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DETERMINANTS OF THE INTENTION TO USE BIG DATA ANALYTICS IN BANKS AND INSURANCE COMPANIES: THE MODERATING ROLE OF MANAGERIAL SUPPORT

Zainab Meskaoui*	Abdelmalek Essaadi University, Tangier, Morocco	zainab.meskaoui@gmail.com
Abdelilah Elkharraz	Abdelmalek Essaadi University, Tangier, Morocco	aelkharraz@uae.ac.ma

* Corresponding author

ABSTRACT

Aim/Purpose	The aim of this research paper is to suggest a comprehensive model that incorporates the technology acceptance model with the task-technology fit model, information quality, security, trust, and managerial support to investigate the intended usage of big data analytics (BDA) in banks and insurance companies.
Background	The emergence of the concept of "big data," prompted by the widespread use of connected devices and social media, has been pointed out by many professionals and financial institutions in particular, which makes it necessary to assess the determinants that have an impact on behavioral intention to use big data analytics in banks and insurance companies.
Methodology	The integrated model was empirically assessed using self-administered questionnaires from 181 prospective big data analytics users in Moroccan banks and insurance firms and examined using partial least square (PLS) structural equation modeling. The results cover sample characteristics, an analysis of the validity and reliability of measurement models' variables, an evaluation of the proposed hypotheses, and a discussion of the findings.
Contribution	The paper makes a noteworthy contribution to the BDA adoption literature within the finance sector. It stands out by ingeniously amalgamating the Technology Acceptance Model (TAM) with Task-Technology Fit (TTF) while underscoring the critical significance of information quality, trust, and managerial support, due to their profound relevance and importance in the finance domain. Thus showing BDA has potential applications beyond the finance sector.

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Findings The findings showed that TTF and trust's impact on the intention to use is considerable. Information quality positively impacted perceived usefulness and ease of use, which in turn affected the intention to use. Moreover, managerial support moderates the correlation between perceived usefulness and the intention to use, whereas security did not affect the intention to use and managerial support did not moderate the influence of perceived ease of use.

Recommendations for Practitioners The results suggest that financial institutions can improve their adoption decisions for big data analytics (BDA) by understanding how users perceive it. Users are predisposed to use BDA if they presume it fits well with their tasks and is easy to use. The research also emphasizes the importance of relevant information quality, managerial support, and collaboration across departments to fully leverage the potential of BDA.

Recommendations for Researchers Further study may be done on other business sectors to confirm its generalizability and the same research design can be employed to assess BDA adoption in organizations that are in the advanced stage of big data utilization.

Impact on Society The study's findings can enable stakeholders of financial institutions that are at the primary stage of big data exploitation to understand how users perceive BDA technologies and the way their perception can influence their intention toward their use.

Future Research Future research is expected to conduct a comparison of the moderating effect of managerial support on users with technical expertise versus those without; in addition, international studies across developed countries are required to build a solid understanding of users' perceptions towards BDA.

Keywords Big Data Analytics, TAM model, behavioral intention to use, Task Technology Fit, information quality, finance, banks, insurance companies, security, trust, managerial support

INTRODUCTION

The emergence of the "big data" age, which was prompted by the widespread use of electronic gadgets such as smartphones, computers, and smart personal gadgets, as well as the expanded usage of social media, has become unignorable (Bazzaz Abkenar et al., 2021). In Morocco, a growing economy, the internet penetration rate was standing at 88% of the total population at the start of 2023 (Kemp, 2023). The financial services industries are increasingly interested in utilizing big data, as it can be involved in a variety of such innovations, such as online decentralized financing, crowdfunding, fintech, property management, cryptocurrency, money exchange, digital payments platforms, and more (Hasan et al., 2020). It has been improving the knowledge of financial systems in more meaningful aspects (Shen & Chen, 2018).

Additionally, it has the ability to transform the financial sector by surmounting obstacles and acquiring insightful knowledge to enhance consumer satisfaction and the whole banking experience (Joshi, 2018). Razin (2015) noted five ways that big data is altering finance: promoting accountability, assessing risk, automating trade, exploiting data about consumers, and altering cultural norms. It will continue to be a key asset for building sophisticated decision-making models by using numerous advanced predictive analytics, one of which is big data analytics (BDA). We can define BDA as a series of techniques and technologies that are built for capturing, structuring, storing, analyzing, and visualizing large and complex data with five distinguishable dimensions, namely, volume, value, veracity, velocity, and variety.

Earlier research has been undertaken to shed light on the value and framework concerning the adoption of BDA in diverse fields (Memon et al., 2017; Soon et al., 2016), public sector (Sahid et al., 2021; Weerakkody et al., 2017), and higher education (Brock & Khan, 2017). These studies highlighted the enablers that are important to be taken into consideration before establishing any BDA strategy. Yet, research within the financial factor has primarily focused on the analysis of best practices to assess the benefits of Big Data (Razin, 2015; Shakya & Smys, 2021). There remains a paucity of research studying the determinants of the usage of BDA in financial institutions (Eresia-Eke et al., 2023; Phan & Tran, 2022). To cover the gap presently existing within this field and guide banking institutions and insurance companies in upgrading standard data analytics systems that fall short of BDA, while exploring real facts of the Moroccan context, a detailed adoption model for BDA will be investigated in this study. With big data being at its initial stage of adoption in Morocco, our research model will be evaluating determinants that can impact prospective BDA users' behavioral intention to use (conventional data analytics users who are familiar with BDA but have not yet started using it).

As discussed in earlier studies, asserting attitudes toward innovation, particularly the study of users' perception of usefulness and ease of use, is a critical strategy (Sahid et al., 2021). Yet, if BDA cannot improve the user's performance on the job and is incompatible with the demands of their tasks, it may not be accepted. Once a user sees BDA systems as inventive, convenient, and beneficial, adoption will occur. As a result, evaluating the suitability of these innovations attributes for the requirement of the users' mission must be conducted after considering how individuals perceive technology. Furthermore, the intention to utilize new innovations can be significantly influenced by the users' perception of security, as highlighted by several researchers (Damghanian et al., 2016; Fife & Orjuela, 2012; Salleh & Janczewski, 2016). Trust is among the hardest challenges for users' adoption of an unfamiliar system (Lallmahomed et al., 2017; C. Liao et al., 2011). This factor has the ability to encourage users to gather, manage, and analyze information using BDA, and share the insights with their network. That way, the quality of BDA is a crucial element when it comes to the usage of data-oriented technologies (Shin, 2016; Verma & Bhattacharyya, 2017). Our study also considers management support as a moderating factor in behavioral intention.

The significance of this research is due, firstly, to the concerns voiced by Sun et al. (2016), who highlighted the lack of literature specifically addressing the factors influencing the adoption of big data technologies. This was explained by Wiener et al. (2020) by the fact that the research on BD is quite limited as it is a relatively new field of study.

Secondly, it contributes to the scarce academic literature on BDA within the framework of a developing economy as highlighted by Eresia-Eke et al. (2023), which is crucial given the fact that literature concerning the adoption of advanced technologies is largely dominated by viewpoints originating from developed countries (Fosso Wamba et al., 2015).

Therefore, this research gap inspires us to answer the following research questions:

- What are the key enablers that significantly influence behavioral intention toward the usage of Big Data Analytics (BDA) in financial institutions?
- Can these identified factors collectively form a robust theoretical foundation for understanding the adoption of BDA in banks and insurance companies in Morocco?
- Does managerial support moderate the impact of perceived usefulness and perceived ease of use on behavioral intention?

In our quest to address these questions, our study develops an integrated framework that brings together the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF), the output quality of the systems, security, users' trust, and managerial support as a moderating factor to theoretically broaden the BDA usage scope. Thus, the aims of this empirical study are the following:

- To establish a comprehensive model that highlights the pertinent drivers significantly impacting behavioral intention towards BDA adoption within banks and insurance companies in Morocco.
- To investigate the impact of information quality of BDA, TAM variables, TTF, security, and trust on the intention to use BDA. Our study will explore the roles of these factors in shaping behavioral intention.
- To assess the influence of managerial support as a moderating factor that enhances or mitigates the effects of perceived usefulness and perceived ease of use on BDA adoption intentions.

