ISSN: 2658-8455
Volume 3, Issue 6-1 (2022), pp.226-246.

IJAFAME
International Journal of Accounting, Finance, Auditing, Management & Economics

Assessing factors of behavioral intention to use Big Data Analytics (BDA) in banking and insurance sector: proposition of an integrated model

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Disclosure Statement :	Authors are not aware of any findings that might be perceived as affecting the objectivity of this study
Conflict of Interest :	The authors report no conflicts of interest.
Cite this article :	MESKAOUI, Z., ELKHARRAZ, A., & PENG, H. (2022). Assessing factors of behavioral intention to use Big Data Analytics (BDA) in banking and insurance sector: proposition of an integrated model. International Journal of Accounting, Finance, Auditing, Management and Economics, 3(6-1), 226-246. https://doi.org/10.5281/zenodo.7395922
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Received: November 01, 2022   *Published online: December 05, 2022*

ISSN: 2658-8455
Volume 3, Issue 6-1 (2022), pp.226-246.

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Abstract

Banking and insurance sectors have long been largely data-driven by nature. However, with the rise in the predominance of data flooding from several sources resulting from the introduction of new customers and markets, with the help of Big Data Analytics, value can be extracted more effectively, and analysis of this type of unstructured data combined with a wide range of datasets can be used to efficiently and precisely extract commercial value. The aim of this paper is to develop a conceptual framework to explain the intention of information technology practitioners in banks and insurance companies to use Big Data Analytics by exploiting the Technology Acceptance Model (TAM) joined by the Task-Technology-Fit paradigm, information quality, security, trust, and the moderating effect of managerial commitment by top management on the relationship between users' perception and their intention to use, in order to conceptualize and test an integrated framework for analyzing and measuring attitudes toward the usage of Big Data Analytics.
This paper contributes by proposing the model to assess the factors that influence users' intention towards the use of Big Data Analytics, by asserting users' perception towards the technology, trust factor, security and the effect of managerial commitment. Although the model we developed in this paper is conceptual and still needs to be tested empirically, it will serve as a basic framework for further research that is designed to evaluate factors affecting IT practitioners' attitudes towards the adoption of Big Data Analytics within the finance sector.

Keywords: Big Data Analytics, TAM, TTF, Security, Trust, Managerial commitment, Bank, Insurance
JEL Classification: O32
Paper type: Theoretical Research

Résumé

Les secteurs de la banque et de l'assurance sont depuis longtemps largement axés sur les données par nature. Cependant, avec l'augmentation de la prédominance de l'inondation de données provenant de plusieurs sources résultant de l'introduction de nouveaux clients et marchés, avec l'aide du Big Data Analytics, la valeur peut être obtenue plus efficacement, et l'analyse de ce type de données non structurées combinées à un large éventail d'ensembles de données peut être utilisée pour extraire efficacement et précisément la valeur commerciale. L'objectif de cet article est de développer un cadre conceptuel pour expliquer l'intention des praticiens des technologies de l'information dans les banques et les compagnies d'assurance d'utiliser le Big Data Analytics en exploitant le Modèle d'Acceptation de la Technologie (TAM) associé au paradigme Adéquation Tache-Technologie, la qualité de l'information, la sécurité, la confiance et l'effet modérateur de l'engagement du management sur la relation entre la perception des utilisateurs et leur intention d'utilisation, afin de conceptualiser et de tester un cadre intégré pour analyser et mesurer les attitudes envers l'utilisation du Big Data Analytics.
Cet article contribue en proposant un modèle pour évaluer les facteurs qui influencent l'intention des utilisateurs vers l'utilisation du Big Data Analytics, en affirmant la perception des utilisateurs envers la technologie, le facteur de confiance, la sécurité et l'effet de l'engagement managérial. Bien que le modèle que nous avons développé dans cet article soit conceptuel et nécessite encore d'être testé empiriquement, il servira de cadre de base pour des recherches ultérieures conçues pour évaluer les facteurs affectant les attitudes des informaticiens envers l'adoption du Big Data Analytics dans le secteur financier.

Keywords: Big Data Analytics, TAM, TTF, Security, Trust, Managerial commitment, Bank, Insurance
JEL Classification: O32
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1. Introduction

In recent years, there has been a nearly universal and growing amount of digital evidence of computer-mediated behaviors and interactions as a result of the spread of the internet, social media, mobile technology, and sensor networks, as well as the declining cost of data storage resources. (Müller et al., 2017) which led to an era of Big Data. Meanwhile, the financial industry exchanges millions of datasets. The quickest concerns in financial services are also seen to be related to fintech. They comprise a range of financial services, including online peer-to-peer, crowd-funding, platforms, wealth and asset management platforms, trading management, cryptocurrency, money transfer, and mobile payments structures. (Hasan et al., 2020) Big data is nevertheless getting more attention in the financial services industry, where information has a significant impact on key production and success aspects. It has been contributing more and more to the development of our understanding of financial operations. (Shen & Chen, 2018).

Big Data has a significant impact on how banks and insurance services are changing, specifically in the context of trade and investment, tax reform, fraud investigation and detection, risk analysis, and automation (Cody Hill, 2018). Using Big Data in banks and insurance will help to overcome various barriers and acquire insightful data to enhance client contentment. Financial analysts will then use alternative data to offer clients the best services and policies and help them make better and optimal investment decisions. As a result, there is a need for a system that can handle enormous volumes, speeds, and varieties of data, which are all enabled by Big Data Analytics (BDA) systems.

Several researches have attempted to discuss the value of Big Data Analytics (BDA) in various fields, such as healthcare (Archenaa & Anita, 2015; Shahbaz et al., 2019; Soon et al., 2016), government services (Archenaa & Anita, 2015; Sahid et al., 2021), Universities online programs (Brock & Khan, 2017). In the field of finance, studies have investigated the influence, the impact, and the applications of Big Data (Hasan et al., 2020; Nobanee et al., 2021). Consequently, understanding the factors that must be taken into account for Big Data Analytics (BDA) adoption in banks and insurance companies is essential prior to any implementation strategy. Therefore, a thorough adoption model for Big Data Analytics (BDA) is required to cover the knowledge gap now present in the literature and assist banks and insurance companies to replace outdated traditional analytics systems that cannot compete with Big Data Analytics (BDA). Implementing Big Data Analytics (BDA) is an approach to exploring massive and dense data sets to help companies to make effective decisions. The study of the implementation of BDA systems requires taking into consideration the factors that influence the adoption and the intention to use them. These factors include security, trust, the user's perception toward the new technology, and the fitness of the system for the tasks. (Dishaw & Strong, 1999) Have developed an integrated model by extending the Technology Acceptance Model with Task Technology Fit constructs in the context of information system adoption, leading to a better explanatory than either model alone. Asserting perceptions towards a technology such as perceived usefulness and perceived ease of use is a necessary approach, as was addressed in previous studies (Müller et al., 2017; Sahid et al., 2021).

Nonetheless, investigating individual perception towards technology needs to be completed with an analysis of the fitness of the technology characteristics for the task requirement, as emphasized by (Goodhue, Goodhue, D. L., R. L. Thompson, 1995). Technology may not be adopted if it is incompatible with the requirements of the user's tasks and cannot improve their job performance. Implementation will also happen once the user considers the technology as useful, simple, and innovative. In addition to the positive perception of the user towards the new technology, the fitness between the characteristics of the technology and the task is an essential construct. Moreover, other factors have been shown as important for the influence of users' behavior towards the adoption of an information technology. Perceived security is an

influential factor in the user's behavioral intention to use an information system (Damghanian et al., 2016; Fife & Orjuela, 2012). In BDA adoption, one of the most difficult factors for a user to adopt a new technology has been demonstrated to be perceived trust (Lallmahomed et al., 2017; Liao et al., 2011). BDA could make it possible for businesses to collect, organize, and disseminate information and create connections between business partners. (Kwon et al., 2014) Which makes the Information quality of the Big Data Analytics (BDA) an essential factor for the behavioral intention to adopt it.(Shin, 2015, 2016; Verma & Bhattacharyya, 2017).
Managerial commitment is also a critical factor that influences the relationship between the employee's perception of technology and their intention to actually use it. Previous researches have been conducted to study the impact of this factor (Brock & Khan, 2017; N. Khan et al., 2014). Yet, previous research hasn't discussed these factors combined as the enablers of behavioral intention to use Big Data Analytics (BDA) in the context of finance, especially for banks and insurance. Hence, this research gap creates a motivation to elaborate an integrated model that theoretically enlarges the scope of the adoption decision by combining TAM and TTF models, security, trust, information quality, and the moderating role of managerial commitment.
The objectives of this review paper are as follows.

