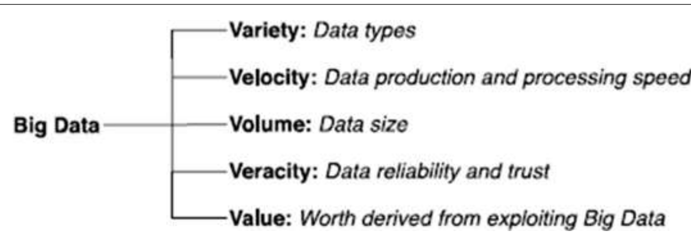

Fig. 3 The V's of big data (Source: Adapted from the literature)

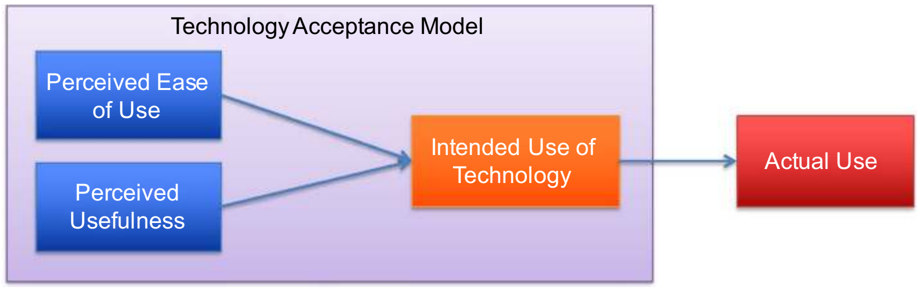

Fig. 4 Original technology acceptance model (Source: [9, 20])

to operate technology *x* would be easy for me" (to measure the perceived ease of use). "Assuming technology *x* is available, I would use it on a regular basis" (to measure the attitude towards usage).

TAM has been replicated with myriad technologies and all provided empirical evidence on the relationship between usefulness, ease of use and system use [64].

Limitations of TAM

Many researchers have adapted and extended the TAM to include additional variables, such as effectiveness [65], uncertainty avoidance and intrinsic motivation [66], organizational beliefs [67] etc. Even Davis and his colleagues have refined the model several times by adding antecedents to the model's dimensions [68] and mediating variables [69]. However, the main criticism is that additional variables are not able to go much beyond the original dimensions [64]. It is also important to mention that additional variables might cause model over-fitting rather than representing a refined model.

Another recurrent criticism and limitation of TAM is the failure to establish a complete causal relationship [70]. In fact, the two dimensions account for less than 40% of the technology usage in the model's regression [24]. In some contexts, such as online banking, the model explains even less extent of technology usage [71]. Hence, it could be argued that TAM can suffer endogeneity or a strong correlation of the independent variable (actual technology usage) with the error term (unknown variables) in the statistical test. There are also criticisms regarding the voluntary approach of technology usage rather than the mandatory and enforced use [72]. This mandatory use is particularly relevant to well-established technologies, like enterprise resource planning or collaboration suites, which cannot be overlooked. Nevertheless, less diffused and enforced systems and technologies, like big data analytics, still depend a lot on voluntary usage.

Organizational learning capabilities (OLC)

Concepts of OLC

The concept of organizational learning has emerged in the field of organizational studies and has received increasing attention in the field of information systems and technology management [31]. Some studies found empirical evidence to support the theory that organizational learning has a direct impact on ERP system's usage and an indirect impact on user satisfaction [22]. Other researchers have also acknowledged the importance of training for the successful implementation of new technology [33].

Even though technology adoption presents a learning curve, the dimensions of OLC in technology adoption are often overlooked by the literature [73]. There are a couple of explanations for neglecting the concept of organizational learning in information system adoption. First and foremost is the overuse of TAM to explain system usage. Second, the lack of consensus and measurement tools for organizational learning [21, 35]. The following section establishes the concept of OLC and its dimensions.

Definition of OLC

Learning is an important component in the organizational context as it enables innovation for competitive advantage creation and expansion [74]. It is also mentioned that through organizational learning, business responds agilely to customer demands, thrive in new markets and technologies and also develop innovative products [75].

The concept of organisational learning is often ambiguous due to diverse origins and wide applicability [76]. The proponents of the theory, Argyris and Schön [77] and Fiol and Lyles [78], define organisational learning as a non-hierarchical process to develop collective knowledge geared to improve organisational efficiency. Other researchers claim that the accumulation of knowledge can create competency traps that diminish organisational efficiency [79]. Thus, a better definition of organisational learning is the process of knowledge acquisition, transfer and integration to adapt to different organisational scenarios [80, 81].

OLC is defined as the process of acquisition, transfer and integration of individual and collective knowledge [76, 81]. OLC requires four conditions to work efficiently. First, top management must be committed to develop and promote learning [22, 74, 82]. Second, it requires a shared perspective that allows the organisation to be interpreted as a common entity [21]. Organisations with no common identity and clear objectives fail to transfer and integrate knowledge from the individual level to the organisational level (Kim [83]. Third, it needs a suitable environment to promote the knowledge exchange and collective learning, such that group can learn from individuals and the organisation can learn from the groups [84–87]. Fourth, the company must have an open mind to test new ideas and raise awareness for continuous learning and experimentation [82, 83]. It is important to acknowledge that new ideas are unlikely to succeed at first, so learning from experience is important [80].

Figure 5 shows the four dimensions of OLC: (a) managerial commitment, (b) system perspective, (c) openness and experimentation and (d) transfer and integration.

Even though the four dimensions identify different aspects of OLC, they are closely related to each other. For example, all dimensions emphasize the engagement of executives, managers and employees in the knowledge creation. The studies of Jerez-Gomez et al. [21] and Nwankpa and Roumani [22] provide empirical evidence that OLC dimensions represent a valid framework to assess the organization learning in information system research.

Research model and hypotheses

Table 1 shows the summary of factors used in the theoretical model of this study. The factors F1 to F3 refer to the technology acceptance model (TAM) [9, 20] while factors F4 to F7 incorporate the dimensions of organizational learning capabilities (OLC) [21] into the independent variable.