The next section contains a review of big data analytics adoption research. This is followed by the theoretical background and hypotheses development. Then a discussion of data analysis is presented. Finally, the conclusion, implications, and limitations will be presented.

BACKGROUND RESEARCH ABOUT BDA ADOPTION

The explosion of big data is a result of the fast expansion of social networking and connected technologies (Bankole et al., 2017; Surbakti et al., 2020). Big data concept and big data analytics, according to some experts, have distinct meanings, researchers systematically found that the notion of big data is based on its attributes, while others expanded the concept by introducing the attribute 'analytics' that emphasizes its procedures, instruments, as well and key processes that are employed for analysis and inspection (Mikalef et al., 2018). Big data analytics alludes to complex data languages used by businesses to examine massive databases, such as mining data, and representation (Grossman & Siegel, 2014). Big data analytics are also considered the methods (analytical processes) and technologies (databases and data mining instruments) that a business can employ to assess enormous amounts of data targeted at enhancing their performance in many fields. BDA primarily affects the financial industry by means of algorithmic trading, index efficiency, option pricing, projections of value, market appraisals, risk assessments, and portfolio management (Hasan et al., 2020).

As shown in Figure 1, data management and data analytics are the two main phases of using BDA. The first phase involves actors with an engineering background and the ability to filter new dimensions of data without discarding useful information and apply a data extraction process to convert unstructured data to the required structured information represented in semantics and database designs that are computer-understandable. The second phase, data analytics, speaks more directly to profiles with less technical skills, such as marketers, fraud detectors, and financial analysts.

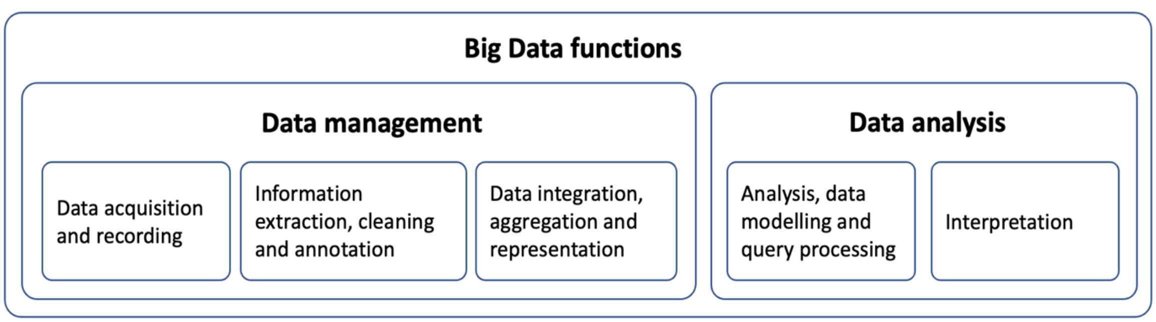

Figure 1: Big Data functions and process (Agrawal et al., 2011)

Many studies have described big data's importance in the financial industry (Begenau et al., 2018; Ewen, 2019; Hussain & Prieto, 2016; Joshi, 2018; Oracle, 2015). Diniz et al. (2018) suggested a model based on the Actor-Network theory in order to comprehend the process of the implementation of big data in three Brazilian banking institutions. They unveiled the significance of a connection between power centers inside the organization, as well as the redefinition of dominant conception within process managers. However, research studies that incorporate end users' perceptions of the use of BDA remain relatively insufficient (Phan & Tran, 2022). Almoqren and Altayar's (2016) findings suggest that technology characteristics, particularly those related to systems and information, influence the adoption of big data-related technologies. Al-Dmour et al.'s (2022) findings, which highlight the influence of organizational, technological, and environmental factors on the adoption of BDA in commercial banks, do not incorporate a combined approach of users' perception with the technological factors. This combination can be represented using two of the most successful technology adoption models: TAM and TTF. In addition, our study considers the moderation of managerial support as a key factor in the adoption of BDA in large-scale organizations such as financial institutions.

The adoption decision of BDA is not only determined by its analysis of profitability but also by the users' intentions (Verma et al., 2018). Some of the key variables influencing whether someone will utilize technology, according to the technology acceptance model suggested by Davis (1987), are related to the usefulness and ease of use. BDA is a user-centered technology. Individuals' perceptions on whether its outputs and models would be useful in obtaining a clear customer journey mapping to predict their behavior and the market trends, or if these modeling techniques can still be easy to generate despite the complexity of the data managed, are essential to their acceptance. Nonetheless, focusing solely on the end user's perception might prove inadequate. According to the theory of task-technology fit proposed by Goodhue (1998), users' willingness to use a new innovation is majorly shaped by the extent to which the features of the system are suitable to their task specifications. Acceptance to use will not occur if the technology features mismatch the required tasks (C.-C. Lee et al., 2007; B. Wu & Chen, 2017). Consequently, the successful adoption of BDA is not only about users' perception of the technology as useful and easy to use; it also requires a match between the task and the characteristics of the technology and the job tasks to be accomplished (Shahbaz et al., 2019). Due to these reasons, as suggested by Dishaw and Strong (1999), there is a necessity to develop a combination of TAM and TTF to better interpret the usage intention of BDA rather than using each one of them alone.

Furthermore, considering the data-driven aspect of BDA, the quality of the output it generates is of great importance for its ease of use and usefulness. In a prior study, information quality was shown to exert a favorable and indirect effect on the users' perceived usefulness and ease of use of BDA, but solely through the factor of perceived benefit of BDA (Verma et al., 2018). In our study, we assume a direct impact of information quality on the usefulness and ease of use of BDA in the financial field. Moreover, Kondratyeva et al. (2021) and Ambhire and Teltumde (2011) highlighted data security concerns arising from the introduction of new innovations in the banking sector, which can produce detrimental effects for institutions and their customers. Malaka and Brown (2015) and Shahbaz et al. (2019) underscored the significance of trust in the success or failure of information system adoption.

Managerial support is also considered in our study as a key moderating factor in the relationship between the users' perceptions. Previous research on medium-sized enterprises has demonstrated that management support is a key factor in assessing the adoption of BDA (Maroufkhani et al., 2020). However, despite the exponential increase in interest in deriving value from big data, the analysis of the literature came up short in showing a rigorous attempt to investigate a combination of individual, technological, and organizational factors that affect behavioral intended usage of BDA among the users of data analytics users in banks and insurance companies in emerging economies, such as Morocco.

HYPOTHESES DEVELOPMENT AND CONCEPTUAL FRAMEWORK

The intended rate regarding information systems utilization is among the primary indicators of the success of an IS implementation. Usage of systems includes users' acceptance of technology (Aggelidis & Chatzoglou, 2009). Initially developed by Davis (1987), the Technology Acceptance Model (TAM) is an adaptation of the social psychology theory of reasoned action of Fishbein and Ajzen (Kardoyo et al., 2015). The main principles of these theories involve the examination and assessment of the relationships among subjective norms, usefulness, ease of use, attitudes, intention, and actual behavior. In recognition of its pragmatism and predictive relevance, TAM has been applied to numerous IT research studies addressing IT acceptance.

PERCEIVED USEFULNESS

Through the examination of attitudes, the indirect effect of perceived usefulness on the adoption of Google products for collaborative learning has been demonstrated (Cheung & Vogel, 2013). Y.-H. Lee et al. (2011) used the TAM model to show that employees' behavior toward e-learning systems was significantly impacted by five perceptions of innovation characteristics. Additionally, Verma et al. (2018) found both direct and indirect significant impacts of BDA characteristics on its perceived usefulness, which in turn had a significant effect on the perceptions of BDA usage held by managers. Therefore, our research proposed an integrated model using the TAM framework with its two main constructs to evaluate their relationship in the context of banks and insurance companies. It posits that TAM will provide a better understanding of BDA acceptance because it is a heavily technologically oriented, user-centered, and innovation-focused research field (Shin, 2016).