- To elaborate an integrated model composed of the critical elements that impact the behavioral intention to use BDA.
- To serve as a theoretical basis for further empirical studies in several fields, such as banks and the insurance sector.

The following in this review paper is structured as follows: Section 1 contains a detailed review of Big Data and Big Data Analytics implementation research, and Section 2 contains a review of behavioral change prediction. Intention Theories, research models, and hypotheses have been presented in section 3. And finally, a conclusion has been presented as a final section.

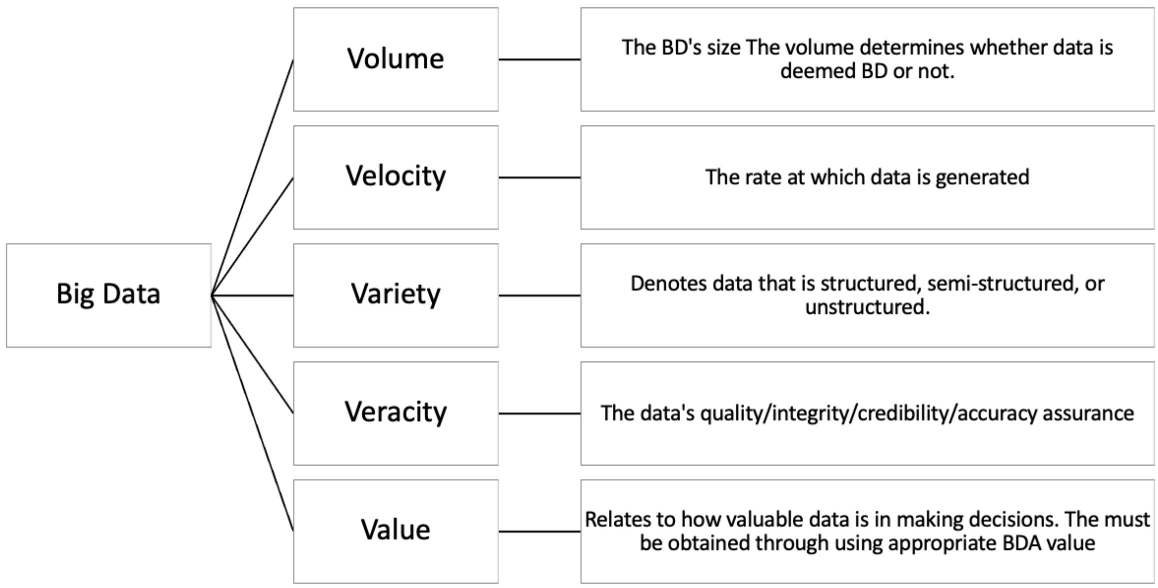
2. Theoretical background

2.1. Big Data concept

The convergence of the physical and virtual worlds can be defined as Industry 4.0. Technology that uses Big Data and Big Data Analytics (BDA) to develop decision-making systems is a hallmark of the digital revolution. (Sahid et al., 2021). A huge dataset in terms of volume, velocity, and variety surpasses the modern technological environment. This data set is known as Big Data (BD) (Brock & Khan, 2017).
Big Data can provide valuable insights that can help businesses make better decisions. (Hilbert & López, 2011) developed a three-part conceptual framework to characterize Big Data in higher education: using the framework to portray, connecting the data systems to organize the academic data, and developing a research design to help frame a set of investigational methodologies (Daniel, 2015; Omonaiye et al., 2016). (Assuncao et al., 2013) presents issues in areas other than storage, such as managing data, administration, and analytics. Big Data can bring to banks and insurance companies numerous benefits with a good commercial impact, Big Data can improve customer insight, involvement, and experience levels, develop better fraud detection and prevention systems; and more effective market trading analysis.
Banks and the insurance sector nowadays produce and receive a large amount of data thanks to new innovations and programs that support them to collect a rising number of records, tracking devices, databases, monitors, trading and account systems, stock feeds, customer feedback and other data... Users can generate gigabytes of data per month by exchanging photographs and videos, sending thousands of emails, and sharing other users' social media content, making it a massive source of big data. Standard database and software solutions can't process the large

amounts of information referred to by Big Data. The data was gathered from various sources, some of which were internal and some of which were external.
Big Data consists of three types of data: structured data, which is ordered information gathered through database systems, spreadsheets, and computers; unstructured data, such as emails, texts, and voicemails, which is dynamic information that is not stored in a specific location; and the last one is semi-structured data. It does not have fixed fields and instead uses labels or other indicators to capture data items (XML and HTML-tagged texts are examples).
(Laney, 2001) established the 3Vs, Volume, Velocity, and Variety, as the now-accepted definition of BD. The additional two Veracity and Value variables were then added to the model, making it a 5V model. According to (Bello-Orgaz et al., 2016)'s 5V model 5V model, Big Data can be described using the following characteristics:

Figure 1: 5V model of Big Data



Source: (Bello-Orgaz et al., 2016)

- **VOLUME**

From the dawn of written language to 2003, humanity generated around five exabytes of data. Every two days, the same quantity of data is created in 2011. Every 10 minutes, the same amount of data is created in 2013 (Kirk Borne, 2013).
Nowadays, the volume can be characterized by the enormous quantity of data generated by human and robotic interactions. Computer data, application logs, web browsing logs, whether data, emails, contracts, geographic information systems and geographical data, survey data, reports, spreadsheets, and social media data are all sources of data nowadays (Bankole et al., 2017; Sheikh, 2013). This massive volume of data requires specific advanced technologies, called Big Data Analytics (BDA) because it demands scalable systems and distributed querying, Big Data poses an immediate threat to traditional data storage architecture (Dumbill, 2012).

- **VARIETY**

Data is typically "structured" when it is entered into a database based on the type of data, especially operational data (i.e., character, numeric, floating point, etc.) (Minelli et al., 2013).
Over time, various sources of data have generated increasingly unstructured data that goes beyond the scale of a traditional application (Minelli et al., 2013). Are considered unstructured data the text, audio, video, image, geospatial, and Internet data (including click streams and log

files). Finally, semi-structured data is frequently a synthesis of various data categories with some pattern or framework that is less precisely defined than structured data. Call center logs, for instance, can include the following information: customer name, date of call, and complaint, where the complaint material is unstructured and difficult to synthesize into a data repository (Minelli et al., 2013).

- **VELOCITY**

Velocity is how fast data is generated, gathered, assimilated, and evaluated. Businesses are under pressure to process information in real time or with close to real-time replies as a result of the world's accelerating speed. This characteristic describes the accelerating rate at which this data is produced, as well as the expanding rate at which relational databases can process, store, and analyze the data. Velocity describes the rate at which fresh data is produced and the rate at which data is transferred (Ishwarappa & Anuradha, 2015).
A Big Data-using company will have a significant and ongoing flow of data being produced and sent to its final destination. Data may be generated by devices, networks, cellphones, or social networks. This information must be rapidly processed and analyzed, often in close to real time. Although Big Data and large-scale data sets are characterized using the three Vs, it is crucial to include two more Vs in the gathering of the insights from Big Data, Veracity and value.

- **VERACITY**

It is impossible for all of the data to be 100% accurate when coping with a high volume, velocity, and variety of data; there will inevitably be some inaccurate data. The level of data that is being collected can differ substantially. The veracity of the source data determines how reliable the analysis's data will be (Ishwarappa & Anuradha, 2015).
The importance of considering data quality is highlighted by veracity (J. Steven Perry, 2017). Therefore, at a time when the volume, velocity, and variety of data are rapidly growing, the authenticity of Big Data is a major concern. (Oracle, 2013).