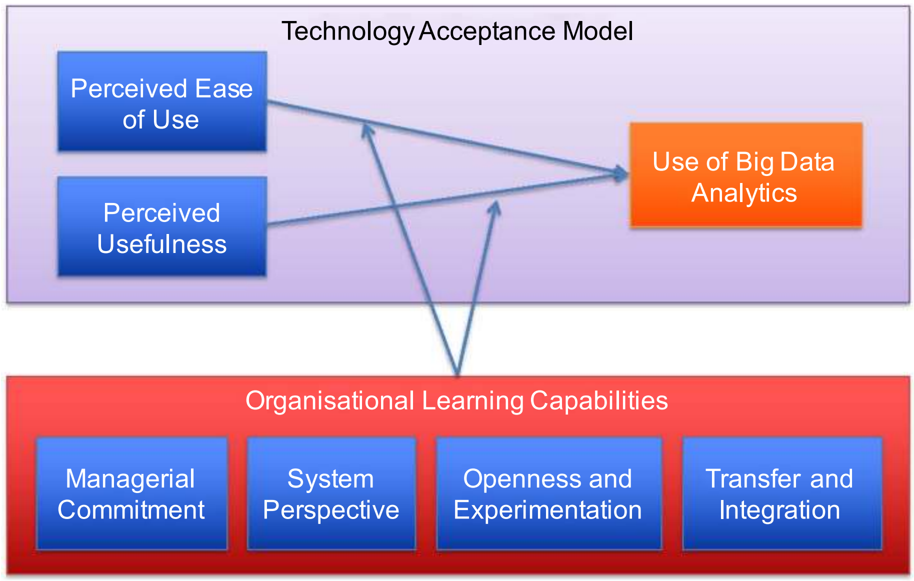

Fig. 5 Theoretical Framework for Evaluating the Intended Usage of Big Data (Source: Adapted from Davis [9] and Jerez-Gomez et al. [21])

Having done the literature review to establish the linkages between the variables involved in the process of understanding the role of TAM together with OLC in adapting big data technology, the following hypothesis are framed. The first two hypotheses are framed by considering the relation between perceived ease of use, perceived usefulness and usage of big data analytics.

H_1: Perceived ease of usage is positively related to the intended usage of big data analytics.

H_2: Perceived usefulness is positively related to the intended usage of big data analytics.

TAM is often criticized as it does not account for other factors of technology adoption [70]. So, more contemporary studies focus on other theories, such as organizational learning and knowledge management in order to understand environmental factors beyond personal perceptions to adopt a new technology [80]. So, the second set of hypotheses helps to explore OLC model in the adoption of big data analysis. These are framed in four stages as per the four constraints of the OLC model—managerial commitment, system perspective, openness and experimentation and transfer and integration.

Hypothesis 3a: Managerial commitment positively moderates the relationship between perceived ease of usage and intended usage of big data technologies.

Hypothesis 3b: Managerial commitment positively relates to the intended usage of big data analytics.

Hypothesis 3c: Managerial commitment positively moderates the relationship between perceived usefulness and intended usage of big data technologies.

Table 1 Enabling factors for the research model

No	Factor	Name	Supported by	Relevance
F1	tamUse	Intended usage of technology	Davis [20], Davis [9], Venkatesh and Davis [68], Legris et al. [24], Khan [103, 104], Bashir et al. [105], [116, 117]	Independent variable. Refers the degree of technology usage and adoption
F2	tamPeou	Perceived ease of use	Davis [9], Amoako-Gyampah and Salam [67], Bagozzi [70], Chuttur [64], Khan [106, 107], Bashir [108]	Individuals are motivated to adopt a new technology when using a particular system would enhance job performance
F3	tamPu	Perceived usefulness	Davis [9], Legris et al. [24], Amoako-Gyampah and Salam [67], Bagozzi [70], Chuttur [64], Khan et al. [103, 107]	Individuals are motivated to adopt a new technology when using a particular system would be free of a steep learning curve
F4	olcMc	Managerial commitment	Nonaka [74], Senge and Suzuki [82], Nonaka and Takeuchi [86], Jerez-Gomez et al. [21], Khan et al. [109, 110]	Support and leadership of top management to create and build knowledge within the organization can motivate the usage of new technologies
F5	olds	System perspective	Senge and Suzuki [82], Kim [83], Templeton et al. [31], Jerez-Gomez et al. [21], Nwankpa and Roumani [22], Das and Khan [111], Khan and Fournier-Bonilla [112]	Understanding of the organisation with clear goals and objectives can impact on adoption of new systems and technologies
F6	olcOe	Openness and experimentation	Kim [83], Dierkes et al. [80], Jerez-Gomez et al. [21], Roome and Wijen [73], Nwankpa and Roumani [22], Khan et al. [55], Khan and Alhusseini [113]	A favorable climate and structures that encourage individuals to try new ideas can motivate individuals to embrace a project without the fear of being punished or laid off in the event of failure
F7	loci	Transfer and integration	Nonaka [74], Senge and Suzuki [82], Nonaka and Takeuchi [86], Kim [83], Jerez-Gomez et al. [21], Nwankpa and Roumani [22], Khan and Uwemi [114], Uwemi and Khan [115]	The exchange and integration of knowledge across departments and functional areas can improve adoption of new systems and technology

The next set of hypotheses refers to the interaction between system perspective of OLC and TAM model.

Hypothesis 4a: System perspective positively moderates the relationship between perceived ease of usage and intended usage of big data technologies.
Hypothesis 4b: System perspective positively relates to the intended usage of big data analytics.
Hypothesis 4c: System perspective positively moderates the relationship between perceived usefulness and intended usage of big data technologies.

For the next dimension, openness and experimentation the hypotheses are

Hypothesis 5a: Openness and experimentation positively moderates the relationship between perceived ease of usage and intended usage of big data technologies.
Hypothesis 5b: Openness and experimentation positively relates to the intended usage of big data analytics.
Hypothesis 5c: Openness and experimentation positively moderates the relationship between perceived usefulness and intended usage of big data technologies and the last set of hypothesis for the transfer and integration dimension is

Hypothesis 6a: Transfer and integration positively moderates the relationship between perceived ease of usage and intended usage of big data technologies.
Hypothesis 6b: Transfer and integration positively relates to the intended usage of big data analytics.
Hypothesis 6c: Transfer and integration positively moderates the relationship between perceived usefulness and intended usage of big data technologies.

Thus, by going through the literature review and by understanding the linkages between among the variables, the following conceptual framework in Fig. 6 is proposed for the analysis.

Methodology

This study is an explanatory research and attempts to connect the existing knowledge to understand the relationship among existing theories. The research model proposed in this work expands the TAM framework by incorporating the dimensions of the OLC model to expand the model and better comprehend the adoption of big data analytics. The hypotheses formulated after the literature review and research model are tested using quantitative research methods with mathematical modelling and statistical analysis.

The study is primary data based and data is collected from the students belonging to the information technology programs at the University of Liverpool Online. The participation request email is sent and is followed up to remind the students about the survey, as recommended by Dillman's Tailored Design Method [88]. Thus, among the total number of students, 34% (359) responded back. The measurement scales used in this study are tested for validity and reliability.