Perceived usefulness, among the two determinants of TAM, is considered the most significant variable and the main explanatory factor behind new technology adoptions (Venkatesh & Davis, 2000; J.-H. Wu & Wang, 2005). Perceived usefulness can be described as "the extent to which an individual perceives that the system can enhance their capability to accomplish their job" (Brock & Khan, 2017). It is measured by individuals' perception of how much an innovation will improve their work. Users' thoughts and intentions to accept new technology are positively influenced if they believe that using the technology will improve their work efficiency and output. The impact of perceived usefulness on the intention of users to adopt a new information technology has been evaluated by several firm-level studies across different fields (Ambak et al., 2016; Esteves & Curto, 2013; Soon et al., 2016; B. Wu & Chen, 2017). Moreover, perceived usefulness is considered the primary driver behind BDA acceptance. Despite the significance of data analytics in banks and the insurance sector, empirical studies in this area are still lacking.

Hypothesis 1: The intention to use BDA is positively influenced by perceived usefulness.

PERCEIVED EASE OF USE

The second factor in the TAM is known as perceived ease of use, which was described by Davis (1989) as "the degree of ease involved when using an information system." This factor examines the underlying properties of an IT system, such as its clarity, usability, and adaptability (Gangwar et al., 2014). It is crucial to study the complexity of a new innovation before considering its adoption. Based on empirical evidence, the level of acceptance toward a new technology among users is correlated with the degree of its ease of use. Interest in adopting an IT system will evolve if the users perceive it to be effortlessly understandable, easy to handle, and user-friendly (Kuo & Lee, 2009). Hence, the willingness of data analytics users to start using BDA is contingent upon their perception of how effortless it is to utilize, taking into consideration the variety of data that BDA is designed to process. Numerous empirical studies have examined how the ease of use of BDA affects the users' intention to use it, both directly and indirectly (Shahbaz et al., 2019; Sivarajah et al., 2017; Soon et al., 2016). The majority of research indicates that the perception of ease of use exerts a favorable influence, both directly and indirectly, on the intention to use an innovation. In addition, numerous studies have established a direct association between perceived ease of use and usefulness (Verma et al., 2018). While BDA is essential to analyze customer insights for better financial product design, the new aspect of it may create doubt regarding its convenience.

Hypothesis 2: Behavioral intention to use BDA is directly and positively influenced by perceived ease of use.

Hypothesis 3: Perceived usefulness is directly and positively impacted by perceived ease of use.

Information Quality

Data can be gathered from an array of sources in the big data age, necessitating the use of an effective framework or solution to coordinate heterogeneous data and create comprehensive information (Dubey et al., 2016). Consequently, decision-makers need to give thoughtful attention to the system's characteristics, such as the quality of the output. Our model posits that in addition to considering the analysis capabilities and task fit of BDA, as well as the impact of trust and security on technology acceptance, users will also evaluate the relevance of BDA's outputs, specifically the information quality. As stated by DeLone and McLean (1992), information quality is described as the users' perception of the quality of the output produced by information technology, and indicators like precision, dependability, and timing are important when it comes to evaluating information quality.

Many studies have discovered that system attributes and individuals' apprehension of innovation are positively correlated (Pai & Huang, 2011). In a study conducted by Zheng et al. (2013), information and system quality were found to be significant factors for the variation of the intention to adopt an information-exchange virtual community, they demonstrated how perceived individual advantages, which ultimately decide users' intent to continue consuming and producing information, are directly affected by the quality of the information. In order to gather and provide information about customers and markets for better financial analysis, information quality is essential. Verma et al.'s (2018) findings demonstrated information quality's ability to explain BDA's benefits. Users' attitudes are determined by the quality of the information they receive. Therefore, insufficient quality of big data analysis could lead to the generation of low-quality information, which in turn can have a negative impact on strategic and top management decisions (Ren et al., 2017). As theorized by TAM, the effect of external variables, such as the characteristics of the technology, on the intention to use, will be mediated by perceived ease of use and perceived usefulness (Kuo & Lee, 2009). Consequently, these two variables are expected to mediate the impact of the information quality on the intention to use:

Hypothesis 4: Perceived usefulness of BDA will be directly and positively influenced by their information quality.

Hypothesis 5: Perceived ease of use of BDA will be directly and positively influenced by their information quality.

Task and Technology Characteristics

From a Task-Technology Fit (TTF) perspective, the term "task" refers to the "activities undertaken by individuals to transform inputs into outputs in order to satisfy their information needs" (Goodhue & Thompson, 1995). The non-routineness, the interdependence, and the time rigor are examples of qualities that may vary across tasks (Goodhue, 1995). Task characteristics, which are an essential determinant of the TTF model, are used to encourage users to adopt information systems that align with their needs. Technological characteristics, representing the tools used in their work, are also a major factor in the TTF model. When faced with more challenging tasks, even with the same technical capabilities, technologies may struggle to keep up with the demand (Junglas et al., 2008).

For instance, the processing of a large amount of unstructured and semi-structured data necessitates specialized engineering techniques that can only be accomplished through the use of BDA. Advanced analytics with sophisticated applications, including statistical models, regression methods, and advanced analytical problem-solving systems, are the key features of BDA, due to how complex and diverse the data has become.

In the case studies of BDA, Shahbaz et al.'s (2021) study in the unique context related to the management system that combines big data analytics and environmental air pollution, revealing that TTF is enhanced by task and technological features. Wang and Lin (2019) argued the direct impact of the fitness of task characteristics on the features of BDA technologies in mobile cloud applied to healthcare systems. Sahid et al. (2021) demonstrated that TTF is directly and positively impacted by the two tasks and technology features related to the use of BDA by Malaysian public agencies.

Hypothesis 6: TTF is directly impacted by the technology characteristics of BDA.

Hypothesis 7: TTF of BDA is directly influenced by task characteristics.

Task-Technology Fit

Task technology fit (TTF) pertains to "the extent to which a technology facilitates an individual's completion of their tasks" (Goodhue & Thompson, 1995). In our case, TTF can be defined as the degree to which analytical users take advantage of BDA attributes to perform statistical and predictive analysis of complex financial customer data. A well-fitted task and technology alignment increase the likelihood of widespread BDA adoption. Conversely, a poor task-technology fit reduces users' intention to adopt the technology. Compared to basic data analytics, BDA offers a broad range of functionalities tailored to the complexities of the new generation of data in the financial services sector, leading to a higher TTF. The impact of TTF has been studied in several fields, including healthcare and government agencies (Sahid et al., 2021; Shahbaz et al., 2019), environmental air pollution management systems (Shahbaz et al., 2021), and mobile cloud healthcare systems (Wang & Lin, 2019).

Hypothesis 8: Behavioral intention to use BDA is positively correlated and impacted by TTF

Perceived Trust

The literature defines trust as the confidence in the reliable functioning of a particular system without tampering with its outcomes (Pavlou & Fygenson, 2006). Perceived trust in the data system involves a sense of confidence and assurance (Cui et al., 2018). In this regard, trust is crucial since it determines people's expectations from the interaction because rewards cannot be assured in interpersonal communication. According to the notion of trust, if a new technology does not behave in a manner that is expected, users may hesitate to interact with it, highlighting the importance of perceived trust in influencing the intention to use it (Pavlou, 2014).

The impact of trust has been proven by much previous research, such as e-payment adoption (Nguyen & Huynh, 2018), internet banking (Kim et al., 2009), and big data adoption in healthcare systems (Shahbaz et al., 2019). It is typical practice to use trust in the technology's operation to allay cognitive concerns among employees with limited experience and familiarity with an innovative technology (C. Liao et al., 2011). When it concerns the adoption of BDA in financial institutions, perceived trust is especially crucial, since it might affect a user's intention if they lack confidence in the capacity of the analytic system to ensure that financial decisions are based on reliable information that meets regulatory and governance requirements.

Hypothesis 9: BI to use BDA is significantly related to the variations of the trust.