- **VALUE**

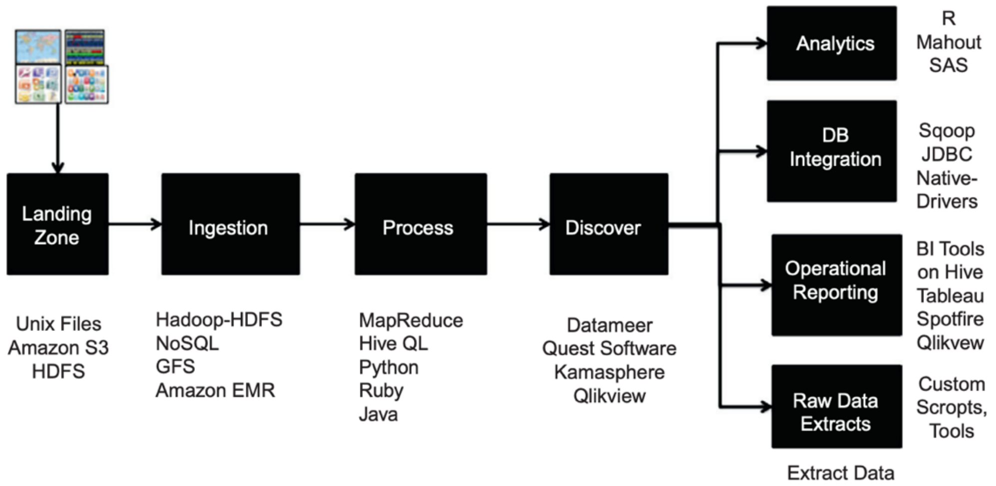
The most crucial component of large data is value. Nonetheless, Big Data has enormous potential usefulness. Having access to big data is great, but unless we can use it to create value, it is worthless. Businesses will need a return on investment since establishing an IT infrastructure system to hold big data has become increasingly expensive (Ishwarappa & Anuradha, 2015). Big data is becoming more prevalent, raising the value concern. Disposing of useless and unnecessary information is necessary to make the remaining information valuable. Additionally, finding relevant information and rapidly extracting it for timely analysis is challenging. (Lycett, 2013) stated that the remaining relevant material must be useful for gaining knowledge and domain-specific analysis.

2.2. Big Data Analytics and implementation research in banking and insurance sector

Big data analytics refers to the technologies (database and data mining tools) and procedures (analytical processes) that a corporation can use to evaluate massive amounts of complicated data for numerous applications aimed at improving the firm's performance in various aspects. (Malaka & Brown, 2015) Consider BDA as an advanced analytical approach and technology that uses big data to gather greater understanding and make better decisions. (Elragal & Klischewski, 2017) defined BDA as the application of deep learning techniques to huge datasets, which incorporates data collection, analysis, predictive modeling, and other aspects of modern business intelligence (MAMPU, 2020).

Despite some academics using these terms interchangeably, they argued that big data (BDA) and BDA capabilities (BDAC) had different meanings and concepts, the same researchers systematically discovered that while some research focused on the data and its properties, others extended the definition by using the term "analytics," which puts importance on the procedure, tools, and procedures needed to examine the data(Mikalef et al., 2017).
The BDAC definition may become evident as attention shifts to the influence of big data's hidden values that are extracted by analytical procedures (Dubey et al., 2018). The concept "BDA" applies to sophisticated methods used by corporations to analyze big data, including data mining, visualization, and sense-making (Grossman & Siegel, 2014).
Since the significant operational and strategic advantages of BDA, it has evolved into a tool that can help businesses operate at their most productive levels. Furthermore, the BDA infrastructure needs sophisticated technology for data administration, visualization, analysis, and storage.

Fig 2: Conceptual Big Data processing platform



Source: (Krishnan, 2013)

The banking and insurance sector is increasingly confronting difficulties in managing and profiting from very large amounts of structured and unstructured data generated by innovative IT devices, social media platforms, and corporate information systems. BDA has the potential to promote breakthrough technology and provide opportunities for large businesses and financial institutions to offer higher-quality services than they previously thought possible, for collecting, storing, transmitting, analyzing, and visualizing large amounts of organized and unstructured data (Sahid et al., 2021). Proper data analysis and a strategy for deploying Big Data technologies could help to foster a sense of informed decision-making (Lidong Wang & Randy Jones, 2017). BDA appears to be showing that high data storage, management, analysis, and visual technologies are all part of the learning process (Philip Chen & Zhang, 2014). In the industrial sector, for instance, data science methods and technology are frequently utilized to enable firms to make informed decisions and to provide relevant data to scientific specialists and researchers to confirm or disprove science models, ideas, and hypotheses (Sahid et al., 2021).
Given the benefits and the fame of BDA systems, it is important to look at the elements that drive BDA adoption in the banking and insurance sectors. Although empirical research that studies the factors that can influence BDA adoption remains insufficient and none of our models have been fully exploited yet to explain the intention to use it in the banking and insurance sector. Researchers have a great opportunity to understand how BDA can be implemented

ISSN: 2658-8455
Volume 3, Issue 6-1 (2022), pp.226-246.

IJAFAME
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because of the discrepancy between the potential benefits of BDA and its slow and low-geared adoption. Many developing countries are in the early stages of adopting BDA, hence, banks and insurances need to include a clear policy and procedure for using it. BDA deployments involve changes to the original business processes due to the absolute requirement of adapting organizational procedures to match the system's characteristics. (G. Wang et al., 2016) consider BDA systems as an inter-organizational system that must be implemented by a number of stakeholders from diverse departments. The standardization of Big Data and its system integration with other information systems are required by BDA systems. As a result, a large number of suppliers and service providers need to be controlled.

There is a significant amount of financial value to be gained from the massive amounts of insurance and banks clients claim documentation, most of which is text-based and contains descriptions entered by agents at call centers as well as notes about specific claims and situations, financial services companies have a chance to increase their level of customer engagement and proactively enhance the customer experience as a result of the digitization of financial and insurance products and services and the growing trend of consumers engaging with businesses or organizations in the digital space, these institutions have always been subject to fraud, they can be defrauded by both individuals and organized crime, and the intricacy and sophistication of these scams are growing with time. Furthermore, the increased desire for faster trade execution forced banks and insurances to begin becoming a digital environment many years ago.

According to (Philip Chen & Zhang, 2014) traditional information systems projects face greater difficulties in such situations, making BDA adoption more costly, complex, and prone to failure. As a result, data warehousing and traditional business intelligence have failed to meet the needs of complicated BDA systems.

Several studies have been undertaken to investigate BDA in various fields. (Tsai et al., 2015) presented an overview of BDA to foster the development of an elevated platform processing algorithm for BDA, they didn't forecast a user's behavior when it comes to the utilization of big data analytics. Using a technology organization environment model, (Malaka & Brown, 2015) looked into the adoption of big data analytics from an organizational perspective, although their study didn't take the individual approach to big data usage into consideration. Using the technological acceptance model and the diffusion of innovation model, (Soon et al., 2016) illustrated the adoption of big data analytics in Malaysia and investigated the moderating influences of training. The scope was expanded to all the types of companies, which limited the relevance of the study results. (Shahbaz et al., 2019) developed an integrated model to investigate the adoption of BDA in healthcare institutions using TAM, TTF, and resistance to change factors, although the model didn't include managerial support factor and the effect of the quality of the system.

In order to fill a gap in the literature, this paper's primary goal is to provide thorough research insights into the adoption of BDA, to assist banks and insurance companies in identifying the critical enablers that influence the adoption of BDA and evaluate the moderating role of managerial commitment on the user's perception towards the use of BDA.

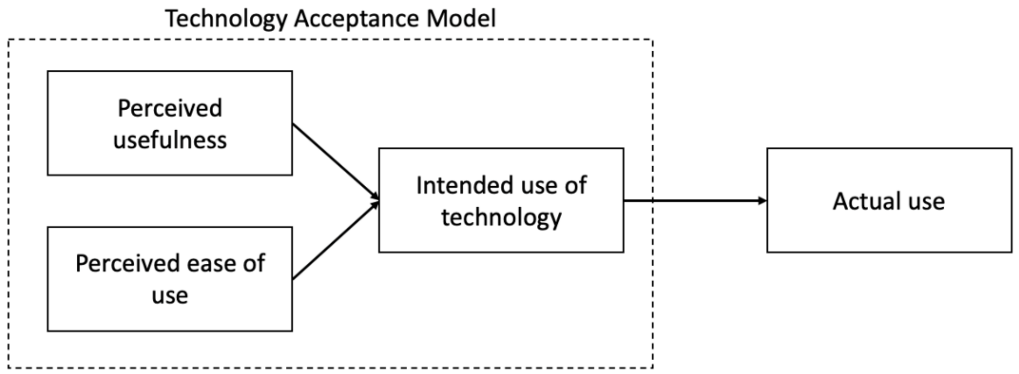
In order to meet the stated objectives, TAM and TTF models were used to make a combination between the user's perception and the fit between the task and technology, added to the model the moderating effect of the managerial commitment on the user's perception towards the use of BDA and two of the most important factors when it comes to information system adoption, trust and security.