The framed hypotheses are tested using multivariate regression with ordinary least square, i.e., linear regression estimation. Baron and Kenny's [89] mediation and

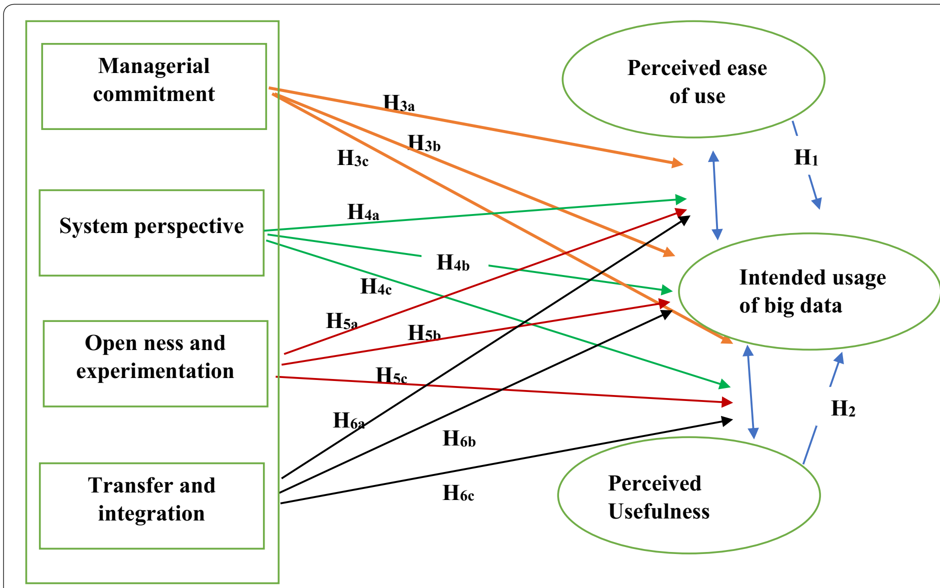

Fig. 6 Research framework

moderation tests are employed to test the moderation effect. This study uses computerized simulation of quasi-Bayesian Monte Carlo method based on normal approximation for variance estimation to test for mediation effect. To avoid over fitting or misspecification, both regression and the Monte Carlo simulation controlled important variables such as company size, IT department's size, investments in technology, etc. are used in analysis.

Sampling and data collection

To test the hypotheses, a survey is designed for students of University of Liverpool Online in the following graduate programs pertaining to various disciplines of Masters in Science program. As this study is dealing about the technology integration so as to increase its utility, a group of students who are pursuing post-graduate degree in technology related disciplines is selected for the study. Overall, 1035 students are sampled from the all the disciplines. The data for the variables is collected using a seven-point Likert-type scale. The questionnaire is designed using Type form, online survey tool designed to collect data [90]. The results are downloaded from Type form (Excel file) and loaded into the statistical software for data analysis.

Model validation

This study uses structural equation modelling (SEM) and multivariate regression analysis with ordinary least squares (OLS) estimation for testing the hypotheses proposed. Structural equation modelling represents a contemporary statistical technique for testing and estimating the relation between the factors and variables [91]. This study tests the reliability and validity of the constructs using confirmatory factor analysis (CFA). Statistical analysis is performed with the statistical software: R Project for Statistical Computing [92]. Figure 7 summarizes the procedures followed in research methods and realization. Design and data collection took place at the beginning. Next, the confirmatory factorial analysis is run for explicit evaluation of unidimensionality of measurement scales. This step assures that the measurement model is suitable for structural model. Finally, the structural model is tested to confirm or reject proposed hypotheses [93, 94].

This study explores seven constructs in two distinct contexts (models). The first context is the TAM framework. It consists of the following constructs: (a) perceived ease of use (tamPeou); (b) perceived usefulness (tamPu); and, (c) intended usage of technology. All scales are extracted from the literature to assure validity and reliability. The model is validated using CFA, composite reliability (CR), average variance extracted (AVE) and convergent and discriminant validity, as recommended by the literature [91]. The model required iterative scale purification and hence, five variables had to be dropped. All variables exhibit proportion of variance above the recommended levels ($R^2 > 0.50$). The final model fit for the multi-item scales [χ^2 (93.3, N = 359) $p > 0.001$; GFI > 0.95; NFI > 0.97; CFI > 0.98; RMSEA = 0.048], which are in the expected range [93]. The model reliability for each construct, measured by CR and AVE are also above the expected minimum (CR > 0.75; AVE > 0.60) [95]. Table 2 shows the parameters estimates for each item for the TAM.

The second model is the OLC model, which consists of the following constructs: (a) managerial commitment (olcMc); (b) system perspective (olcSp); (c) openness and

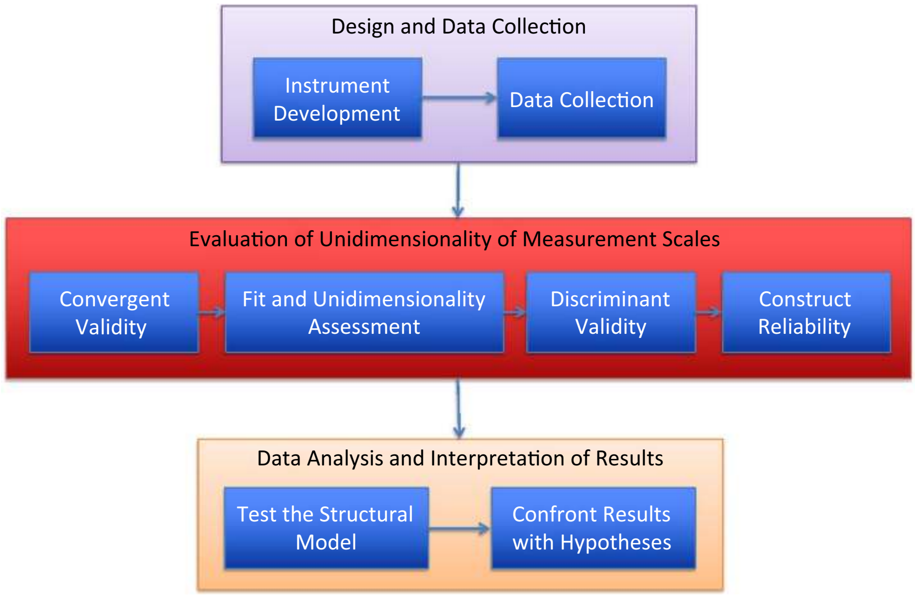

Fig. 7 Procedures for research using structural equation modelling and confirmatory factor analysis (Source: Adapted from Koufteros [94], Kline [93] and Bollen [91])