Perceived Security

As stated by Arpaci et al. (2015) and Cui et al. (2018), perceived security refers to "the user's subjective perception of how safe a certain system is for delivering and storing confidential data." Handling enormous amounts of data extracted from various sources at high speeds will increase the organizational risks of capitulating to information security misuse in any big data environment. The potential for information security misuse within businesses has frequently been stated as a consequence of human conduct (Pahnila et al., 2007). Users of analytics systems are concerned about data security when employing BDA systems, primarily due to concerns about unauthorized access, disclosure, and use by eventual incautious organization divisions (Broeders et al., 2017). Numerous research investigations have shown the significance of security factors in determining the acceptability of different IT innovations, such as cloud computing (Ackermann et al., 2012), and B2C electronic commerce (Hartono et al., 2014). Since the financial sector deals with sensitive information with major financial impact, perceptions of information security are a major concern. Utilization rates of BDA may be influenced by how employees view its level of security. If they perceive that BDA is free from the risk of misuse of sensitive information, they are more likely to adopt it.

H10: Behavioral intention to use BDA is positively correlated with perceived security.

Managerial Support

The moderating effect of managerial support in our study is a circumstance where it strengthens or diminishes the impact of the users' perception of BDA on their intention to use them. According to Senge (1991), management dedication is "participating in and maintaining measures that assist individuals realize a mission." Akgün et al. (2007) described it as a measure of an organization's capacity to support and facilitate the commitment to knowledge growth and establishment. Since IT implementation has a significant effect on the company's overall strategic orientation, including creating a competitive edge and boosting performance, support from the top of the organizational hierarchy is essential. In this way, managers can effectively create an environment for learning that promotes the expansion and maintenance of their institutions. Managerial support plays a significant role as an organizational parameter, affecting the correlation between users' perceptions of BDA and their intended usage. Management should understand the significance of knowledge and encourage an environment that regards the innovation, acquisition, and sharing of knowledge as core values.

Several studies have highlighted the role of managerial support as a key variable explaining the success of IS adoption (Brock & Khan, 2017; Jayeola et al., 2022; Levitt & March, 1988). When management support is prevalent throughout the organization, technology adoption would follow. In research conducted by J.-H. Wu et al. (2008), which included management support and variables that undermine trust to investigate the variables affecting healthcare professional users' utilization of systems related to adverse event reporting, the researchers discovered support from top management had an impact on the employees' perceptions and subjective norms. Managerial support, according to Kagoya and Mbamba (2020), contributes positively to maintaining user participation traits that are essential for the adoption of e-government to be successful. Marei et al. (2021) discovered that top management support is a relevant factor linking organizational characteristics to e-procurement utilization. In conclusion, it is argued that the substantial impacts of the usefulness and ease of use on behavioral intention are more likely to be experienced by banks and insurance companies with high levels of managerial support.

Hypothesis 11: The relationship between the perceived usefulness of BDA and the intention to use them is positively moderated by managerial support.

*Hypothesis 12: The relationship between the perceived ease of use of BDA and the intention to use them is positively moderated by managerial suppo*rt.

Figure 2 illustrates our research model.

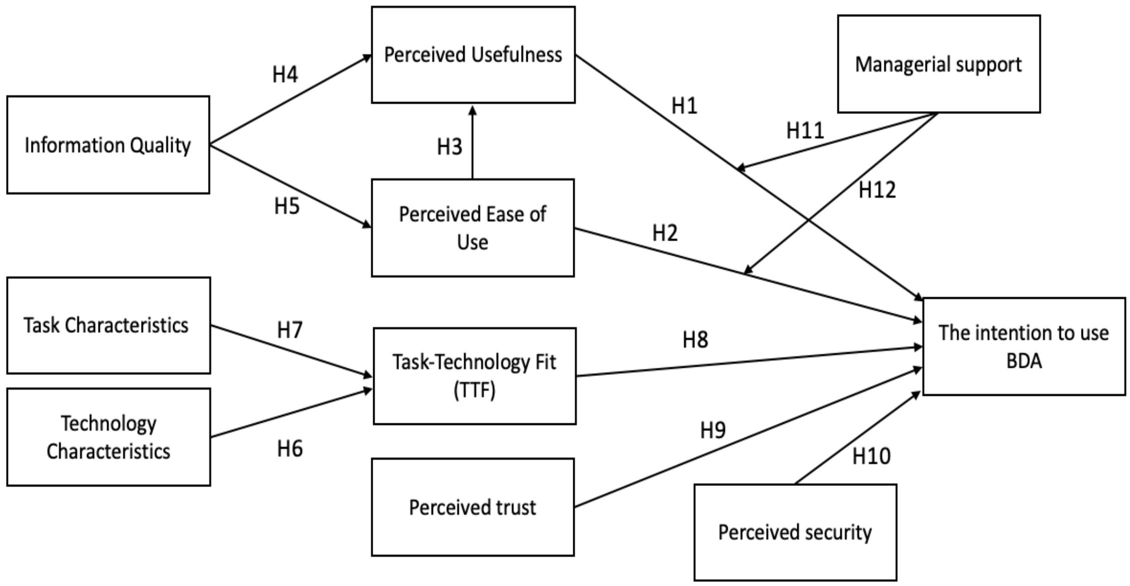

Figure 2. Proposed research model

RESEARCH METHODOLOGY

DEVELOPMENT OF MEASURES

The study's instruments, presented in the Appendix, were adapted from previously conducted empirical studies, with some modifications to suit the context of our research. Specifically, behavioral intention was gauged using a three-item scale used by Venkatesh and Bala (2008) and Verma et al. (2018). Information quality was evaluated using a set of five items adopted from the study of Zheng et al. (2013). Perceived usefulness was measured using a six-item scale drawn from the studies conducted by Bach et al. (2016) and Cheng et al. (2006). Similarly, perceived ease of use was assessed using a six-item scale referenced in the studies of Cheng et al. (2006) and B. Wu and Zhang (2014). For the evaluation of technology characteristics, task characteristics, and task-technology fit, we relied on scales comprising four items, three items, and six items, respectively, detailed in the study by Zhou et al. (2010). To measure managerial support, we employed a five-item scale introduced by Jayeola et al. (2022). For evaluating the security factor, we utilized a five-item scale from Cheng et al. (2006), and trust was measured using a four-item scale presented in the study by Gefen et al. (2003). The constructs were measured using a Likert scale ranging from '1 = strongly disagree' to '5 = strongly agree.' The questionnaire consisted of three sections. The first part presented the objective of the study and assured respondents that the information gathered would be used for academic purposes. The items for each construct of the model were displayed in the second part. The last part contained interrogations related to the respondents' function features and the organization aspects.

SAMPLE CHARACTERISTICS AND DATA COLLECTION

Based on the literature, the questionnaire was primarily developed in English, which was then translated into French using the assistance of a professional to ensure its applicability to our targeted sample. It was translated back into English to guarantee the equivalence of the meanings of the question (Brislin, 1970). First, a pre-test was conducted with data analytics experts in banks and insurance firms, including managers, project managers, and actuaries. The necessary adjustments were made to the questionnaire following their valuable suggestions. The sample targeted by the study consisted of prospective BDA users from banks and insurance companies, specifically users experienced in data management and data analytics systems such as data analysts, actuaries, software engineers, marketers, business and risk analysts, and others. A respondent-driven sampling technique and convenience sampling procedure were employed to select participants (Al-Jabri & Roztocki, 2015).

The survey was conducted using a combination of paper-based questionnaires and online methods. Initially, paper-based questionnaires were distributed to prospective BDA users, who were also invited to share them with their coworkers, resulting in the feedback of 36 answers, 8 of which contained missing values. The rest of the data were collected through direct messages on LinkedIn app and Facebook groups. It was also requested that the participants share the link to similar profiles. The tool used for the questionnaire (Google Forms) ensured the consistency of the data collection, without the risk of incomplete responses.

Considering that Structural Equation Modeling (SEM) is the research methodology of the present study, we carefully considered the sample size. Following the guidance outlined by Stevens (2012, pp. 287-314), which recommends a minimum of 15 respondents per predictor, we determined that a minimum of 150 respondents was necessary for our research. Our sample, consisting of 181 individuals, comfortably exceeds this requirement. Table 1 provides a comprehensive overview of the sample characteristics, including the respondents' education level, position, department, and years of experience.