2.3. Prediction of behavioral Intention Theories

2.3.1. Technology Acceptance Model (TAM)

Since the early 1970s, user acceptance of technology has always been one of the most important components of system usage to measure the success of information system implementation in the field of information systems management (Aggelidis & PD, Chatzoglou, 2009). And since the paper will deal with the behavior and perception of users towards the use of Big Data Analytics as an information system, it will be interesting to adopt the TAM. The Technology Acceptance Model (TAM) is the subject of multiple theoretical and exploratory studies related to user behavior towards the use of information technology (Cheung & Vogel, 2013). The model represents two main constructs in the analysis and highlighting of user behaviors towards the use of the information system, perceived ease of use and perceived usefulness. The first construct has been defined as the level at which a person believes that using a specific technology would be effortless (Davis, 1989; Verkasalo et al., 2010). On the other hand, the second construct indicates the degree to which an individual believes that the improvement of his or her work performance will be determined by the use of a specific technology. (L. S. Huang et al., 2017).
The TAM has been updated and extended by many researchers to include additional characteristics such as effectiveness (Segars & Grover, 1993) and organizational beliefs (Amoako-Gyampah & Salam, 2004). The approach explains even less of the degree of technology usage in particular circumstances, such as online banking (Pikkarainen et al., 2004). Thus, in our integrated model, the two main constructs of the original TAM were deployed to evaluate the causal relationship with the intention of using the BDA.

Figure 3: Original Technology Acceptance Model



Source : (Davis & Venkatesh, 1996)

2.3.2. Task-Technology Fit Model (TTF)

Lack of task focus is a limitation in TAM's ability to evaluate BDA usage. Individuals use BDA as a tool to complete tasks effectively. Inconsistent outcomes in IT evaluations are a result of the lack of task focus in assessing BDA and its adoption, use, and performance (Goodhue, 1995). Task-Technology Fit (TTF) stands for the ability of technology to match its capabilities to the task's requirements, or the capacity of technology to assist a task (Tam & Oliveira, 2016). Previous research has looked at TTF from a variety of angles to see if the user's work is suitable for technology and collective decision-making, resulting in the effective adoption of an information system in a variety of situations. (Massive open online courses) (I. U. Khan et al., 2018), e-commerce (Inge Klopping & Earl McKinney, 2004), electronic medical records (Gan & Cao, 2014).

ISSN: 2658-8455
Volume 3, Issue 6-1 (2022), pp.226-246.

IJAFAME
International Journal of Accounting, Finance, Auditing, Management & Economics

As a result, based on the mentioned literature, we conclude that the effective adoption of BDA by financial institutions is largely dependent on the technology's fit with the user's task needs, which has yet to be investigated by academics.

Figure 4: Task Technology Fit model

Source: (Goodhue & Thompson, 1995)

3. Hypothesis development and research model

3.1. Hypothesis development

According to (Davis et al., 1992) "Perceived usefulness" and "Perceived ease of use" of specific information systems and services are powerful indicators of attitude towards and intention to adopt them. Perceived usefulness assesses an information system's exogenous qualities, such as mission outcomes and objectives such as task effectiveness and efficiency (Wixom & Todd, 2005). Individuals who believe the BDA system is more helpful will be more likely to accept it (Amoako-Gyampah & Salam, 2004). According to (Wu & Wang, 2005)perceived usefulness of a technology has been considered to be more significant than the perceived ease of use in company-level research.

Perceived usefulness is likewise believed to be the major driver of BDA adoption. Earlier studies have shown that the usefulness of BDA has a positive association with the intention to use. These studies have been successfully examined in a variety of domains (Esteves & Curto, 2013; Shin, 2016; Weerakkody et al., 2017). If the user believes that using BDA will improve their work productivity, this will have a positive impact on their perception of its utility and then it will impact their willingness to adopt it. Therefore, BDA usefulness hasn't been applied to the banking and insurance sectors. Thus, we present the following hypotheses:

H1: Perceived usefulness will have direct and positive influence on the intention to use BDA systems

(Davis et al., 1992) defined perceived ease of use as "the degree of ease involved when using an information system." It was highlighted that the ease of use of an information system can contribute to its acceptance. The inherent qualities of an information system, such as convenience of use, adaptability, and simplicity, are assessed in terms of perceived ease of use (Gangwar et al., 2015).

In an era of convoluted ecosystems and fast-changing innovations, BDA has the ability to benefit financial institutions by cost reduction, minimizing risk factors, and assisting with effective decision-making. Users are more likely to adopt a new technology if they believe it is adaptable, easy to comprehend, manageable, and convenient to use. TAM acknowledges that perceived ease of use has a direct and indirect impact on behavioral intention to adopt. The direct effect suggests that perceived ease of use, independent of the usefulness, can enhance an individual's attitude towards adopting a new technology (Ayeh et al., 2013) while the indirect effect proposed that if a new technology is easy to use, users will find it more effective, since a simpler system demands lower effort to complete a task. which will shape a good attitude and intention toward the adoption of the technology (Kuo & Lee, 2009). Individual technology adoption has usually been influenced by "Perceived usefulness" and "Perceived ease of use" (Koufaris, 2002; Szajna, 1994). Therefore, the following two hypotheses have been developed:

H2: Perceived ease of use will have direct and positive influence on the intention to use BDA systems

H3: Perceived ease of use will have direct and positive effect on perceived usefulness of BDA Systems

Information quality refers to the requested properties (e.g., applicability, reliability, punctuality, completeness, intelligibility, and accessibility) of the information system outputs (Petter et al., 2014). The quality of information is essential in creating a positive attitude toward the advantages of adopting a certain information technology (Akter et al., 2013). The information quality of a BDA refers to the quality of the output of BDA, such as patterns, graphs, predictions, tables, and insights. The quality of information influences attitudes regarding information and system experience, which shapes behavioral attitudes such as perceived usefulness and ease of use, and, as a result, behavioral beliefs and the intention to adopt Big Data Analytics. According to (Wixom & Todd, 2005), poor and useless big data leads to poor information quality, which can have negative effects on practical and strategic decision-making (Ji-fan Ren et al., 2016).

Throughout relevant studies on the Technology Acceptance Model (TAM), (Venkatesh & Davis, 2000) pointed out that information quality has a positive impact on perceived usefulness; in other words, if the information quality of the knowledge management system is good, the output figures will be correct, constructive, and reusable, and users will believe the system is capable of providing accurate information and knowledge. (Zhou, 2011) created a model based on the D&M IS success model and TAM, stating that information quality is a critical element influencing perceived usefulness. Perceived ease of use is also a purpose of information quality, according to (Zhou, 2011). Thus, the following two hypotheses are proposed:

H4: Information quality directly and positively influences perceived usefulness of BDA

H5: Information quality directly and positively influences perceived ease of use of BDA

Technological characteristics are the tools (hardware, software, and data) used by end-users in carrying out their tasks (Goodhue & Thompson, 1995). It is referred to as the equipment, programming, and data that users employ to complete their tasks, which are referred to as technology characteristics. In general, the fewer functions provided by information systems, the less likely people are to use them. (S. L. Wang & Lin, 2019a) showed in their case study the positive impact of the technology characteristics of BDA on the task technology fit.

