Investigating the Determinants of the Big Data Analytics Adoption with SEM and fsQCA Analysis

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Abstract: - Big data is one of the most important driving forces for firms seeking a competitive advantage. This study examines the effects of system quality, information quality, perceived benefits, perceived ease of use, and perceived risks on the adoption of Big Data Analytics (BDA) by firms. The proposed model was tested using survey data collected from 210 firms that employ BDA tools. First, the validity and reliability of the constructs were assessed, and then the hypotheses were tested using both structural equation modeling (SEM) and fuzzy-set qualitative comparative analysis (fsQCA). The results reveal that (i) information and system quality positively affect perceived benefits, (ii) perceived risk negatively affects perceived benefits, (iii) perceived benefits positively influence perceived usefulness, and (iv) perceived ease of use and perceived usefulness positively affect the intention to adopt BDA systems. This study contributes to the big data literature by developing a comprehensive and empirically grounded research model. While extending the Technology Acceptance Model (TAM), it highlights the role of external factors, specifically information and system quality, in shaping perceived benefits and influencing BDA adoption. Furthermore, by incorporating system and information quality into the TAM framework and applying a dual-method approach (SEM and fsQCA), this study provides novel theoretical and methodological insights into BDA adoption.

Key-Words: - *Big data analytics, technology acceptance model, adoption, system quality, information quality, fsQCA analysis.*

Received: May 12, 2025. Revised: August 14, 2025. Accepted: September 11, 2025. Published: April 22, 2026.

1 Introduction

The rapid development of information technologies and the widespread use of the Internet and social media have driven the digital transformation of institutions [1], [2]. Parallel to these developments, user-generated data has grown rapidly in recent decades. Data has emerged as a new means of creating value to support business growth [3]. Firms analyze data to identify opportunities and generate business value. In today's highly competitive and turbulent market environment, many companies adopt advanced information technologies to secure a competitive advantage [1]. Big data technologies provide firms with new opportunities, as big data analytics (BDA) can enhance both competitive advantage and performance.

Big Data Analytics (BDA) refers to techniques and technologies used to extract hidden patterns from vast amounts of structured and unstructured data to generate knowledge, improve productivity, foster innovation, and support better decision-making [4], [5], [6]. Accordingly, BDA systems require advanced technologies for data storage, management, analysis, and visualization [7]. BDA also helps companies operate more effectively by enhancing customer relationship management and strengthening marketing activities [8]. BDA is crucial for firms due to its ability to generate information, thereby providing cumulative value and knowledge to top management [8]. Consequently, companies strive to seize the opportunities offered by BDA and leverage them for competitive advantage [9]. As a result, BDA has the potential to create economic value by enabling firms to improve existing products, develop new products and services, and enhance overall performance. Many studies examine intention to adopt BDA, but few address organizational determinants. Based on TAM, this study explores factors shaping BDA adoption. BDA increases transparency through information sharing [1], [10], and helps firms use data and strengthen partner ties [11]. Thus, system and information quality are critical, yet underexplored, determinants [1]. In light of the above discussion, this study proposes a research model incorporating perceived usefulness, perceived ease of use, information and system quality, perceived benefit, and perceived risk as critical factors influencing organizational adoption of BDA systems.

This study contributes to big data literature with an empirically grounded model. It analyzes how system and information quality affect perceived benefit; how perceived risk, benefit, and ease of use influence usefulness; and how usefulness and ease of use shape adoption intention. It enriches TAM by integrating external factors and applying SEM and fsQCA, offering a novel methodological contribution.

2 Theoretical Background

2.1 Big Data Analytics

Big data has emerged as one of the most significant trends of the past decade, driving a substantial increase in scholarly research. It has played a pivotal role in transforming business operations, with many firms adopting big data to secure competitive advantage and improve overall performance [5]. Several studies define big data in terms of its characteristics [12] or its sources [13], while relatively few adopt both perspectives. Conceptually, big data is viewed as a novel information technology and architecture designed to extract value from vast volumes of structured and unstructured data through timely and efficient analysis.

Big data is a multidimensional concept encompassing several characteristics: volume, variety, velocity, veracity, and value [14], [15]. Volume refers to the vast amount of data collected to uncover hidden information and patterns. Velocity denotes the speed of data generation or delivery. Variety refers to the diversity of data sources and the structured or unstructured nature of data. Veracity represents the reliability and accuracy of the data being analyzed [6], [16], [17]. Value captures the importance of data in generating economic value for companies [15].