Table 1. Characteristics of the respondents and departments

Variable	Category	Frequency	Percentage
Organization	Banks	98	54%
	Insurance companies	73	40%
	Assistance companies	10	6%
Education	Bachelor degree	12	7%
	Master degree	139	77%
	Doctoral and more	30	17%
Experience	More than 10 years	38	21%
	6 to 10 years	79	44%
	3 to 6 years	29	16%
	0 to 3 years	35	19%
Role in the Organization respondents	CEO/CFO/COO	7	4%
	Manager/Project managers	34	19%
	Data analyst/Actuary/Software engineer	57	31%
	Risk analyst/Financial Analyst/Business analyst	50	28%
	Marketer/Communication/Others	33	18%
Department	Strategy and development	28	15%
	Technical Pole/Production	37	20%
	IT, Support	30	17%
	Risk management	25	14%
	Pole finance	30	17%
	Fight against fraud	1	1%
	Marketing and communication	27	15%
	Human resources	3	2%

The foundation of this work lies in the use of the partial least squares (PLS) optimization method and regression-based assessment of latent variables. This approach is used to develop a model that illustrates the way the 10 suggested variables, which were assessed using a variety of items (Appendix), relate to one another. PLS software was used for the model evaluation. This software is a powerful tool for analyzing straightforward and robust models in business and management fields of study (Hair et al., 2014). In order to minimize the residual variance of all the model-dependent variables, the PLS approach chooses the model parameters to be used (Hsu et al., 2007). Thanks to its appropriateness of small to moderate-sized samples and capacity for modeling latent constructs in non-normal conditions, the Smart PLS tool was chosen. This method is employed across two phases:

- Evaluating the outer models by evaluating their convergent and discriminant validity and reliability.
- Measuring the importance of the correlations connecting the variables to evaluate the structural model.

Table 2. Construct validity, reliability, and loadings

Constructs	CA	Loadings	CR	AVE
Behavioral Intention (BI)	0.911	0.897 - 0.939	0.913	0.849
Information Quality (IQ)	0.916	0.841 - 0.896	0.917	0.749
Managerial support (MS)	0.889	0.782 - 0.867	0.891	0.693
Perceived Ease of Use (PEU)	0.887	0.895 - 0.908	0.887	0.816
Perceived Security (PS)	0.949	0.890 - 0.922	0.952	0.829
Perceived Trust (PT)	0.885	0.837 - 0.890	0.886	0.743
Perceived Usefulness (PU)	0.937	0.857 - 0.913	0.938	0.800
Task-Technology Fit (TTF)	0.874	0.881 - 0.900	0.876	0.799
Task Characteristics (TaskC)	0.871	0.876 - 0.904	0.873	0.795
Tech Characteristics (TechC)	0.884	0.888 - 0.926	0.884	0.812

CA: Cronbach's alpha; CR: Composite reliability; AVE: Average variance extracted

Validity and Reliability of the Measurement Models

Also known as the "outer model," one of the PLS Path models' components is the measurement model as stated by Hair et al. (2014). It has the objective of describing the relationship between the constructs and evaluating the indicators (items) validity and reliability. The validity of the items is measured using discriminant and convergent validity, while their reliability is represented by average variance extracted, composite reliability, and Cronbach's alpha in Table 2. In our case, composite reliability values vary from 0.886 to 0.952. Additionally, Cronbach's alpha values range from 0.871 to 0.949. These findings demonstrate that reflective constructs are reliable as long as they are above the advised reliability threshold of 0.7 (Nunnally & Bernstein, 1994). To assess the discriminant validity of a construct, its average extracted variance should be greater than the shared variance with other model constructs, which can be estimated by the squared correlation between the two variables (Fornell & Larcker, 1981). In our analysis, to address the issue of discriminant validity, we conducted an examination of the measurement items to identify and remove those contributing to the problem. Specifically, items that loaded lower on their designed constructs compared to other constructs, with a cross-loading difference exceeding the recommended threshold of 0.1 (Gefen & Straub, 2005; Hung et al., 2018) were deleted. This led to the removal of three items from perceived ease of use (PEU2, PEU3, PEU6), one from perceived usefulness (PU6), three from TTF (TTF2, TTF5, TTF6), and one from technology characteristics (TechC4). As a result of this refinement, the square root values of the Average Variance Extracted (AVE) for all constructs surpassed the inter-construct correlations, thereby ensuring construct validity (Zheng et al., 2013). These results are shown in Table 3. Additionally, Table 4 shows that all the HTMT values are below the threshold of 0.9 (Henseler et al., 2015). Consequently, the discriminant validity of the variables was successfully established.

The level of convergence between individual indicators representing a construct and indicators measuring other constructs is known as convergent validity. When a variable's AVE value is above 0.5 (AVE threshold), it sufficiently demonstrates convergent validity by explaining more than half the variance of its components. The AVE values, as shown in Table 2, exceeded 0.500, ranging from

0.743 to 0.849. Finally, the loading of factor values shown in Table 2 varied between 0.782 and 0.939, demonstrating that there was no issue regarding the constructs' cross-loading.

Table 3. Discriminant Validity (Fornell-Larker Criterion)

Con-structs	Nb of items	BI	IQ	MS	PEU	PS	PT	PU	TTF	Task C	Tech C
BI	3	0.921									
IQ	5	0.727	0.865								
MS	5	0.782	0.644	0.833							
PEU	3	0.806	0.677	0.650	0.903						
PS	5	0.689	0.570	0.570	0.680	0.911					
PT	4	0.786	0.614	0.664	0.739	0.784	0.862				
PU	5	0.817	0.787	0.673	0.811	0.655	0.715	0.894			
TTF	3	0.794	0.630	0.658	0.734	0.619	0.698	0.749	0.894		
TaskC	3	0.763	0.739	0.728	0.655	0.610	0.639	0.771	0.727	0.892	
TechC	3	0.762	0.644	0.656	0.668	0.528	0.591	0.740	0.706	0.780	0.901

Table 4. Discriminant Validity (HTMT*0,9)

Con-structs	BI	IQ	MS	PEU	PS	PT	PU	TTF	Task C	Tech C	MS x PU	MS x PEU
BI												
IQ	0.796											
MS	0.868	0.715										
PEU	0.896	0.751	0.734									
PS	0.736	0.608	0.619	0.738								
PT	0.874	0.680	0.746	0.833	0.855							
PU	0.884	0.848	0.739	0.889	0.690	0.784						
TTF	0.888	0.703	0.746	0.834	0.674	0.792	0.826					
TaskC	0.856	0.827	0.827	0.744	0.666	0.726	0.852	0.830				
TechC	0.850	0.715	0.739	0.755	0.573	0.667	0.814	0.803	0.889			
MS x PU	0.201	0.227	0.232	0.147	0.132	0.183	0.171	0.275	0.291	0.188		
MS x PEU	0.222	0.332	0.227	0.187	0.224	0.283	0.289	0.322	0.379	0.277	0.787	

Assessment of Structural Model

The assessment of the structural model for hypothesis testing follows the demonstration of the measurement models' reliability and validity. In this stage, the associations linking the constructs were estimated through path coefficient and R squared values (Table 6), and the bootstrapping process, with 499 iterations cumulative, was executed to test the internal model's path coefficient values.

Figure 3 and Table 5 present the path (β) coefficient statistics, which led to the rejection of two of the twelve proposed hypotheses. As anticipated, perceived usefulness, perceived ease of use, task technology fit, and trust exhibited considerable and positive influence on behavioral intention to use BDA, collectively explaining 83.5% of its variance. These findings support respectively hypotheses H1, H2, H8, and H10. Information quality significantly affects the ease of use (R^2=45.9%) and usefulness (R^2=76.2) of BDA. Task and technology features explain 57.7% of the variance in TTF (Table 6). However, unexpectedly, perceived security's impact on the intention was not significant (β=0.024, p=0.801). The positive values of Q2, as presented in Table 6, demonstrate the strong predictive power of the inner model at the structural level (Magno et al., 2022). The results highlight the large predictive relevance of behavioral intention, perceived usefulness and task technology fit since they all have Q-squared values above 0.5 (Shmueli et al., 2016).