Table 2 Parameters estimates for TAM

Latent variable	Item	Estimate	Std. error	t-value	R^2
Intended usage of technology (CR = 0.94; AVE = 0.80)	tamUse1	1.690	0.075	22.470*	0.837
	tamUse2	1.799	0.073	24.562*	0.926
	tamUse3	1.475	0.084	17.657*	0.618
	tamUse5	1.676	0.077	21.744*	0.806
Perceived ease of use (CR = 0.90; AVE = 0.69)	tamPeou2	0.953	0.056	17.032*	0.605
	tamPeou3	1.059	0.051	20.591*	0.777
	tamPeou4	0.989	0.049	20.325*	0.764
	tamPeou5	0.904	0.053	17.151*	0.611
Perceived usefulness (CR = 0.96; AVE = 0.85)	tamPu2	1.433	0.061	23.611*	0.882
	tamPu3	1.443	0.060	24.005*	0.899
	tamPu4	1.383	0.058	23.638*	0.883
	tamPu6	1.192	0.060	19.969*	0.724

* $p < 0.001$

experimentation (olcOe); and, (d) transfer and integration (olcTi). All the variables exhibit proportion of variance above the recommended levels ($R^2 > 0.50$). The final model fit for the multi-item scales [χ^2 (75.2, N = 359) p > 0.001; GFI > 0.96; NFI > 0.98; CFI > 0.98; RMSEA = 0.052], which are in the expected range [93]. The model reliability for each construct, measured by CR and AVE, are also above the expected minimum (CR > 0.75; AVE > 0.60) [95]. Table 3 shows the parameters estimates for each item for the OLC.

The raw scores of the factor scales are converted in summated scales by the arithmetic mean of the items of each construct. OLC variables are also converted to dichotomous variables for better reliability in the moderation tests (Ping Jr [96–98].

Table 3 Parameters estimates for OLC

Latent variable	Item	Estimate	Std. error	t-value	R^2
Managerial commitment (CR = 0.78; AVE = 0.64)	olcMc2	1.119	0.071	15.843*	0.570
	olcMc3	1.313	0.072	18.129*	0.705
System perspective (CR = 0.87; AVE = 0.68)	olcSp2	1.132	0.062	18.200*	0.672
	olcSp3	1.305	0.067	19.418*	0.732
	olcSp4	1.199	0.068	17.636*	0.644
Openness and experimentation (CR = 0.84; AVE = 0.73)	olcOe1	1.312	0.066	20.000*	0.751
	olcOe4	1.184	0.062	19.028*	0.701
Transfer and integration (CR = 0.89; AVE = 0.67)	olcTi1	1.222	0.071	17.237*	0.609
	olcTi2	1.325	0.066	20.045*	0.741
	olcTi3	1.191	0.061	19.415*	0.712
	olcTi4	1.260	0.073	17.337*	0.614

* $p < 0.001$

Data analysis

This study employs multivariate methods to test the hypotheses. The moderation method is one of the most popular approaches to study the influence of external variables in a causal model [99]. A traditional causal model explores the relationship between independent variables (e.g., tamPeou and tamPu) and the dependent variable (e.g., tamUse). By adding a third variable (i.e., OLC moderators) it is possible to better understand the mechanism through which the causal variable affects the outcome [99].

In both moderation and mediation tests, the following variables are controlled: (a) company size, computed as the natural logarithm of the number of full-time employees; (b) IT department size, computed as the natural logarithm of the number of full-time employees in the IT department, (c) experience, measured by the numbers of year working in the current position; (d) company seniority, measured by the number of years working in the company; (e) degree of internationalization, measured by the percentage of international clients; (f) investments in technology, measured by the percentage of investments in hardware, software and consulting services in the past couple year; (g) industry; and (h) course undertaken.

Descriptive statistics

Table 4 depicts the number of respondents per program at the University of Liverpool Online (contCour). The majority of the respondents are from the M.Sc. in Information Systems and Management (34.26%). Followed by the M.Sc. in Information Technology (15.88%), M.Sc. in Computer Security (14.76%) and M.Sc. in Software Engineering (12.53%). This result presents a very similar distribution compared to the population extracted from the communities: M.Sc. in Information Systems and Management (36.8%) followed by M.Sc. in Information Technology (14.9%), M.Sc. in Computer Security (15.21%) and M.Sc. in Software Engineering (15.7%). Therefore, it can be concluded that the sample is significant to the population regarding the course distribution.

Table 5 reports the age of the respondents (contAge). The age distribution follows the probabilistic Gaussian curve (normal distribution) commonly expected in any demographic composition. Most of the respondents are between 31 and 40 years old; which is expected for experienced professionals undertaking a Master's degree.

Table 4 Respondents per program

Program	Freq.	%	Cumul. %
M.Sc. in computer security/computer information security	53	14.76	14.76
M.Sc. in information systems and technology	35	9.75	24.51
M.Sc. in information systems management	123	34.26	58.77
M.Sc. in information systems project management	24	6.69	65.46
M.Sc. in information technology	57	15.88	81.34
M.Sc. in internet systems	14	3.90	85.24
M.Sc. in software engineering	45	12.53	97.77
M.Sc. in web sciences and big data	5	1.39	99.16
PG Cert in information systems and technology	3	0.	100.00
Total	359	100.0	–

Table 5 Age of respondents

Age (years)	Freq.	Percentage
≤25	8	2.23
26–30	69	19.22
31–35	118	32.87
36–40	87	24.23
41–50	69	19.22
51 and over	8	2.23
Total	359	100

Figures 8, 9, 10 and 11 show the frequency report for OLC's constructs. Figure 11 reports the respondents' perception of companies' managerial commitment for organizational learning. The questions are as followw: olcMc1 is "In this company, employee learning is considered a key factor", olcMc2 is "The company's management looks favourable for carrying out changes in any area to adapt new conditions", olcMc3 is "In this company, innovative ideas that work are rewarded", and olcMc4 is "In this company, employee learning is considered as an investment". It is a crucial factor as the top management play an important role by providing support and resources to implement new technologies [22]. Overall, respondents' answers are positive regarding their companies' managerial commitment for organizational learning, less than 25% reply "neither agree nor disagree", or "somewhat disagree", and less than 10% reply "disagree" or "completely disagree".