Big data has revolutionized information-processing technologies and analytical techniques, thereby enhancing information-processing capabilities across domains [18]. Companies employ big data analytics (BDA) tools to process and analyze data, support decision-making, and improve overall performance. The diversity and scale of data enable firms to derive deeper insights, facilitating more informed decisions and predictions [19], [20]. Data analysis enables organizations to generate insights into their environment and monitor market dynamics more effectively [21]. Data analytics is a dynamic capability vital for organizational agility. [22] stresses that big data is not merely technical but also a strategic resource; with VRIN attributes (value, rarity, inimitability, non-substitutability), it enables sustainable competitive advantage.

Organizations must integrate big data with insights from business analytics to create substantial value. This integration has led to the emergence of the term “big data analytics” (BDA). Analytics refers to the application of quantitative methods (e.g., statistics, econometrics, simulation) that enable organizations to make timely and effective decisions [15]. In addition, BDA provides organizations with critical information by offering statistical support for interdisciplinary research that facilitates growth [23]. BDA has been applied in industry and practice for several years, and its adoption has continued to expand alongside increases in data volume and scale and advances in computing technologies.

As shown in [24], BDA adoption depends not only on technical capacity but also on management support, organizational alignment, and competitive pressure. Thus, BDA is both a technological and strategic decision. This study uniquely treats system and information quality as central, not supporting, determinants of BDA adoption within TAM—a perspective seldom emphasized in prior research.

2.2 Technology Acceptance Model

Technology adoption has been the focus of extensive research in recent years, leading to the development of several theories that provide new insights [25]. Some theories focus on the “process” dimension by investigating adoption mechanisms in depth, while others, such as the Technology Acceptance Model (TAM), the Technology-Organization-Environment (TOE) framework, and the Unified Theory of Acceptance and Use of Technology (UTAUT), examine the relationships between technology adoption and its antecedents. Each of these models employs the same outcome variable (use or intention to use) but incorporates multiple factors to explain technology adoption [26].

TAM, based on the theory of reasoned action [27], is a widely applied model for explaining behavior across domains [28]. It includes perceived usefulness (PU), perceived ease of use (PEOU), and behavioral intention (BI). PU and PEOU are the key determinants of use. PEOU is “the belief that using a technology requires no effort,” while PU is “the belief that it improves job performance” [1], [27], [29]. Since big data boosts organizational insights, perceived benefit is a critical factor [30], reflecting the balance between benefits and sacrifices. By shaping value and utility perceptions, it directs user behavior and system use [31]. Unlike studies based only on TAM, this research extends the model with perceived benefit, risk, system quality, and information quality, offering a broader framework for BDA adoption.

2.3 Big Data Analytics Quality

Big data analytics (BDA) quality refers to the capability of a BDA platform to generate valuable business insights. According to [32], the economic value derived from a big data environment is determined by the quality of both technology and information. Furthermore, information quality and technology jointly provide managers with credible insights in this environment [33]. As emphasized in [24], system and information quality are critical determinants of BDA adoption, as they enhance perceived benefits and strengthen organizational readiness for implementation. High-quality insights from BDA can influence organizational performance by supporting the development of better applications, new products, and improved customer relationships [4].

Data quality is a multifaceted concept including completeness, accessibility, and consistency [34]. Completeness concerns whether BDA maintains all data needed for present and future use. Consistency means uniformity of data across networks and applications. Both are essential for a company’s IT infrastructure, a vital resource for long-term competitive advantage [11]. Data accessibility refers to a user’s ability to obtain data depending on cultural context, physical capacity, and available technology [34]. Data quality can be conceptualized as a set of parameters that reflect an information system’s ability to produce high-quality data [35]. Furthermore, data quality is a critical success factor for big data projects [36], [37]. As highlighted in [38], system quality in big data environments encompasses usability, reliability, and flexibility, enabling platforms to adapt to user needs and deliver accurate and accessible information for business decision-making. Information quality is defined as outputs that are both easy to understand and beneficial for users, as well as outputs that meet their information needs [33], [39]. Despite advances, information quality problems persist due to erroneous or irrelevant information caused by software errors, data issues, or mismatched user requirements [1]. Data quality forms the basis of information quality. Poor data quality results in poor information quality, which in turn has negative consequences for companies [40]. A flexible system can be readily adapted to meet changing user information needs, ensuring that users receive up-to-date and relevant information, thereby enhancing information quality [39].