MANAGERIAL SUPPORT MODERATING EFFECT

The study demonstrated that managerial support moderated the influence of usefulness on behavioral intention. The interaction term, perceived usefulness X managerial support (β=0.141, p=0.040), positively impacted the behavioral intention. Hence, advanced managerial support strengthens the inter-correlation between BDA's usefulness and the intention to use them, providing support for H11.

However, the results did not support hypothesis H12, which theorizes that managerial support significantly moderates the impact of ease of use on behavioral intention (β=-0.090, p=0.162).

Table 5. Results of hypothesis testing.

Hypo-thesis	Path	Coef Beta	T values	P-Value	Decision
H1	PU->BI	0.239	3.861	0.000	Supported
H2	PEU->BI	0.145	2.013	0.044	Supported
H3	PEU->PU	0.514	9.342	0.000	Supported
H4	IQ->PU	0.438	8.129	0.000	Supported
H5	IQ->PEU	0.677	17.904	0.000	Supported
H6	TaskC->TTF	0.450	4.469	0.000	Supported
H7	TechC->TTF	0.355	3.357	0.001	Supported
H8	TTF->BI	0.204	3.492	0.000	Supported
H9	PS->BI	0.024	0.252	0.801	**Rejected**
H10	PT->BI	0.193	2.099	0.036	Supported
H11	MS->PU/BI	0.141	2.057	0.040	Supported
H12	MS->PEU/BI	-0.090	1.398	0.162	**Rejected**

Table 6. Explained variance (R^2) and prediction summary (Q^2)

Constructs	R^2	Q^2
BI	0.835	0.760
PEU	0.459	0.453
PU	0.762	0.614
TTF	0.577	0.562

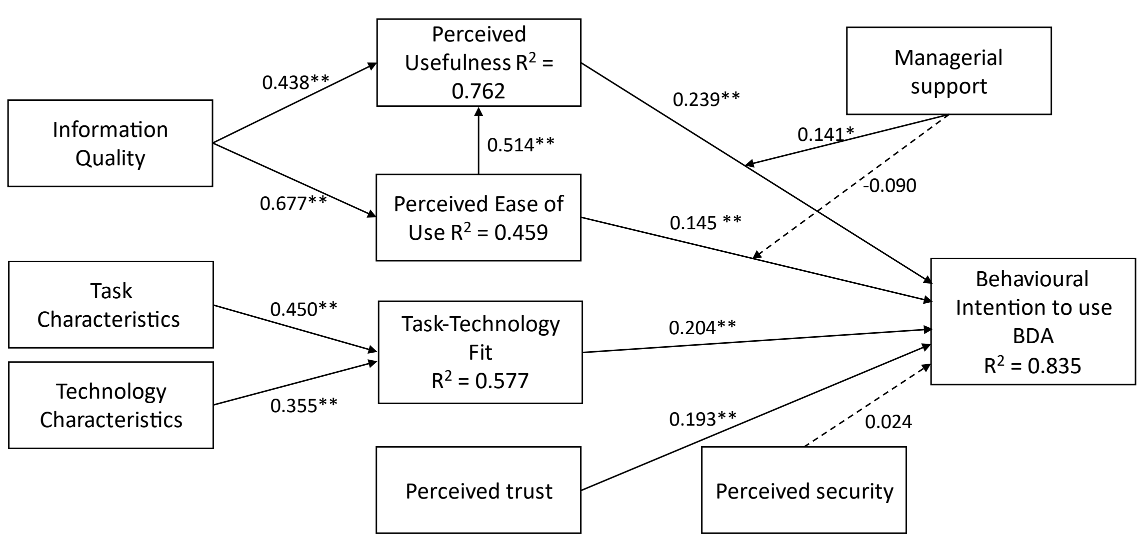

Figure 3. Results of the path coefficients of control variables and R-squared
Dotted lines indicate non-significant paths; **significant at p<0.01; *significant at p<0.05

The importance-performance map representation (IPMA) of PLS path modeling results serves the purpose of recognizing and understanding the importance of different latent variables in explaining variations in the model's outcomes (Höck et al., 2010). Figure 4 displays IMPA for the intention to use, which includes the index values of the latent variables in the structural model, excluding the intention to use itself (the target construct), and the total effects of preceding latent variables. The results indicate information quality, perceived ease of use, perceived usefulness and managerial support have the highest importance, with total impacts of 28.6 for information quality, 26.7 for perceived ease of use, 23.9 for perceived usefulness, and 25.9 for managerial support. This means that a unit increase in information quality can lead to an increase in the intention to use BDA by up to 28.6. Thus, these four variables should receive greater attention when implementing BDA.

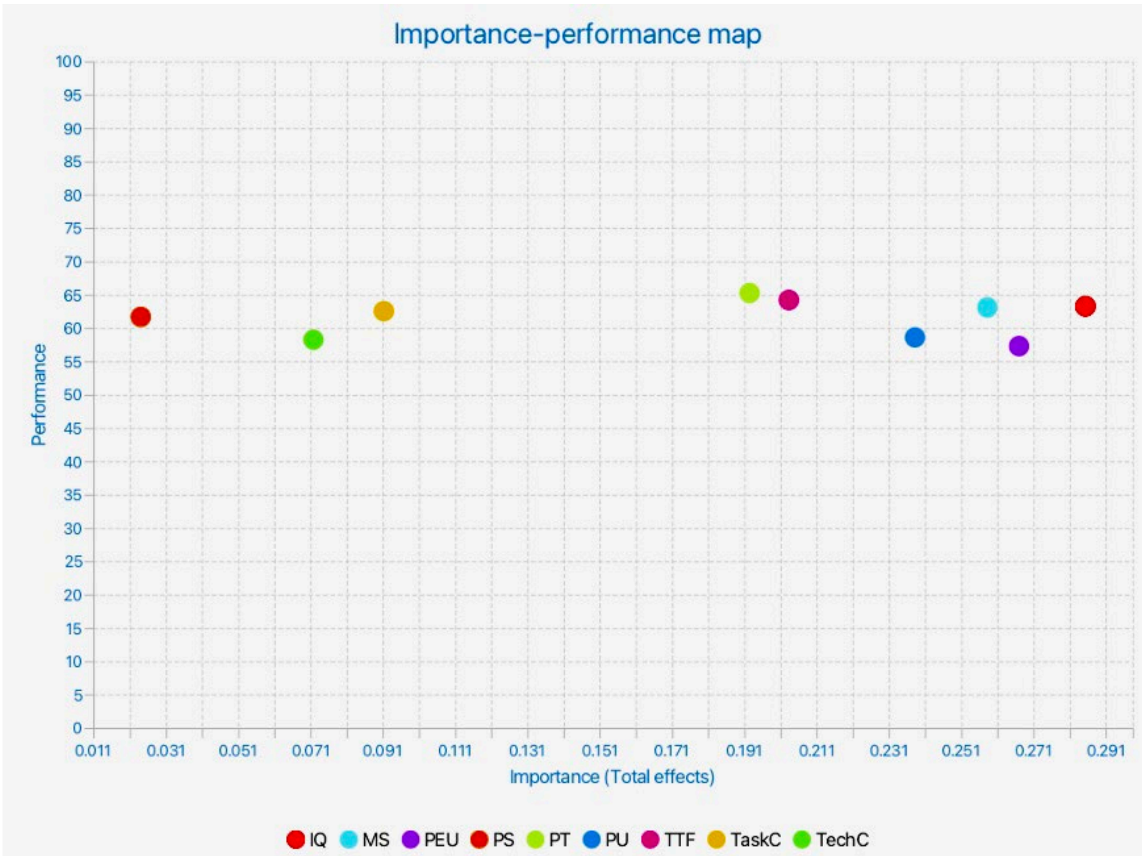

Figure 4. Importance-performance map for the intention to use BDA in banks and insurance companies

DISCUSSION

Our integrated model aims to gain an in-depth definition of the theorized relationships among the factors explaining users' intention to use BDA in Moroccan banks and insurance companies. This study contributes to the body of research on BDA, given the lack of studies on cutting-edge technology from a Moroccan perspective. Our approach extends previous studies on BDA by combining the TAM model with the TTF framework and addressing the effect of managerial support, security, trust, and the quality of information as commented in research by Al-Jabri and Roztocki (2015) and C.-H. Liao and Tsou (2009). The study's complete evaluation of their combination and investigation of their interactions with one another and with BDA's adoption is its most significant contribution.