Figure 9 reports the respondents' perception about company system perspective. System perspective refers to the understanding of organizational objectives and according to Jerez-Gomez et al. [21], individuals that do not understand the "bigger picture" may not engage in the adoption of new technologies. The questions are as follows: olcSp1 is "All trained employees have generalized knowledge regarding this company's goals and objectives", olcSp2 is "All subunits that make up this company (departments, sections, divisions work teams and individuals) are well aware of how they contribute to achieve the overall goals and objectives", olcSp3 is "All parts that make up my company are interconnected working together in a coordinated manner", and olcSp4 is "Everyone

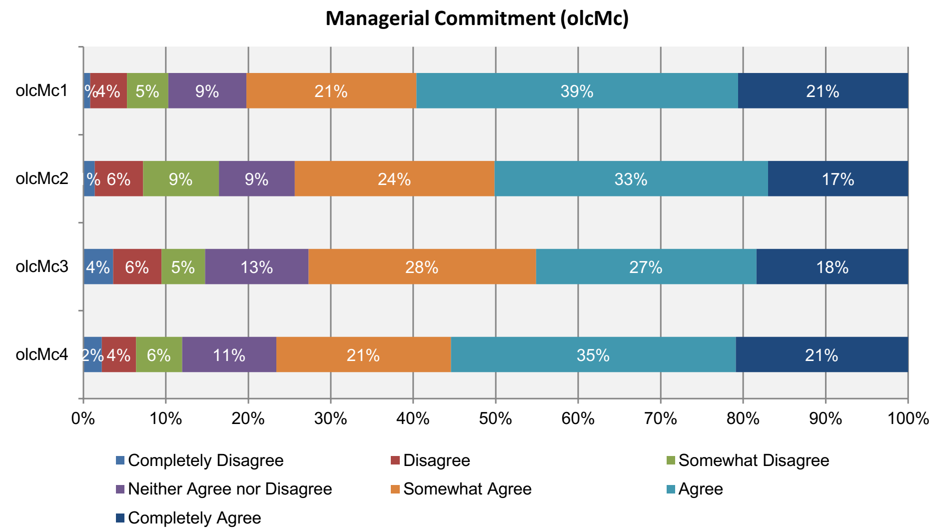

Fig. 8 Respondents' perception of managerial commitment

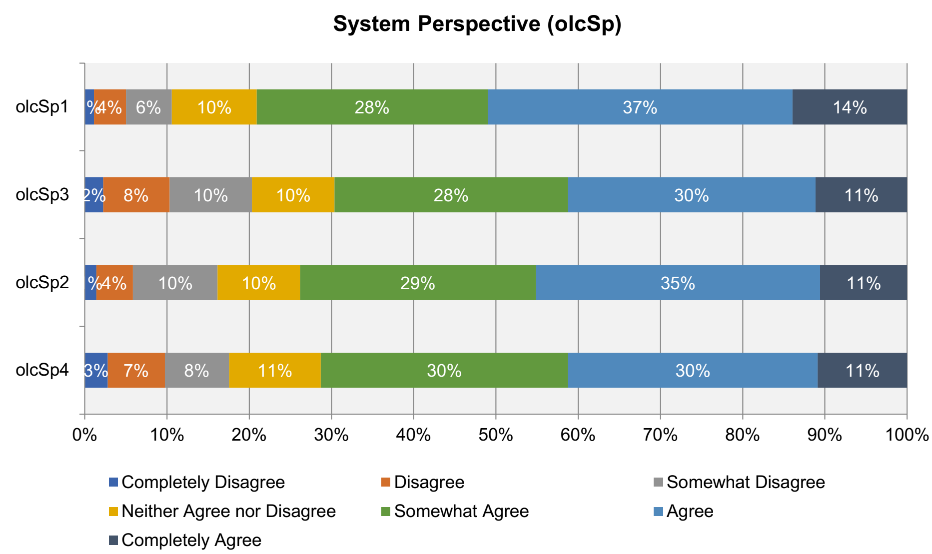

Fig. 9 Respondents' perception of system perspective

clearly understands the chain of command and processes within this company". Overall, respondents' answers are positive in regards of their system perspective. More than 70% of the respondents answered "somewhat agree", "agree", and "completely agree".

Figure 10 depicts the respondents' perception of company openness and experimentation for learning. According to Nwankpa and Roumani [22], an open company is more keen to explore new technology and often harvest the benefits of early adoption. The questions to assess this dimension are the following: olcOe1 is "My company promotes experimentation and innovative ideas as a way of improving business processes", olcOe2 is "My company follows up on the activities of other companies within the sector and is willing to adopt those practices and techniques that it believes to be useful and

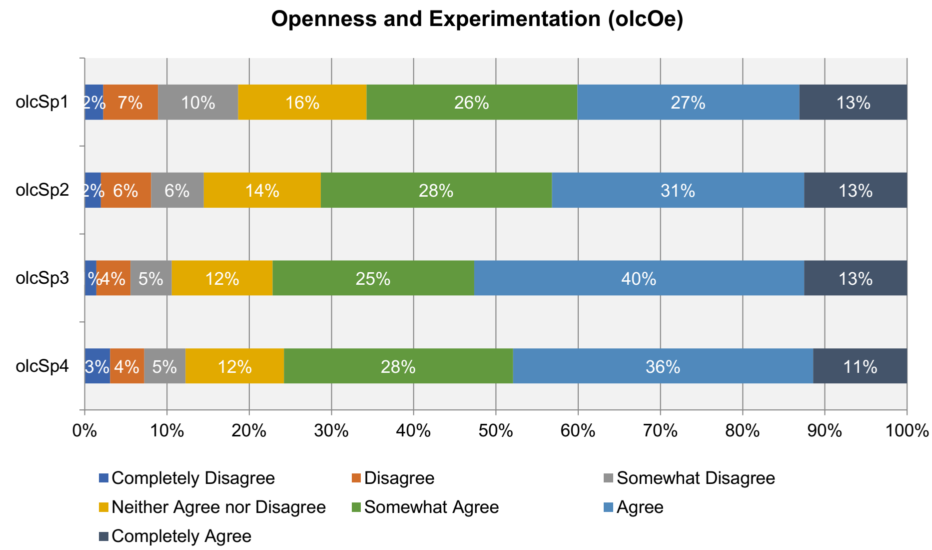

Fig. 10 Respondents' perception of openness and experimentation

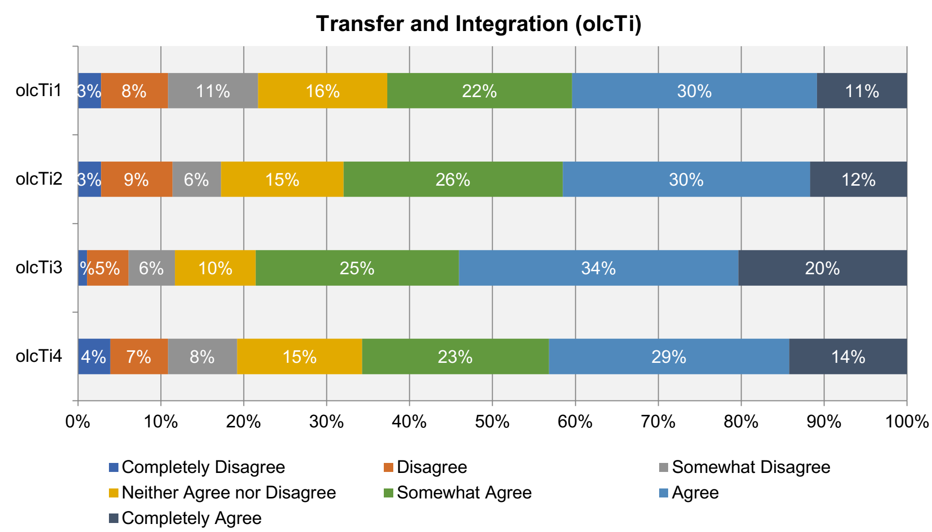

Fig. 11 Respondents' perception of transfer and integration of knowledge

interesting", olcOe3 is "Experience and ideas provided by external sources (clients, consulting firms, etc.) are considered important for this company learning", and olcOe4 is "The culture of this company encourages expression and opinions as well as suggestions regarding the procedures and methods".