(Sahid et al., 2021) tried to demonstrate if technology characteristics have a major positive impact on task technology fit of BDA in public agencies. In general, the less relevant information is provided by the system, the less likely individuals are to use it. Users' perceptions of information systems are impacted by system features. Thus, the following hypothesis is proposed:

H6: Technological characteristics has direct influence on the Task-Technology fit of BDA

(Dale L Goodhue, 1995) defined task characteristics as "the actions carried out by users in transforming inputs into outputs.". Tasks are described in the broad TTF framework as actions taken by individuals in transforming inputs to outputs to meet their information needs. According to (Dale L Goodhue, 1995), task non-routineness, task dependency, and time significance are the key three characteristics of a task. The challenge in our case is that data has become more diverse, massive, and complex, and it requires specific technology to fit its complexity.

(Tam & Oliveira, 2016) tested the impact of task characteristics on task-technology fit in mobile banking, (S. L. Wang & Lin, 2019b) demonstrated the positive relationship between task characteristics of BDA and the task-technology fit of BDA in the case of mobile cloud healthcare. The features of a task that a user might employ information technology for are called task characteristics. They can take different aspects: task routineness, task interdependence, and scheduling. Users are encouraged to use information systems to meet their requirements by task characteristics, which are a primary determinant. The more complicated the task is, the less traditional IS is effective. Therefore, we propose the following hypothesis:

H7: Task characteristics has direct influence on the Task-Technology fit of BDA

(Goodhue & Thompson, 1995) defined task-technology fit as the degree to which a technology assists an individual in performing his or her tasks. Thus, our study can define Task-Technology Fit as the degree to which the users use BDA to perform their analysis and predictions. TTF is the concept of fit between task and technology characteristics, which will have a beneficial impact on the usage of technology and individual performance (Goodhue, 1998).
Users will pay more attention to a technology's novelty, such as BDA and the tasks it accomplishes after they start using it (Viswanath Venkatesh et al., 2012). When users believe that technology is capable of assisting with the work at hand, they perform well autonomously. Consequently, we can hypothesize that TTF is a good factor influencing user intention to use BDA, as proposed in the following hypothesis.

H8: Task-Technology fit will significantly influence the intention to use BDA

Trust is defined as the idea that a person or thing will behave in a desirable manner without manipulating the outcome (Pavlou & Fygenson, 2006). When a person lacks experience and knowledge with a new innovative technology or information system, trust in the usage of the technology is commonly employed to alleviate mental uneasiness (Liao et al., 2011).
Numerous researches have shown that perceived trust is a critical component for success or failure of information system adoption, particularly the adoption of electronic payment systems (Nguyen & Huynh, 2018) crypto currencies (Shahzad et al., 2018). Trust is an important component when it comes to BDA adoption because a lack of trust in a system's capability to deliver insightful information from complex data can have a negative impact on the user's intention. We can present, based on this, the following hypothesis:

H9: Perceived trust has a significant relationship with BIs to use BDA

According to (Arpaci et al., 2015; Cui et al., 2018) the degree to which an individual believes that using a certain system for sending and recording sensitive data is safe and secure is referred to as perceived security. Perceived technology security examines the potential for technological uncertainty and the user’s perception of the technology to bring them reliable information (Salisbury et al., 2001). Perceived security is the factor that prevents a user from considering the benefits of a system and persuades him to utilize a system that he opposes (Malaka & Brown, 2015).
Researchers have looked into the importance of security in different fields (Chellappa & Pavlou, 2002; Hartono et al., 2014; D. L. Huang et al., 2008). Users have concerns about information security as a result of informational privacy, misuse of sensitive information, and utilization by many uncaring departments when using BDA systems (Andrew G. Ferguson, 2017; Broeders et al., 2017; Shahbaz et al., 2019).
Users will be more likely to use BDA if they believe the institution's BDA services have been designed and have a secure framework in place

H10: Perceived security has a significant relationship with BIs to use BDA

The first dimension of organizational learning capabilities is also known as managerial commitment. (Senge, 1991) considers managerial commitment as "engaging in and maintaining

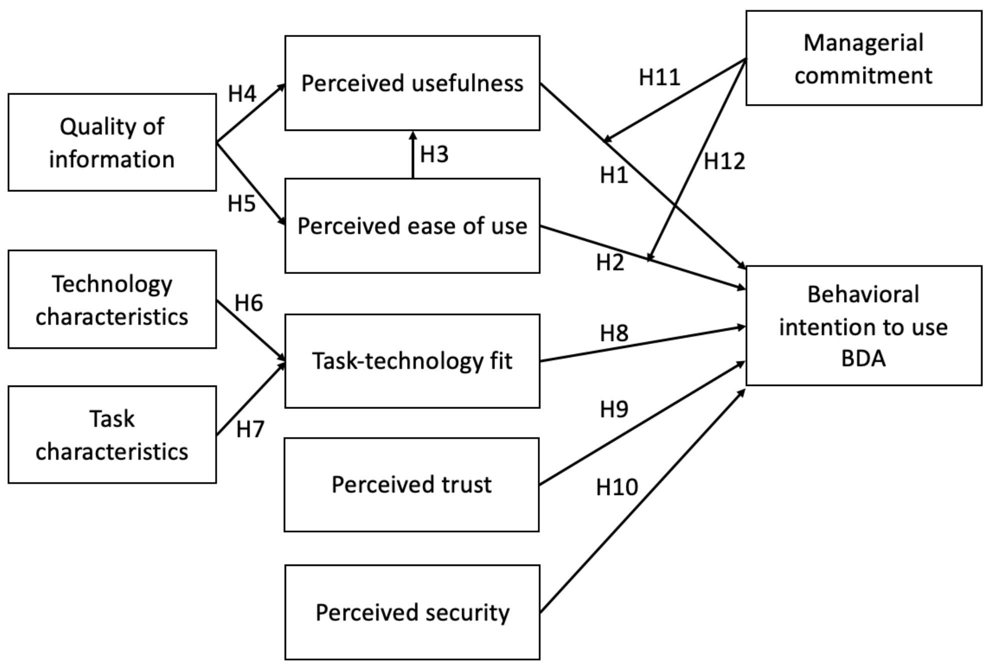
behaviors that help others achieve a goal". According to (Akgün et al., 2007), it is defined as the ability of businesses to foster and enable leadership commitment to develop and build knowledge within the organization. Top managers and stakeholders play an important role in the development and commitment to a learning climate for the employees, and (Cooper, 2006) emphasized the importance of the dedication of the leaders in a learning organization.
Management should lead the change process, assuming responsibility for building an organization that can regenerate and adapt to new challenges. (Lei et al., 1999). Management should comprehend the value of learning and become involved in its accomplishment, as it is an active aspect of the firm's success (Senge, 1991; Slater & Narver, 1995; Williams, 2001). In this manner, management may successfully create and support a learning environment that aids in the success and maintenance of their businesses. (Brock & Khan, 2017) have assessed the moderating effect of managerial commitment in the usage of Big Data Analytics by students following online programs technology disciples. Managerial commitment plays a major part as an organizational factor that influences the relationship between the user's perception of Big Data Analytics and their intention to use it. We then present the following hypothesis.

H11: Managerial commitment positively moderates the relationship between perceived usefulness and behavioral intention to use Big Data Analytics

H12: Managerial commitment positively moderates the relationship between perceived ease of use and behavioral intention to use BDA

3.2. Proposition of a research Model

Figure 5: Proposed research framework



Source: Authors

4. Conclusion

Based on the literature review, we developed our research model as a theoretical basis and an attempt to connect existing knowledge to understand the relationship among existing theories. The research model we proposed in this work is a combination of the TAM and TTF models, quality of information factor, trust and security, as well as the moderating effect of managerial commitment.

We first presented a literature review on the concept of Big Data, Big Data Analytics and the importance of its implementation in banks and insurance sectors, and the research gap that motivated our study. The second section contained predictions of behavioral intention reference models. We then justified the relationship between the different variables.

With an improved research model, this study goes a step further and makes a contribution to the subject of technological adoption.

Theoretical contributions:

Our research has several theoretical contributions, first, It highlights the key components that are crucial for implementing BDA systems, it emphasizes the importance of orienting the evaluation of factors of behavioral intention to use BDA towards the individual level, In the same way, it puts forward the central consideration of the adequacy of tasks with the technology used and displays the importance of the organizational level through the managerial commitment.

Second, the literature needs a solid theoretical foundation for additional research and a broad and comprehensive research model that is not particular to one area of the business in order to make the transition from the previous analytics systems to a BDA system. This research model will be beneficial and promote a theory for further BDA studies.