System quality refers to “the degree to which the system is easy to use for accomplishing a given task.” In the context of BDA, system quality reflects users’ perceptions of the overall quality of the BDA system [39]. System quality has long received considerable attention as an information-providing tool that evaluates overall operations and communication [41]. As noted by [35], “system quality describes desirable system traits such as ease of use, efficiency, reliability, learning, and features like intuitiveness, flexibility, and response time.” Key components include reliability, privacy, adaptability, integration, and response time. For BDA, system quality is vital, as it supports decision-making. [42] shows that ease of use, compatibility, and satisfaction significantly affect BDA effectiveness, reinforcing the quality–experience link. This study unifies these dimensions into a testable framework, moving beyond fragmented prior research.

3 Hypotheses Development

This study aims to investigate the effects of data quality, system quality, perceived risk, perceived ease of use (PEU), and perceived usefulness (PU) on the intention to adopt BDA systems. Examining the effects of these variables on the intention to adopt BDA systems contributes to theory development and provides practical insights for designing successful BDA systems. The proposed model, presented in Figure 1, incorporates the core TAM variables and their hypothesized relationships. This study hypothesizes that perceived risk, perceived benefit, and system and information quality influence PEU and PU, which in turn affect the intention to adopt BDA systems.

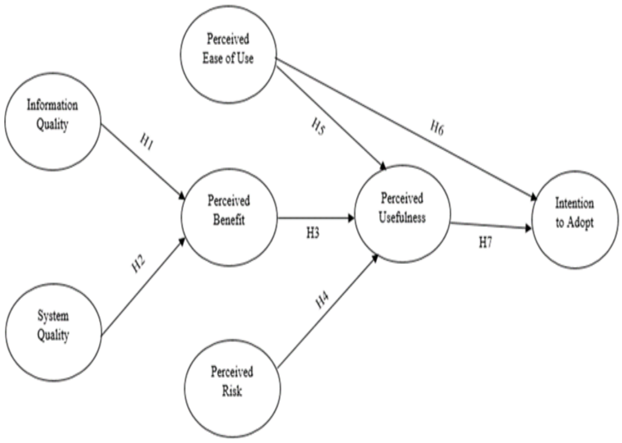

Fig. 1. Proposed Model
Source: created by the authors

3.1 Big Data Analytics Quality

Data quality is determined by the nature of the data, the analytical processes applied to it, and, in particular, the new technologies that enable these processes [43]. For an organization's information system to be valuable, it must be of high quality and capable of providing high-quality data. According to [25], high-quality data is a critical asset for improving customer satisfaction, revenues, and profits. Data quality plays an essential role in decision-making and operational processes [4].

Information quality is determined by a system's ability to convey the intended meaning and purpose of data [39]. As organizational databases are part of a broader information system environment, companies require an integrated platform to provide information across departments. Accordingly, information quality is a crucial consideration for businesses, as it can be misinterpreted by individuals who do not fully comprehend its complexity [4]. Low-quality information creates confusion and increases information-processing costs, as users may waste time and effort processing irrelevant material [44]. By contrast, high-quality information is valuable for users seeking relevant content, and it supports effective decision-making. For example, users can assist others by providing valuable, relevant information [1]. Individuals are unlikely to use information that is not aligned with their decision-making needs or work requirements. Information should be clear and easy to understand to maximize the contextual knowledge conveyed [45].

System quality is one of the most critical indicators of successful big data implementation. A BDA system should be capable of integrating data from multiple sources, remain easily accessible to users, deliver data on time, and safeguard private information [41], [46], [47]. In general, system quality has been shown to influence the acceptability and adoption of IS and Internet/Web services through expected benefit. This suggests that when system quality is high, users perceive the system as more useful, believe it will enhance their productivity or efficiency, and demonstrate favorable attitudes toward systems with greater user satisfaction. According to [46], system quality is a key and essential component of a BDA system. Indeed, information quality largely depends on system quality, which ensures the expected benefits of BDA.

A big data analytics (BDA) system is beneficial if it provides high-quality information that assists users in decision-making and enhances productivity. As a result, data quality is critical for providing numerous benefits to users. Thus, the following hypotheses are proposed:

H1: *Information quality has a positive effect on perceived benefit.*

H2: *System quality has a positive effect on perceived benefit.*

3.2 Perceived Benefit

Perceived benefit refers to the anticipated advantages, both operational and strategic, that a new technology can provide to an organization [30], [48]. Prior research defines perceived benefits as direct and indirect. For BDA, direct benefits include cost savings and efficiency, while indirect benefits reflect opportunities from technology use [30]. [25] stresses that successful BDA adoption requires stakeholder commitment and trust. A shared understanding of the benefits of a project enables participants to establish common ground and a shared sense of purpose [1]. Because information system benefits are complex [49], users' beliefs largely determine outcomes. Perceived benefit is crucial in shaping intention to use BDA. [50] Notes perceived usefulness reflects performance beliefs. Sharing expected benefits fosters understanding, and perceived benefit is expected to enhance PU by creating shared perceptions. Hence, the following hypothesis is proposed:

H3:*Perceived benefit has a positive effect on perceived usefulness.*

3.3 Perceived Risk

Perceived risk (PR) is a psychological construct that has received significant attention and has been characterized in various ways. According to [51], users of new technologies perceive risk when faced with uncertainty, as they are concerned about undesirable outcomes. Perceived risk is defined as a feeling of doubt regarding potential negative consequences of adopting or using a new product or service [52], [53]. The use of information systems has been shown to generate emotional distress among both users and employees. Several studies have demonstrated that perceived risk negatively affects attitudes toward using new technologies [51], [54]. Risk is an important factor because of the uncertainty associated with the adoption of new technologies. Perceived risk has two key determinants: uncertainty and consequence. As noted by [52], perceived risk is often described as a sense of doubt concerning potential negative consequences of using a product or service. Therefore, the following hypothesis is proposed:

H4: *Perceived risk has a negative effect on perceived usefulness.*

3.4 Perceived Ease of Use

Perceived ease of use (PEU) is defined as "the degree to which an individual believes that using an innovation will be free of effort" [27]. PEU facilitates the initial adoption of a new technology and plays an important role in its continued use [27]. Managers' intention to adopt a new technology increases when they perceive the technology as resilient, understandable, controllable, and suitable for their organization [55]. PEU has been extensively examined in studies on user acceptance of new technologies [50], [56]. Similar to PU, PEU is considered a critical determinant of technology acceptance and adoption [57]. In the Technology Acceptance Model (TAM) literature, PEU has both a direct effect on the intention to adopt new technologies [55] and an indirect effect through PU [58]. The direct effect of PEU enhances the intention to adopt new technologies, regardless of their perceived usefulness. Moreover, the easier a technology is to use, the more useful it is perceived to be, which in turn positively influences individuals' intention to use the technology. Several studies have shown that both PU and PEU positively affect the intention to adopt new technologies. PEU is also identified as a critical factor in strengthening the adoption of BDA systems [59]. Furthermore, PEU has been shown to strengthen perceived usefulness [55], [60], [61]. In addition, a BDA system with superior ease of use enhances perceptions of its usefulness [55]. Consequently, the following hypotheses are proposed:

H5: *Perceived ease of use has a positive effect on perceived usefulness.*

H6: . *Perceived ease of use has a positive effect on the intention to adopt BDA systems.*

3.5 Perceived Usefulness

Perceived usefulness (PU) is defined as "the degree to which individuals believe that using a particular system will enhance their job performance" [27]. Perceived usefulness is recognized as one of the most critical determinants of user acceptance and technology adoption [27], [28]. When managers believe that the implementation of a new technology can improve business performance and productivity, their willingness to adopt the technology increases. Numerous studies based on the Technology Acceptance Model (TAM) have empirically demonstrated the significance of perceived usefulness in shaping the intention to adopt new technologies [58], [62]. Prior research has consistently shown that PU positively affects individuals' intention to use new technologies [28], [62]. Moreover, users are more likely to intend to adopt BDA systems if they perceive the systems to be easy to use and capable of improving their performance [1]. Accordingly, the following hypothesis is proposed:

H7: *Perceived usefulness has a positive effect on the intention to use BDA systems.*

4 Methodology

4.1 Measures

A survey was developed to collect data from a representative of selected firms. For the measurement of research variables, we used multi-item and 5-point Likert scales adopted from prior studies. Measures for system quality (9 items) and information quality (9 items) were developed based on [4] and [11]. Survey items for perceived benefit (8 items) were derived from [3], while the measurement items of perceived risk (4 items) were adopted from [53]. The items of perceived ease of use (8 items) and perceived usefulness (3 items) were adopted from [1]. Survey items for intention to adopt BDA systems (3 items) were derived from [3]. The demographic variables, such as respondents' experience, industry and the size of organization, were used as control variables.