Vast majority of the respondents "somewhat agree", "agree", or "completely agree" with the statement of each question. Just a small percentage perceived their company as not favourable to openness and experimentation. It is an expected outcome as most IT professionals are keen to explore new technologies, and companies often provide such an environment. Nevertheless, not every company is open to experimentation with new technology, such as big data analytics, as they can be very costly and deliver little economic benefit [84, 85, 87].

Figure 11 reports the respondents' perception of commitment for knowledge transfer and integration. This dimension refers to the organizational culture and formal procedures to disseminate knowledge throughout the company. The questions to evaluate this dimension are: olcTi1 "Errors and failures are always discussed and analysed in this company at all levels", olcTi2 "In this company, there are processes and structures that offer employees the chance to talk about new ideas, programs and activities that might be useful to the company", olcTi3 "This company encourages collaboration, team work and information dissemination" and olcTi4 "The company has a mechanism that allows what has been learnt in past situation to remain valid and accessible to employees".

The majority of respondents perceive their company as favourable to knowledge transfer and integration and very few disagree to some extent that their company promotes for knowledge dissemination. According to Kim [83], organizational learning affects individual learning that then results in the adoption of new technologies. It is an expected outcome in the IT industry, because of the fast changing environment. Companies need to learn new competencies to keep up and adopt newer technology, and the only alternative is to promote knowledge exchange within the organization [22].

Inferential statistics, hypotheses tests and discussion

Table 6 reports the means, standard deviations, and correlations of all variables used in this study. The results showed significant correlation between dependent and independent variables. It is expected as other studies using TAM [68] and OLC dimensions [21] also reported a similar degree of correlation. This should not represent a problem for multivariate models, as variables exhibit of variance above the recommended levels ($R^2 > 0.50$) and low standard error ($SE < 0.08$)

Regression and moderation test

This study uses SEM and OLS to test the hypotheses. The equation describing the OLS model to be estimated is

$$\hat{\boldsymbol{y}}\boldsymbol{his} = \boldsymbol{\beta_0} + \boldsymbol{\beta_S X_S} + \boldsymbol{\beta_C X_C} + \boldsymbol{\beta_M X_M} + \boldsymbol{\varepsilon}$$

where $\hat{y}\boldsymbol{h}$ is the dependent variable, $\boldsymbol{\beta_0}$ is the intercept, $\boldsymbol{\beta_S}$ is the vector of coefficients of the substantive dependent variables, $\boldsymbol{X_S}$ is the vector of the substantive dependent variables, $\boldsymbol{\beta_C}$ is the vector of the coefficients of the control variables, $\boldsymbol{X_C}$ is the vector of control variables, $\boldsymbol{\beta_M}$ is the vector of the coefficients of the moderation variables, $\boldsymbol{X_M}$ is the vector of moderation variables, and ε is the estimate error.

The model to test intended use of technology (tamUse) as dependent variable of the equation takes the form

$$\begin{aligned} tamUse_i = {} & \beta_{0(intercept)} + \beta_1 \times contSize + \beta_2 \times contSizeIt + \beta_3 \times contExp1 + \beta_4 \times contExp2 \\ & + \beta_5 \times contInds + \beta_6 \times contCour + \beta_7 \times contIntr + \beta_8 \times contInvst + \beta_9 \times contAge \\ & + \beta_{10} \times tamPu + \beta_{11} \times tamPeou + \beta_{12} \times olcMcDic + \beta_{13} \times olcSpDic + \beta_{14} \times olcOeDic \\ & + \beta_{15} \times olcTiDic + \beta_{16} \times tamPeou{:}olcMcDic + \beta_{17} \times tamPeou{:}olcSpDic \\ & + \beta_{18} \times tamPeou{:}olcOeDic + \beta_{19} \times tamPeou{:}olcTiDic + \beta_{20} \times tamPu{:}olcMcDic \\ & + \beta_{21} \times tamPu{:}olcSpDic + \beta_{22} \times tamPu{:}olcOeDic + \beta_{23} \times tamPu : olcTiDic + \varepsilon \end{aligned} \tag{1}$$

Table 6 Descriptive statistics and correlation

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. tamUse	–													
2. tamPeou	0.46***	–												
3. tamPu	0.53***	0.59***	–											
4. olcMc	0.35***	0.21***	0.18***	–										
5. olcSp	0.31***	0.20***	0.14**	0.63***	–									
6. olcOe	0.31***	0.22***	0.18***	0.73***	0.73***	–								
7. olcTi	0.33***	0.19***	0.13*	0.73***	0.72***	0.82***	–							
8. contSize	0.16**	0.01	0.06	0.14**	0.08	0.09	0.15**	–						
9. contSizeIt	0.13*	−0.06	−0.06	0.19***	0.08	0.16**	0.21***	0.75***	–					
10. contExp1	0.04	0.02	0.00	−0.01	0.06	0.03	−0.01	−0.15**	−0.14**	–				
11. contExp2	0.08	0.03	0.05	0.05	0.07	0.03	0.01	−0.02	−0.06	0.25***	–			
12. contAge	0.04	−0.06	0.00	0.08	0.07	0.08	0.03	0.10^{+}	0.05	0.24***	0.21***	–		
13. contIntr	0.05	−0.02	−0.05	0.19***	0.06	0.09^{+}	0.14**	0.21***	0.23***	−0.02	−0.13*	0.01	–	
14. contInvs	0.08	−0.05	0.00	0.06	0.05	0.09	0.10^{+}	0.00	0.13*	−0.01	−0.06	0.04	0.03	–
Mean	3.80	4.78	4.96	5.12	4.96	5.01	4.98	6.64	3.85	4.99	6.68	35.88	15.08	38.18
SD	1.71	1.03	1.39	1.38	1.30	1.36	1.33	2.36	2.22	3.52	7.77	7.54	17.74	35.91
Scale	1:7	1:7	1:7	1:7	1:7	1:7	1:7	log(n)	log(n)	1:n	1:n	1:n	%	%

$^{+}$ $p < 0.1$

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

where, contSize is company size, contSizeIt is company's IT department size, contExp1 is respondent's experience, contExp2 is respondent's seniority, contInds is industry, contCour is graduate course, contIntr is company's level of internationalization, contInvst is company's level of investments in technology, contAge is age of the respondent; tamPu is TAM's perceived usefulness of technology, tamPeou is TAM's perceived ease of use of technology, olcMcDic is OLC's managerial commitment dimension; olcSpDic is OLC's system perspective dimension, olcOeDic is OLC's openness and experimentation dimension and olcTiDic is OLC's transfer and integration dimension. Variables with prefix *cont* are control variables and variables with suffix *Dic* are dichotomous variables.