Practical contributions:

This study is crucial for strategy makers who intend to establish a BDA system by highlighting elements that are crucial at first. Architects of BDA systems can benefit from the research model's method for comprehending and evaluating the relative influence of information and system characteristics and users of the BDA system can direct the architects' efforts in the right directions if they believe that issues with the reliability of BDA information are a major problem.

Limitations and future directions:

Our integrated model is based on an exploratory qualitative approach. A survey of IT practitioners in the banking and insurance sectors is needed to bring our model into the Moroccan context.

References:

(1). Aggelidis, & PD, Chatzoglou, V. (2009). Using a modified technology acceptance model in hospitals. *International Journal of Medical Informatics*, *78*(2), 115–126. https://doi.org/10.1016/J.IJMEDINF.2008.06.006

(2). Akgün, A. E., Byrne, J. C., Lynn, G. S., & Keskin, H. (2007). Organizational unlearning as changes in beliefs and routines in organizations. *Journal of Organizational Change Management*, *20*(6), 794–812. https://doi.org/10.1108/09534810710831028/FULL/XML

(3). Akter, S., D'Ambra, J., & Ray, P. (2013). Development and validation of an instrument to measure user perceived service quality of mHealth. *Information & Management*, *50*(4), 181–195. https://doi.org/10.1016/J.IM.2013.03.001

(4). Amoako-Gyampah, K., & Salam, A. F. (2004). An extension of the technology acceptance model in an ERP implementation environment. *Information & Management*, *41*(6), 731–745. https://doi.org/10.1016/J.IM.2003.08.010

(5). Andrew G. Ferguson. (2017). "Policing Predictive Policing" . *Washington University Law Review*. https://openscholarship.wustl.edu/law_lawreview/vol94/iss5/5/

(6). Archenaa, J., & Anita, E. A. M. (2015). A survey of big data analytics in healthcare and government. *Procedia Computer Science*, *50*, 408–413. https://doi.org/10.1016/J.PROCS.2015.04.021

(7). Arpaci, I., Yardimci Cetin, Y., & Turetken, O. (2015). Impact of Perceived Security on Organizational Adoption of Smartphones. *Cyberpsychology, Behavior and Social Networking*, *18*(10), 602–608. https://doi.org/10.1089/CYBER.2015.0243

(8). Assuncao, M. D., Calheiros, R. N., Bianchi, S., Netto, M. A. S., & Buyya, R. (2013). Big Data Computing and Clouds: Trends and Future Directions. *Journal of Parallel and Distributed Computing*, *79–80*, 3–15. https://doi.org/10.1016/j.jpdc.2014.08.003

(9). Ayeh, J. K., Au, N., & Law, R. (2013). Predicting the intention to use consumer-generated media for travel planning. *Tourism Management*, *35*, 132–143. https://doi.org/10.1016/J.TOURMAN.2012.06.010

(10). Bankole, O. A., Lalitha, V. V. M., Khan, H. U., & Jinugu, A. (2017). Information technology in the maritime industry past, present and future: Focus on LNG carriers. *Proceedings - 7th IEEE International Advanced Computing Conference, IACC 2017*, 759–763. https://doi.org/10.1109/IACC.2017.0157

(11). Bello-Orgaz, G., Jung, J. J., & Camacho, D. (2016). Social big data: Recent achievements and new challenges. *An International Journal on Information Fusion*, *28*, 45–59. https://doi.org/10.1016/J.INFFUS.2015.08.005

(12). Brock, V., & Khan, H. U. (2017). Big data analytics: does organizational factor matters impact technology acceptance? *Journal of Big Data*, *4*(1), 1–28. https://doi.org/10.1186/S40537-017-0081-8/TABLES/8

(13). Broeders, D., Schrijvers, E., van der Sloot, B., van Brakel, R., de Hoog, J., & Hirsch Ballin, E. (2017). Big Data and security policies: Towards a framework for regulating the phases of analytics and use of Big Data. *Computer Law & Security Review*, *33*(3), 309–323. https://doi.org/10.1016/J.CLSR.2017.03.002

(14). Chellappa, R. K., & Pavlou, P. A. (2002). Perceived information security, financial liability and consumer trust in electronic commerce transactions. *Logistics Information Management*, *15*(5/6), 358–368. https://doi.org/10.1108/09576050210447046

(15). Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education*, *63*, 160–175. https://doi.org/10.1016/J.COMPEDU.2012.12.003

(16). Cody Hill. (2018). *Where big data is taking the financial industry: Trends in 2018 – Crayon Data*. Crayondata.Com. https://www.crayondata.com/where-big-data-is-taking-the-financial-industry-trends-in-2018/

(17). Cooper, M. D. (2006). Exploratory analyses of the effects of managerial support and feedback consequences on behavioral safety maintenance. *Journal of Organizational Behavior Management*, *26*(3), 1–41. https://doi.org/10.1300/J075V26N03_01

(18). Cui, F., Lin, D., & Qu, H. (2018). The impact of perceived security and consumer innovativeness on e-loyalty in online travel shopping. *Https://Doi.Org/10.1080/10548408.2017.1422452*, *35*(6), 819–834. https://doi.org/10.1080/10548408.2017.1422452

(19). Dale L Goodhue. (1995). Understanding User Evaluations of Information Systems on JSTOR. *Management Science*. https://www.jstor.org/stable/2633074

(20). Damghanian, H., Zarei, A., & Siahsarani Kojuri, M. A. (2016). Impact of Perceived Security on Trust, Perceived Risk, and Acceptance of Online Banking in Iran. *Http://Dx.Doi.Org/10.1080/15332861.2016.1191052*, *15*(3), 214–238. https://doi.org/10.1080/15332861.2016.1191052
(21). Daniel, B. (2015). Big Data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology*, *46*(5), 904–920. https://doi.org/10.1111/BJET.12230
(22). Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008
(23). Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace1. *Journal of Applied Social Psychology*, *22*(14), 1111–1132. https://doi.org/10.1111/J.1559-1816.1992.TB00945.X
(24). Davis, F. D., & Venkatesh, V. (1996). A critical assessment of potential measurement biases in the technology acceptance model: three experiments. *International Journal of Human-Computer Studies*, *45*(1), 19–45. https://doi.org/10.1006/IJHC.1996.0040
(25). Dishaw, M. T., & Strong, D. M. (1999). Extending the technology acceptance model with task–technology fit constructs. *Information & Management*, *36*(1), 9–21. https://doi.org/10.1016/S0378-7206(98)00101-3
(26). Dubey, R., Gunasekaran, A., & Childe, S. J. (2018). Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. *Management Decision*, *57*(8), 2092–2112. https://doi.org/10.1108/MD-01-2018-0119
(27). Dumbill, E. (2012). *Planning for Big Data: O'Reilly Media*.
(28). Elragal, A., & Klischewski, R. (2017). Theory-driven or process-driven prediction? Epistemological challenges of big data analytics. *Journal of Big Data*, *4*(1), 1–20. https://doi.org/10.1186/S40537-017-0079-2/FIGURES/3
(29). Esteves, J., & Curto, J. (2013). A Risk and Benefits Behavioral Model to Assess Intentions to Adopt Big Data. *Journal of Intelligence Studies in Business*, *3*(3), 37–46. https://doi.org/10.37380/JISIB.V3I3.74
(30). Fife, E., & Orjuela, J. (2012). The Privacy Calculus: Mobile Apps and User Perceptions of Privacy and Security: *Http://Dx.Doi.Org/10.5772/51645*, *4*(1), 1–10. https://doi.org/10.5772/51645
(31). Gan, Q., & Cao, Q. (2014). Adoption of electronic health record system: Multiple theoretical perspectives. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 2716–2724. https://doi.org/10.1109/HICSS.2014.352
(32). Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management*, *28*(1), 107–130. https://doi.org/10.1108/JEIM-08-2013-0065/FULL/XML
(33). Goodhue, D. L. (1995). Understanding User Evaluations of Information Systems. *Http://Dx.Doi.Org/10.1287/Mnsc.41.12.1827*, *41*(12), 1827–1844. https://doi.org/10.1287/MNSC.41.12.1827
(34). Goodhue, D. L. (1998). Development and Measurement Validity of a Task-Technology Fit Instrument for User Evaluations of Information System. *Decision Sciences*, *29*(1), 105–138. https://doi.org/10.1111/J.1540-5915.1998.TB01346.X