Influence of Information Quality

Our study highlights the importance of considering information quality as a potential variable in evaluating the success of BDA adoption for banks and insurance companies. Compelling evidence supports the hypothesis, suggesting a strong impact of information quality on the ease of use among prospective BDA users in these industries. This result is in accordance with Kuo and Lee (2009) and Verma et al. (2018). By eliminating ambiguity and improving trustworthiness, high-quality information may make BDA seem easier to use. However, low-quality information can make it seem more difficult by causing confusion and doubt. A system is more inclined to be considered as simple to utilize if the users have belief in the accuracy and completeness of the information it offers.

As confirmed in this study, in order to gather and provide information about clients and financial markets, information quality is crucial (Kwon et al., 2014; Verma et al., 2018). This leads to the development of shared views among the users of the innovation and all the members of financial organizations. The present study found that information quality also impacts positively perceived usefulness, which is consistent with Kwon et al. (2014) and Verma et al. (2018), but inconsistent with Güzey and Dal (2022). This finding can be explained by the fact that data analytics users in banks and insurance companies will not experience the advantages of BDA systems if the insights or information they receive from these systems is untimely, erroneous, or inadequate.

Influence of Perceived Usefulness and Ease of Use

Behavioral intention was directly influenced by perceived ease of use, which is consistent with the research conducted by Ayeh et al. (2013) but inconsistent with B. Wu and Chen (2017). It can be explained by the positive impact of users' belief in the ease of use of BDA on its acceptance, and the intention to use it. This result also implies that if the users find it challenging to work with BDA systems, it is possible that they will prefer other alternative solutions, such as traditional business intelligence. To encourage these users to adopt BDA systems, it is crucial to ensure that the interface and solutions are simple to use and easy to comprehend. Furthermore, these solutions must be able to seamlessly integrate with the existing systems used by banks and insurance companies in Morocco. By providing an easy and pleasant user experience, these financial institutions may increase the likelihood that analytics users will accept the usage of BDA systems and acknowledge the advantages they may offer to their organizations. The perceived usefulness of BDA systems exerted a pronounced impact on individuals' intentions to engage with BDA, consistent with the findings of Lin et al. (2011). These results demonstrate that data analytics users in banks and insurance companies in Morocco believe that their intention to use BDA is motivated by their usefulness, the usefulness of BDA in the competitive advantages of financial institutions by attracting more customers, increasing organizational performance, and reducing product time to market (Maritz et al., 2020), especially from a complicated data of significant volume. It is important to emphasize that both of the variables – perceived usefulness and ease of use – played a mediating role between the information quality and the intention to use. The importance of the information quality, highlighted by the IMPA in Figure 4, is significantly explained by the users' perceptions of BDA's usefulness and ease of use.

The study also confirms a direct and positive correlation between the ease of use and the usefulness of BDA, which is in line with the findings of Ayeh et al. (2013), Bruner and Kumar (2005), C.-H. Liao and Tsou (2009), and Silic et al. (2018), but inconsistent with Amoako-Gyampah and Salam (2004). These findings suggest that users are more likely to explore the technology further, learn more about its capabilities, and feel less challenged by it when they believe it to be simple to use. It can boost their self-assurance in their ability to manage the system, which might result in a favorable opinion of it. Consequently, users are more likely to maintain their intention to use the system, which raises utilization rates and improves task performance.

INFLUENCE OF TASK TECHNOLOGY FIT

Regarding the TTF model, as confirmed in many recent studies applied to BDA adoption (Sahid et al., 2021; Wang & Lin, 2019), the fit of the technology with the task is another major predictor of behavioral intention to use BDA in the line of work of finance. This implies that technology characteristics should align with the user's particular tasks to encourage them to adopt the system. Considering that BDA technology is able to integrate statistics, visual analysis, semantics, digital learning, and graphics, analytics specialists in financial institutions can plan to adopt BDA. Similar to the way models must be evaluated and various financial data types and sources must be compared in order to generate associations and particular insights, technology fit is necessary. Additionally, the results that are in agreement with the study of Khidzir et al. (2017), and incompatible with other ones (Kang et al., 2022), prove that task characteristics and technological features impact task and technology compatibility.

INFLUENCE OF PERCEIVED TRUST

Furthermore, the findings highlighted the impact of perceived trust on behavioral intention to use BDA, which is aligned with the studies of Dhagarra et al. (2020) and Silic et al. (2018) but discordant with the findings of Ayeh et al. (2013). Trust is crucial to the acceptance of any new innovation, and in the case of BDA, which deals with various forms of data, it becomes even more important to ensure accurate and consistent outputs that serve as a basis for making strategic decisions and building new financial products. Users are less likely to intend to utilize BDA if they do not trust the quality of the data being used for analysis. The adoption of BDA has its functional risks, which can have a negative influence on their adoption, particularly for banks and insurance companies, given that the financial sector is considered the backbone of economies. If BDA is not conducted in an unbiased and transparent manner, it can erode trust in their technologies and make them less predisposed to be used.

INFLUENCE OF PERCEIVED SECURITY

While the results of this research did not validate the findings of Johnson et al. (2020) and Schuster (2022) regarding the significant impact of perceived security, it might be important to consider the context. Security is a critical concern in financial activities, which demands the implementation of appropriate security measures, to address informational fraud and the exploitation of sensitive information by malicious actors. These measures are required for every information system utilized in banks or insurance companies, and it is crucial to ensure that staff members are well-informed about them. As a result, data analytics users may already have a level of assurance that security concerns have been addressed, which makes security less of a concern for them in the use of a new analytics innovation.

THE MODERATING ROLE OF MANAGERIAL SUPPORT

Finally, a test was conducted to determine whether managerial support moderates the relationship between users' perceptions and their behavioral intention to use BDA. As anticipated by the literature, many researchers have emphasized the significance of managerial support in the acceptance of new technology (Jerez-Gómez et al., 2005). In practice, managerial support is positively related to the usefulness of a system and the intention to adopt it. The better managerial support, the stronger the impact of perceived usefulness on the intention to use, which makes this result inconsistent with Brock and Khan (2017). Top management in banking institutions and insurance companies encourages the utilization of BDA by defining new strategic goals that big data is expected to help to achieve and build new services or products that require advanced data analysis. Additionally, communicating about the benefits of adopting this new technology will build enthusiasm and support for the technology and increase the likelihood of being embraced by employees.

Although unexpectedly, according to our results, managerial support did not have a significant moderating effect on the relationship between the ease of use and the intention to use BDA, which is consistent with the results of Brock and Khan (2017). Advanced data analytics are a user-centered concept, in other words, BDA is not solely a tool of communication. Consequently, it may not necessarily need the implication of top management. Therefore, the influence of top management may be limited in shaping perceptions of the usefulness, particularly among users with prior knowledge of data analytics. Another plausible explanation can be related to the quality of training and support provided to the users. While top management can allocate resources for training and support, it is the quality and effectiveness of that analytics system that ultimately shapes perceptions of ease of use. BDA enables banks and insurance companies to better understand client needs than their rivals, who have not adopted BDA.

THEORETICAL CONTRIBUTIONS

First, while enlarging the target of the BDA adoption study to include banks and insurance firms by merging the TAM model with TTF, this work initially advances the concept of the adoption of BDA in the context of the financial sector. It supports the essential roles of users' perceptions of TAM and TTF (Shahbaz et al., 2019), proving that the combination of these models is more effective than using them individually.

Second, the applicability of research models should not rely on the direct effect of the constructs on behavioral intention. Some relationships can be better assessed using appropriate mediating factors that are linked to users' beliefs (Besoain & Gallardo, 2022); for instance, the influence of the information quality of BDA on the intention to use through the users' perceptions (Kuo & Lee, 2009), as well as the TTF model and its main factors.