The above Table 7 speaks about the hypotheses in this study. For Model 1, β_{10} to β_{23} are constrained to zero in order to examine the effect of controls variables on the dependent variable. As expected, none of the control variables show significant impact on the dependent variable and the regression model R^2 is 0.09 and F-tests are not significant ($F = 1.15$; $p > 0.1$). For Model 2, β_{12} to β_{23} are constrained to zero to test Hypothesis 1 and 2. As expected, the perceived usefulness (tamPu) and perceived ease of use (tamPeou) have a positive and significant relationship with the use and intended usage of big data analytics (tamUse), thus supporting Hypotheses 1 and 2. It is an expected result as the TAM framework has been largely tested with a variety of technologies [64], and it is not expected to have a different outcome. The Model 2 is statistically significant ($F = 6.91$; $p < 0.01$) and exhibits $R^2 = 0.39$; hence 39% of the variance is explained by Model 2, which is about 30% more compared to Model 1.

For Model 3, β_{16} to β_{23} are constrained to zero to test the Hypotheses 3b, 4b, 5b, and 6b. This model examines the relationship of OLC dimensions over TAM. The regression model is statistically significant ($F = 7.08$; $p < 0.01$) and exhibits $R^2 = 0.43$; hence 43% of the variance is explained by Model 3, which is 4% more compared to Model 2. As expected managerial commitment (olcMc) does have a positive and significant relationship with the use and intended usage of big data analytics (tamUse), thus supporting Hypothesis 4a. It is an expected outcome according to the literature [21] and to practice, as managerial commitment is a key factor for adopting new technology and the fostering of innovation. Despite the nature of OLC dimensions, the regression does not show system perspective (olcSp), openness and experimentation (olcOe), and transfer and integration (olcTi) as significant. Thus, the model does not support Hypotheses 4b, 5b, and, 6b.

The last regression aims to test the moderation Hypotheses 3a, 4a, 5a, 6a, 3c, 4c, 5c, and 6c. Model 4 provides an interaction of continuous variables (tamPu and tamPeou) with dichotomous variables (olcMcDic, olcSpDic, olcOeDic, and OlcTiDic), the interpretation of the coefficient is as follows: β_{10}, is the slope of tamPu of olcMcDic, olcSpDic, olcOeDic, and OlcTiDic at 0 (below average OLC), while β_{20} to β_{23}, is the change of slope for olcMcDic, olcSpDic, olcOeDic, and OlcTiDic at 1 (above average OLC). Likewise, β_{11}, is the slope of tamPeou of olcMcDic, olcSpDic, olcOeDic, and OlcTiDic at 0 (below average OLC), while β_{16} to β_{19}, is the change of slope for olcMcDic, olcSpDic, olcOeDic, and OlcTiDic at 1 (above average OLC). The regression model is statistically significant ($F = 5.98$; $p < 0.01$) and exhibits $R^2 = 0.44$; hence 44% of the variance is explained by Model 4, which is 1% more compared to Model 3.

Contrary to expectations, management commitment (olcMc) does not provide significant moderation on perceived usefulness (tamPu) or perceived ease-of-use (tamPeou), thus showing no support for Hypotheses 3a, and 3c. System perspective (olcSp) does not provide significant moderation on the perceived usefulness (tamPu) but does provide a significant moderation effect on perceived ease of use ($\beta = 0.59$; $p < 0.05$), thus supporting Hypothesis 4a but not 4c. Contrary to expectations, openness and experimentation (olcOe) does not provide significant moderation on perceived usefulness (tamPu) or perceived ease-of-use (tamPeou), thus showing no support for Hypotheses 5a and 5c. Transfer and integration of knowledge (olcTi) does not provide significant moderation on perceived ease-of-use (tamPeou) but does show a significant moderation effect on perceived usefulness ($\beta = 0.42$; $p < 0.05$), thus supporting Hypothesis 6c but not 6a.

There is no evidence in the literature to support the significant negative moderation effect of Hypothesis 6b ($\beta = -0.74$; $p < 0.1$). This could represent a residual error or multicollinearity side effect, although no indications of significant residuals in the model are found, as shown below in Table 7.

Likewise, variance inflation factor (VIF) of centralized variables (shown with suffix Cent: tamUseCent, tamPuCent, and tamPuCent, in the output, Appendix E) are below the cut point proposed by Kutner et al. [100] of $\beta_{VIF} < 10$ and $\sqrt{\beta_{VIF}} < 2$. Variable centralization did not affect the models' results. Some authors discuss that odd results in the regression with moderators can be also an indication of a different effect, i.e., mediation.

Effect simulations and mediation test

Table 8 shows the results of the mediation test computed using the quasi-Bayesian Monte Carlo simulation. The equation describing the simulation model to be estimated is the same as described previously, but moderation variables take the role of mediator in the simulation. The purpose of this simulation is to evaluate the significance of the indirect effect (mediation) in each interaction.

As expected, none of the interactions in the formula $[(\text{tamPu} + \text{tamPeou}) \times (\text{olcMc} + \text{olcSp} + \text{olcOe} + \text{olcTi})]$ shows a significant average causal mediation (ACME) and proposed mediation values. According to Kenny [99], a mediation effect is worth considering when $ACME > 0.30$. In all interactions average direct effect (ADE) are significant and above 0.50. It indicates that the interaction of OLC dimensions with TAM dimensions has a direct effect on the dependent variable, thus not showing any mediation.