(35). Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, *19*(2), 213–233. https://doi.org/10.2307/249689

(36). Goodhue, Goodhue, D. L., R. L. Thompson, and B. D. L. G. (1995). *[PDF] Task-Technology Fit and Individual Performance | Semantic Scholar*. https://www.semanticscholar.org/paper/Task-Technology-Fit-and-Individual-Performance-Goodhue-Thompson/668e58d4e3479317257a41ce66c688a8aa663399

(37). Grossman, R. L., & Siegel, K. P. (2014). Organizational Models for Big Data and Analytics. *Journal of Organization Design*, *3*(1), 20–25. https://doi.org/10.7146/jod.9799

(38). Hartono, E., Holsapple, C. W., Kim, K. Y., Na, K. S., & Simpson, J. T. (2014). Measuring perceived security in B2C electronic commerce website usage: A respecification and validation. *Decision Support Systems*, *62*, 11–21. https://doi.org/10.1016/J.DSS.2014.02.006

(39). Hasan, M. M., Popp, J., & Oláh, J. (2020). Current landscape and influence of big data on finance. *Journal of Big Data*, *7*(1), 1–17. https://doi.org/10.1186/S40537-020-00291-Z/FIGURES/2

(40). Hilbert, M., & López, P. (2011). The world's technological capacity to store, communicate, and compute information. *Science*, *332*(6025), 60–65. https://doi.org/10.1126/SCIENCE.1200970

(41). Huang, D. L., Rau, P. L. P., & Salvendy, G. (2008). Perception of information security. *Http://Dx.Doi.Org/10.1080/01449290701679361*, *29*(3), 221–232. https://doi.org/10.1080/01449290701679361

(42). Huang, L. S., Quaddus, M., Rowe, A. L., & Lai, C. P. (2017). An investigation into the factors affecting knowledge management adoption and practice in the life insurance business. *Https://Doi.Org/10.1057/Kmrp.2011.2*, *9*(1), 58–72. https://doi.org/10.1057/KMRP.2011.2

(43). Inge Klopping, & Earl McKinney. (2004). *Extending the Technology Acceptance Model Extending the Technology Acceptance Model and the Task and the Task--Technology Fit Model to Technology Fit Model to Consumer E Consumer E-Commerce Commerce*. https://www.researchgate.net/publication/237251740_Extending_the_Technology_Acceptance_Model_Extending_the_Technology_Acceptance_Model_and_the_Task_and_the_Task--Technology_Fit_Model_to_Technology_Fit_Model_to_Consumer_E_Consumer_E-_Commerce_Commerce

(44). Ishwarappa, & Anuradha, J. (2015). A Brief Introduction on Big Data 5Vs Characteristics and Hadoop Technology. *Procedia Computer Science*, *48*(C), 319–324. https://doi.org/10.1016/J.PROCS.2015.04.188

(45). J. Steven Perry. (2017). *What is big data? More than volume, velocity and variety… - IBM Developer*. https://developer.ibm.com/blogs/what-is-big-data-more-than-volume-velocity-and-variety/

(46). Ji-fan Ren, S., Fosso Wamba, S., Akter, S., Dubey, R., & Childe, S. J. (2016). Modelling quality dynamics, business value and firm performance in a big data analytics environment. *Https://Doi.Org/10.1080/00207543.2016.1154209*, *55*(17), 5011–5026. https://doi.org/10.1080/00207543.2016.1154209

(47). Khan, I. U., Hameed, Z., Yu, Y., Islam, T., Sheikh, Z., & Khan, S. U. (2018). Predicting the acceptance of MOOCs in a developing country: Application of task-technology fit model, social motivation, and self-determination theory. *Telematics and Informatics*, *35*(4), 964–978. https://doi.org/10.1016/J.TELE.2017.09.009

(48). Khan, N., Yaqoob, I., Hashem, I. A. T., Inayat, Z., Mahmoud Ali, W. K., Alam, M., Shiraz, M., & Gani, A. (2014). Big data: Survey, technologies, opportunities, and challenges. *Scientific World Journal*, *2014*. https://doi.org/10.1155/2014/712826

(49). Kirk Borne. (2013). *Big Data, Small World: Kirk Borne at TEDxGeorgeMasonU - YouTube*. https://www.youtube.com/watch?v=Zr02fMBfuRA&ab_channel=TEDxTalks

(50). Koufaris, M. (2002). Applying the Technology Acceptance Model and flow theory to online Consumer Behavior. *Information Systems Research*, *13*(2), 205–223. https://doi.org/10.1287/ISRE.13.2.205.83

(51). Krishnan, K. (2013). *Data warehousing in the age of big data. [electronic book]*. https://books.google.com/books/about/Data_Warehousing_in_the_Age_of_Big_Data.html?hl=fr&id=NgDp2-837P8C

(52). Kuo, R. Z., & Lee, G. G. (2009). KMS adoption: The effects of information quality. *Management Decision*, *47*(10), 1633–1651. https://doi.org/10.1108/00251740911004727/FULL/XML

(53). Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management*, *34*(3), 387–394. https://doi.org/10.1016/J.IJINFOMGT.2014.02.002

(54). Lallmahomed, M. Z. I., Lallmahomed, N., & Lallmahomed, G. M. (2017). Factors influencing the adoption of e-Government services in Mauritius. *Telematics and Informatics*, *34*(4), 57–72. https://doi.org/10.1016/J.TELE.2017.01.003

(55). Laney, D. (2001). 3D data management: Controlling data volume, velocity and variety. *META Group Research Note*, *6*(70), 1.

(56). Lei, D., Slocum, J. W., & Pitts, R. A. (1999). Designing organizations for competitive advantage: The power of unlearning and learning. *Organizational Dynamics*, *27*(3), 24–38. https://doi.org/10.1016/S0090-2616(99)90019-0

(57). Liao, C., Liu, C. C., & Chen, K. (2011). Examining the impact of privacy, trust and risk perceptions beyond monetary transactions: An integrated model. *Electronic Commerce Research and Applications*, *10*(6), 702–715. https://doi.org/10.1016/J.ELERAP.2011.07.003

(58). Lidong Wang, & Randy Jones. (2017). Big Data Analytics for Network Intrusion Detection: A Survey. *International Journal of Networks and Communications*. http://article.sapub.org/10.5923.j.ijnc.20170701.03.html

(59). Lycett, M. (2013). 'Datafication': making sense of (big) data in a complex world. *European Journal of Information Systems 2013 22:4*, *22*(4), 381–386. https://doi.org/10.1057/EJIS.2013.10

(60). Malaka, I., & Brown, I. (2015). Challenges to the Organisational Adoption of Big Data Analytics: A Case Study in the South African Telecommunications Industry. *ACM International Conference Proceeding Series*, *28-30-September-2015*. https://doi.org/10.1145/2815782.2815793

(61). MAMPU. (2020). *MyGOV - Capacities for Digital Transformation | Big Data Analytic | Government Data Optimization And Transformation Services (GDOTS)*. https://www.malaysia.gov.my/portal/content/30614

(62). Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2017). Big data analytics capabilities: a systematic literature review and research agenda. *Information Systems and E-Business Management 2017 16:3*, *16*(3), 547–578. https://doi.org/10.1007/S10257-017-0362-Y

(63). Minelli, M., Chambers, Michele., & Dhiraj, A. (2013). *Big data, big analytics : emerging business intelligence and analytic trends for today's businesses*.