Third, it was important to introduce security and trust views in order to lay the foundation for further research. The results support the appropriateness of trust in the model when investigating individual use intentions of BDA. The study introduces an additional moderating role of managerial support, which enriches the literature related to BDA adoption for future researchers who are aiming to introduce this construct for future studies.

Finally, transitioning from conventional data analytics to BDA requires a strong theoretical basis (Verma et al., 2018). This foundation contains technological features that make the information system useful, less challenging, and suitable to the task required. Individual perceptions encourage the users to adopt a new innovation (Eresia-Eke et al., 2023), while organizational factors can moderate the correlation between individuals' perceptions and their intentions. These insights can also be applied not only in finance but in other contexts in developing countries.

IMPLICATIONS FOR PRACTICE

The study carries multiple practical implications. Our insights can assist top management of financial institutions in improving BDA adoption decisions, through a better understanding of how analytics users perceive BDA. Individuals who considered that BDA technology matched the characteristics of their tasks had higher behavioral intentions and perceived ease of use. The strong combination of the TAM and TTF in our research model suggests that practitioners and prospective BDA users should focus on how well BDA fits the associated tasks, as well as how useful and easy to use. Consequently, it is critical that the tasks be big data-driven. Our research also proved that the users' perception of the usefulness and ease of use of BDA is majorly influenced by its information quality. The accuracy, consistency, and relevance of the information presented by BDA should be ensured by users (Taleb et al., 2021). Top management cannot overlook the impact of the trust factor by proposing the proper analytics and most effective BDA systems and conducting regular financial security assessments.

Managerial support is an essential driver of the usefulness of BDA. It can be inferred from our findings that top management in banks and insurance companies needs to get involved in enhancing the adoption of BDA through the usefulness factor. It can be achieved by defining clear goals for their big data initiatives, investing in the right infrastructure for the success of big data implementation, and encouraging collaboration across departments to share insights and utilize to the fullest extent big data. The research model holds practical utility for practitioners within financial organizations at the initial stage of BDA adoption.

LIMITATIONS AND FUTURE DIRECTIONS

Notwithstanding the attempts to create a sound research framework, this study may still be susceptible to certain limitations that the authors of the paper acknowledge, and based on those limitations, some future research is suggested. The first limitation was related to self-selection and a low response rate, which is one of the issues related to online (Ried et al., 2022). Other than the fact that the sample is not particularly large, the focus of this study was limited to a single innovation (BDA) within a particular sector (banks and insurance companies in Morocco). This focus may affect the relative significance of trust and security given their importance in the financial industry. This research model can be applied to developed countries as well to confirm our model's generalizability. Insights related to privacy, security, and management engagement impacts might be different if applied in a developed country.

BDA adoption in Morocco is still in its initial stage. This study's aim was to evaluate prospective users' intentions to use BDA for finance purposes analysis as a dependent variable. Further research can be conducted in organizations that have already implemented big data. This will help to discover the extent to which this model has the potential to be applied to the case of big data architects' and analysts' intentions for the adoption of BDA systems, by adding the actual use as a final variable.

Finally, as our study included respondents without technical backgrounds related to statistics and mathematics, future analysis could compare the impact of managerial support on prospective users with technical backgrounds versus those without. This comparison would provide insights into the differential effects of managerial support based on the users' technical expertise.

CONCLUSION

This study has contributed to enriching the existing literature in the field of technology acceptance by combining TAM and TTF models to provide an improved comprehensive grasp of the intention and demonstrate the primary factors necessary for users to adopt BDA. The empirical findings offer compelling evidence to back up the proposed model. Of the twelve relationships examined, ten were discovered to be statistically significant, consistent with earlier research applied to various technologies' adoption. First, information quality was found to have an indirect effect on behavioral intention, mediated by users' perceptions. Second, task-technology fit was identified as a significant predictor of the intention variance. Third, the study identified the positive impact of trust but did not show any significant effect of security factor. Finally, while it was revealed that the impact of usefulness on behavioral intention is contingent upon the level of managerial support, its moderation was found to be insignificant for ease of use.

Our integrated model holds much potential to assist professionals and researchers in enhancing the assessment of individual behavior in the adoption of innovative and advanced technologies that rely on data in the contemporary era.

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APPENDIX. QUESTIONNAIRE ITEMS

Construct	Instruments	Sources
Intention to use	BI1: I intend to use BDAs in the future BI2: I am excited about using the BDA systems in my workplace BI3: It is my desire to see the full utilization and deployment of the BDA systems	(Venkatesh & Bala, 2008; Verma et al., 2018)
Information quality	IQ1: The information provided by the BDA is up-to-date. IQ2: The information provided by the BDA is reliable. IQ3: The representation of information content in the BDA is logical and clear. IQ4: The knowledge or information provided by the BDA is important and useful. IQ5: The information or knowledge obtained from the BDA is relevant.	(Zheng et al., 2013)
Perceived usefulness	PU1: Using BDAs can improve my productivity at work. PU2: Using BDAs enhances the company's performance. PU3: I find BDA useful in my work PU4: The use of BDA improves our decision-making. PU5: The use of BDA promotes the competitiveness of our organization. PU6: Overall, BDAs are useful.	(Bach et al., 2016; Cheng et al., 2006)
Perceived ease of use	PEU1: Learning how BDAs work would be easy for me PEU2: My interaction with BDAs would be clear and understandable. PEU3: It would be easy for me to become comfortable with the handling of BDAs. PEU4: The process of implementing BDAs is understandable. PEU5: It is easy to integrate BDAs into existing solutions. PEU6: Overall, BDAs are easy to use.	(Cheng et al., 2006; B. Wu & Zhang, 2014)
Technology characteristics	Tech1: BDAs provide availability advantages. Tech2: BDAs provide real-time information. Tech3: BDAs provide secure functionality. Tech4: BDAs can help with the tasks required for my mission.	(Zhou et al., 2010)
Task characteristics	Task1: I need to manage the BDA system at any time Task2: I need to export BDA information at any time Task3: I need to get information from BDA in real-time.	(Zhou et al., 2010)
Task-technology fit	TTF1: To assist me in my mission, the BDA functions are sufficient. TTF2: In general, the BDA functions fully support my requirements. TTF3: With BDAs, I can access data quickly and easily when I need it. TTF4: BDAs provide accurate data for our purpose. TTF5: BDAs are adapted to the requirements of the nature of my work TTF6: I could get current data from BDA to meet my requirements.	(Zhou et al., 2010)
Perceived trust	PT1: BDAs are reliable. PT2: BDAs keep their promises. PT3: BDAs have the users' interests at heart. PT4: I trust the information and services provided by BDAs	(Gefen et al., 2003)
Perceived security	PS1: BDAs are secured analysis tools PS2: Using BDAs is safe and secure PS3: I would feel confident in exploiting sensitive information on BDAs. PS4: BDAs are a safe way to exploit sensitive information. PS5: Overall, BDAs are a safe place to upload sensitive information.	(Cheng et al., 2006)

Construct	Instruments	Sources
Managerial support	MS1: Managers frequently involve their staff in important decision-making processes. MS2: Staff learning is considered more of an investment than an expense. MS3: The company's management looks favorably at reform in any area in order to adapt to new environmental conditions and/or to stay ahead of them. MS4: The learning ability of employees is considered a key factor in this company. MS5: In our company, innovative ideas that work are rewarded.	(Jayeola et al., 2022)

AUTHORS

Zainab Meskaoui is currently a Ph.D. candidate in Management and Information Systems. She is a member of the research team of Management and Information Systems from the National School of Business and Management, Tangier, Morocco. She received her master's degree in actuary and risk management in Casablanca. Her current research interests are in the areas of technology adoption, behavior, and strategic value.

Abdelilah Elkharraz is currently a Professor of Business Technology at the National School of Business and Management in Tangier. He serves as the head of the Research Team on Management and Information Systems and is also the head of the DCESS-MARH at Abdelmalek Essaadi University in Morocco. He has published many research papers and teaching cases in international journals of repute.