Conclusions

This study provides useful insights as results of integration of two technology adoption frameworks aimed to explain the adoption of big data analytics. The adoption of big data analytics is an important field in the literature through exploring its adoption using either the TAM framework or the OLC model separately or together would represent a significant contribution. Unlike the existing works, this research made a niche by adapting the combined model to the technological domain. In fact, the proposed model is able to explain more variation of the technology acceptance of big data analytics than the TAM alone. Another contribution is the validation of measurement scales and the statistical analysis program. The results of this study have multiple benefits to both business

Table 7 Regression models

	Model 1	Model 2	Model 3	Model 4
(Intercept)	2.45***	−1.7**	−1.47*	−1.21
contSize	0.15*	0.06	0.08	0.09+
contSizeIt	−0.06	0.04	−0.01	−0.01
contExp1	0.03	0.02	0.02	0.02
contExp2	0.02+	0.01	0.01	0.01
contInds-education and research	−0.01	−0.02	−0.04	0.04
contInds-energy and utilities	0.2	0.04	−0.01	0.09
contInds-government	−0.02	−0.24	−0.07	−0.03
contInds-healthcare	0.23	0.2	0.12	0.2
contInds-information technology	0.5	0.32	0.35	0.44
contInds-insurance	0.38	0.14	0.02	0.07
contInds-investment	0.89	0.62	0.64	0.66
contInds-manufacturing	−0.26	−0.21	−0.22	−0.06
contInds-professional service	−0.06	−0.39	−0.4	−0.38
contInds-retail	−0.57	−0.43	−0.26	−0.14
contInds-retail banking	0.76+	0.52	0.43	0.5
contInds-telecoms	0.3	0.09	0.19	0.24
contInds-transport and logistics	−0.67	−0.94	−0.49	−0.46
contCour-M.Sc. in info sys and tech	0.08	0.04	−0.1	−0.02
contCour-M.Sc. in info sys management	0.05	0.04	0.06	0.08
contCour-M.Sc. in info sys project man	0.58	0.41	0.55	0.53
contCour-M.Sc in info technology	−0.03	0.24	0.18	0.21
contCour-M.Sc. in internet systems	−0.7	−0.28	−0.32	−0.29
contCour-M.Sc. in software Engineering	−0.16	0.18	0.11	0.09
contCour-M.Sc. in web sci and big data	0.41	−0.01	0.21	0.04
contCour-PGCert in Info Sys and Tech	1.43	0.42	0.3	0.33
contIntr	0	0	0	0
contInvs	0.01+	0.01*	0.01	0.01
contAge	0	0	0	0
tamPu		0.5***	0.47***	0.46***
tamPeou		0.37***	0.29**	0.21
olcMcDic			0.41*	0.65
olcSpDic			0.27	−0.37
olcOeDic			0.07	−1.05
olcTiDic			0.19	0.78
tamPu:olcMcDic				−0.18
tamPu:olcSpDic				−0.27
tamPu:olcOeDic				−0.11
tamPu:olcTiDic				0.59*
tamPeou:olcMcDic				0.14
tamPeou:olcSpDic				0.42*
tamPeou:olcOeDic				0.32
tamPeou:olcTiDic				−0.74*
R^2	0.09	0.39	0.43	0.44
ΔR^2		0.3	0.04	0.02
F	1.15	6.91***	7.08***	5.98***
df	28,330	30,328	34,324	42,316

+ $p < 0.1$

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

Table 8 Testing for medication with indirect effect

	olcMc	olcSp	olcOe	olcTi
tamPu				
ACME	0.0218	0.00124	0.02366	0.00193
ADE	0.6068***	0.62872***	0.61617***	0.62373***
Total effect	0.6287***	0.62996***	0.63983***	0.62566***
Prop. Med[a]	0.0327	0.00216	0.03441	0.00305
tamPeou				
ACME	0.04643+	0.03663+	0.04914*	0.0335
ADE	0.66878***	0.68892***	0.67901***	0.6856***
Total effect	0.71521***	0.72555***	0.72815***	0.7191***
Prop. Med[a]	0.06238+	0.04793+	0.06376*	0.4390

ACME average causal mediation, *ADE* average direct effect

+ $p < 0.1$

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

[a] Computed using 10,000 quasi-Bayesian Monte Carlo simulation

and academic fields. Though the study has certain limitations, it paves strong path for future analysis.

Business applications

This study has significant managerial implications. According to Al Neimat [101], IT projects frequently fail to meet original objectives, running over budget, time and scope in spite of the measures to overcome this situation. The authors Marakas and O'Brien [102] provide the example of CRM systems: "despite a significant effort to provide a better customer information (in CRM systems), still end-users would often use the ERP system to access customer information" (p. 261). The finding of this work suggests that prior to any system or technology implementation, the organisation needs to convey the technology's ease of use and usefulness and promote organizational changes to improve communication and learning, to ensure its successful adoption. This study also presents relevant information about the actual use of big data analytics techniques in various industries. Information managers can rely on this information as a benchmark for their organisation.

Academic applications

This validation of measurement scales and statistical analysis program allows future researchers to replicate and expand this study. This study provides relevant academic insights as it integrates two technology adoption frameworks to explain the adoption of big data analytics. The adoption of big data analytics is per se an important field of study and exploring its adoption using either the TAM framework or the OLC model separately would represent a significant contribution to the literature. This research takes a step further and contributes to the field of technology acceptance with an expanded research model. In fact, the proposed model is able to explain 44% of the technology acceptance of big data analytics, 5% more than the TAM alone. This aspect of the proposed model can be a source of attraction for applying this to other academic domains.

Limitations

However, this study has important limitations. First is the limited number of respondents. Even though the total number of cases (359) is significant to the population (1035 students) and it allowed robust statistical analysis, it is still a small number to provide a broader generalization. Moreover, this study only surveyed IT students from the online programs at the University of Liverpool. Despite there being no reason to believe these students do not represent the average profile of IT professionals, there yet be bias in the study. The statistical analyses have shown unexpected results, i.e., significant strong negative correlation in the OLS regressions. This problem could be a result of model misspecification, excessive residuals or multicollinearity. The statistical *ex-post* analyses did not find any of these errors in the model, nevertheless further analysis with more robust methods, e.g. multi-level modelling, is warranted. As a limitation with respect to business application, this study does not provide an implementation road map for big data analytics, but high-level references regarding individuals' perception and organizational learning to guide for data projects.

Recommendation for future research

The limitations discussed in both the fields, academic and business, highlight significant prospects for future study. In the academic area, researchers can replicate and expand this study using different methods and techniques. More robust analytical techniques could test the research model using a larger data set to deliver more comprehensive results. Likewise, qualitative research can also provide greater insights regarding technology adoption. Moreover, business professionals can create a pre-implementation assessment instrument to evaluate the technology acceptance. Also, this joint model can be tested in various domains to check the viability of the solutions.

Authors' contributions

Business and academic contributions written in conclusion section. Both authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no competing interests.

Availability of supporting data

All support data files are available and also displayed in Tables and Figures.

Consent for publication

Both authors are providing consent of publication for this research.

Ethical approval and consent to participate

Ethical approval is obtained from University of Liverpool, UK through DA.

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