(64). Müller, O., Junglas, I., Brocke, J. vom, & Debortoli, S. (2017). Utilizing big data analytics for information systems research: challenges, promises and guidelines. *Https://Doi.Org/10.1057/Ejis.2016.2*, *25*(4), 289–302. https://doi.org/10.1057/EJIS.2016.2

(65). Nguyen, T. D., & Huynh, P. A. (2018). The roles of perceived risk and trust on E–payment adoption. *Studies in Computational Intelligence*, *760*, 926–940. https://doi.org/10.1007/978-3-319-73150-6_68/COVER/

(66). Nobanee, H., Dilshad, M. N., al Dhanhani, M., al Neyadi, M., al Qubaisi, S., & al Shamsi, S. (2021). Big Data Applications the Banking Sector: A Bibliometric Analysis Approach: *Https://Doi.Org/10.1177/21582440211067234*, *11*(4). https://doi.org/10.1177/21582440211067234

(67). Omonaiye, J. F., Lalitha, V. V. M., Khan, H. U., Fournier-Bonilla, S. D., & Singh, R. (2016). Ability and Hurdle to Provide Banking Online Services: A Case Study of Banking Employees in Nigeria. *Proceedings - 2nd IEEE International Conference on Cyber Security and Cloud Computing, CSCloud 2015 - IEEE International Symposium of Smart Cloud, IEEE SSC 2015*, 482–487. https://doi.org/10.1109/CSCLOUD.2015.48

(68). Oracle. (2013). *An Oracle White Paper June Oracle: Big Data for the Enterprise - PDF Free Download*. https://docplayer.net/252186-An-oracle-white-paper-june-2013-oracle-big-data-for-the-enterprise.html

(69). Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS Quarterly: Management Information Systems*, *30*(1), 115–143. https://doi.org/10.2307/25148720

(70). Petter, S., Delone, W., & McLean, E. R. (2014). Information Systems Success: The Quest for the Independent Variables. *Https://Doi.Org/10.2753/MIS0742-1222290401*, *29*(4), 7–62. https://doi.org/10.2753/MIS0742-1222290401

(71). Philip Chen, C. L., & Zhang, C. Y. (2014). Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. *Information Sciences*, *275*, 314–347. https://doi.org/10.1016/J.INS.2014.01.015

(72). Pikkarainen, T., Pikkarainen, K., Karjaluoto, H., & Pahnila, S. (2004). Consumer acceptance of online banking: An extension of the technology acceptance model. *Internet Research*, *14*(3), 224–235. https://doi.org/10.1108/10662240410542652/FULL/XML

(73). Sahid, N. Z., Sani, M. K. J. A., Noordin, S. A., Zaini, M. K., & Baba, J. (2021). Determinants factors of intention to adopt big data analytics in Malaysian public agencies. *Journal of Industrial Engineering and Management*, *14*(2), 269–293. https://doi.org/10.3926/jiem.3334

(74). Salisbury, W. D., Pearson, R. A., Pearson, A. W., & Miller, D. W. (2001). Perceived security and World Wide Web purchase intention. *Industrial Management & Data Systems*, *101*(4), 165–177. https://doi.org/10.1108/02635570110390071/FULL/XML

(75). Segars, A. H., & Grover, V. (1993). Re-examining perceived ease of use and usefulness: A confirmatory factor analysis. *MIS Quarterly: Management Information Systems*, *17*(4), 517–525. https://doi.org/10.2307/249590

(76). Senge, P. M. (1991). The fifth discipline, the art and practice of the learning organization. *Performance + Instruction*, *30*(5), 37–37. https://doi.org/10.1002/PFI.4170300510

(77). Shahbaz, M., Gao, C., Zhai, L. L., Shahzad, F., & Hu, Y. (2019). Investigating the adoption of big data analytics in healthcare: the moderating role of resistance to change. *Journal of Big Data*, *6*(1), 1–20. https://doi.org/10.1186/S40537-019-0170-Y/FIGURES/3

(78). Shahzad, F., Xiu, G. Y., Wang, J., & Shahbaz, M. (2018). An empirical investigation on the adoption of cryptocurrencies among the people of mainland China. *Technology in Society*, *55*, 33–40. https://doi.org/10.1016/J.TECHSOC.2018.05.006

(79). Sheikh, N. (2013). Implementing Analytics. *Implementing Analytics*. https://doi.org/10.1016/C2011-0-09029-4

(80). Shen, D., & Chen, S.-H. (2018). *Big Data Finance and Financial Markets*. 235–248. https://doi.org/10.1007/978-3-319-95465-3_12

(81). Shin, D. H. (2015). Effect of the customer experience on satisfaction with smartphones: Assessing smart satisfaction index with partial least squares. *Telecommunications Policy*, *39*(8), 627–641. https://doi.org/10.1016/J.TELPOL.2014.10.001

(82). Shin, D. H. (2016). Demystifying big data: Anatomy of big data developmental process. *Telecommunications Policy*, *40*(9), 837–854. https://doi.org/10.1016/J.TELPOL.2015.03.007

(83). Slater, S. F., & Narver, J. C. (1995). Market Orientation and the Learning Organization: *Https://Doi.Org/10.1177/002224299505900306*, *59*(3), 63–74. https://doi.org/10.1177/002224299505900306

(84). Soon, K. W. K., Lee, C. A., & Boursier, P. (2016). A study of the determinants affecting adoption of big data using integrated technology acceptance model (TAM) and diffusion of innovation (DOI) in Malaysia. *International Journal of Applied Business and Economic Research*, *14*(1).

(85). Szajna, B. (1994). Software evaluation and choice, predictive validation of the technology acceptance instrument. *MIS Quarterly*, *18*(3), 319–324. https://doi.org/10.2307/249621

(86). Tam, C., & Oliveira, T. (2016). Understanding the impact of m-banking on individual performance: DeLone & McLean and TTF perspective. *Computers in Human Behavior*, *61*, 233–244. https://doi.org/10.1016/J.CHB.2016.03.016

(87). Tsai, C. W., Lai, C. F., Chao, H. C., & Vasilakos, A. v. (2015). Big data analytics: a survey. *Journal of Big Data*, *2*(1), 1–32. https://doi.org/10.1186/S40537-015-0030-3/TABLES/3

(88). Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/MNSC.46.2.186.11926

(89). Verkasalo, H., López-Nicolás, C., Molina-Castillo, F. J., & Bouwman, H. (2010). Analysis of users and non-users of smartphone applications. *Telematics and Informatics*, *27*(3), 242–255. https://doi.org/10.1016/J.TELE.2009.11.001

(90). Verma, S., & Bhattacharyya, S. S. (2017). Perceived strategic value-based adoption of Big Data Analytics in emerging economy: A qualitative approach for Indian firms. *Journal of Enterprise Information Management*, *30*(3), 354–382. https://doi.org/10.1108/JEIM-10-2015-0099

(91). Viswanath Venkatesh, James Y.L. Thong, & Xin Xu. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology.*MISQuarterly*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2002388

(92). Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98–110. https://doi.org/10.1016/J.IJPE.2016.03.014

(93). Wang, S. L., & Lin, H. I. (2019a). Integrating TTF and IDT to evaluate user intention of big data analytics in mobile cloud healthcare system. *Behaviour and Information Technology*, *38*(9), 974–985. https://doi.org/10.1080/0144929X.2019.1626486

(94). Wang, S. L., & Lin, H. I. (2019b). Integrating TTF and IDT to evaluate user intention of big data analytics in mobile cloud healthcare system. *Https://Doi.Org/10.1080/0144929X.2019.1626486*, *38*(9), 974–985. https://doi.org/10.1080/0144929X.2019.1626486

(95). Weerakkody, V., Kapoor, K., Balta, M. E., Irani, Z., & Dwivedi, Y. K. (2017). Factors influencing user acceptance of public sector big open data. *Https://Doi.Org/10.1080/09537287.2017.1336802*, *28*(11–12), 891–905. https://doi.org/10.1080/09537287.2017.1336802

(96). Williams, A. P. O. (2001). A Belief-focused Process Model of Organizational Learning*. *Journal of Management Studies*, *38*(1), 67–85. https://doi.org/10.1111/1467-6486.00228

(97). Wixom, B. H., & Todd, P. A. (2005). A Theoretical Integration of User Satisfaction and Technology Acceptance. *Https://Doi.Org/10.1287/Isre.1050.0042*, *16*(1), 85–102. https://doi.org/10.1287/ISRE.1050.0042

(98). Wu, J. H., & Wang, S. C. (2005). What drives mobile commerce?: An empirical evaluation of the revised technology acceptance model. *Information & Management*, *42*(5), 719–729. https://doi.org/10.1016/J.IM.2004.07.001

(99). Zhou, T. (2011). Examining the critical success factors of mobile website adoption. *Online Information Review*, *35*(4), 636–652. https://doi.org/10.1108/14684521111161972/FULL/XML