4.2 Sampling

This study was conducted with managers involved in big data adoption decisions and usage. Respondents from various companies served as key informants. Data were collected from manufacturing and service companies located in the Marmara Region of Turkey, the country's hub of industrial and economic activities. The sampling pool consisted of companies listed in the Istanbul and Kocaeli Chambers of Industry. A simple random sampling plan was applied to identify respondents. Eight hundred respondents were contacted via e-mail, in which the purpose of the study was explained and a link to the online survey was provided. To improve the response rate, the total design method suggested by researchers [63] was employed. A total of 105 responses were received within one month of the initial mailing. As recommended by [63], two reminder e-mails were sent to participants. Seventy-eight responses were received before the second reminder, and three months after the second reminder, an additional 70 responses were obtained. In total, 253 responses were collected out of 800 contacted respondents. The survey was conducted between February 2024 and July 2024. Upon analysis, 43 responses were identified as problematic due to missing data and were excluded. The final dataset comprised 210 valid responses, yielding a response rate of 26.25%. The sample covered small, medium, and large firms. Manufacturing, automotive, and finance were mostly medium or large, while consulting, services, and IT were mainly small. Respondents came from manufacturing (25%), automotive (12%), consulting (21%), services (12%), finance (10%), IT (15%), and others. Educationally, 55% held undergraduate and 45% graduate degrees. In terms of roles, 67% were IT managers, and the rest were senior managers overseeing IT.

A t-test was conducted to compare early and late responses to assess non-response bias. The results indicated no significant differences between the two groups at the 0.05 significance level. Therefore, non-response bias was not considered a concern in this study [64]. Common method bias was also examined to assess the validity and reliability of the underlying variables using Harman's single-factor test and a one-factor confirmatory factor analysis (CFA). Harman's single-factor test showed that the first factor explained 35.05% of the total variance. Since the first factor did not account for the majority of the variance, common method bias was not considered a serious problem [65]. In addition, a one-factor CFA model was employed to further investigate common method variance. After including the common latent factor, the results showed no significant changes in the fit statistics between the two models—namely, the model without a common latent factor and the model with a common method factor. Furthermore, the path coefficients were unaffected by the inclusion of the common latent factor, and the differences between the standardized path coefficients were less than 0.20. Therefore, it was concluded that common method bias was not a serious concern in this study.

5 Analysis and Results

5.1 Assessment of measurement model

Structural equation modelling (SEM) was used to assess the validity and reliability of the scales. As the scales were adopted from prior studies, their content validity was assumed. Confirmatory factor analysis (CFA) was employed to assess the validity of the constructs, including both discriminant and convergent validity. The reliability and validity of the scales were evaluated through a data purification and testing process. The measurement model was specified with both first-order and second-order constructs to ensure the most appropriate representation of all variables. For the first-order constructs, the average variance extracted (AVE) and composite reliability (CR) values were estimated to assess their validity.

As shown in Table 1 (Appendix), the CR values exceed 0.70 (ranging from 0.75 to 0.923), and the AVE values are above 0.50 (ranging from 0.501 to 0.80) for all measures [66]. Convergent validity was further assessed by examining the standardized loadings of the items on their respective constructs. Since all standardized loadings are greater than 0.50 and associated with significant t-values ($t > 2.0$) [67], convergent validity is supported for all constructs [68]. In addition, the AVE of each construct is greater than the squared correlations between construct pairs, providing evidence of discriminant validity. Table 2 (Appendix) presents the descriptive statistics, correlation coefficients, and the reliability and validity results of the constructs. Model fit measures are χ^2 (750) = 1313.52, CFI = 0.91, IFI = 0.91, TLI = 0.90, χ^2/df = 1.75, and RMSEA = 0.06. The results show evidence of a good model fit.

Finally, second-order CFA was conducted to evaluate the dimensionality of the second-order constructs (system quality and information quality).

The results indicated that the loadings of the first-order factors on the second-order factors were all statistically significant ($p < 0.05$), and the fit indices exceeded the recommended cut-off values ($\chi^2(306)$ = 642.58, CFI = 0.92, RMSEA = 0.07), demonstrating good model fit and supporting the dimensionality of the scales.

5.2 Hypothesis Testing

Structural equation modelling (SEM) was employed to test the research hypotheses. System quality and information quality were modeled as second-order constructs. The results of the structural equation model are presented in Table 3 (Appendix). System quality was represented by five indicators, and information quality by four indicators, corresponding to the average values of their respective dimensions. This procedure reduced the complexity of the model [69]. PEU, PU, PB, PR, and IA were treated as latent variables.

Information quality and system quality were found to be positively related to expected benefit ($\beta = 0.28$, $p < 0.05$; $\beta = 0.44$, $p < 0.01$, respectively). Thus, hypotheses H1 and H2 were supported. Perceived benefit was positively associated with perceived usefulness ($\beta = 0.46$, $p < 0.01$), while perceived risk had a negative effect on perceived usefulness ($\beta = -0.49$, $p < 0.01$). In contrast, perceived ease of use showed no significant effect on perceived usefulness ($\beta = -0.14$, $p > 0.05$). Accordingly, H3 and H4 were supported, whereas H5 was not supported. Finally, perceived ease of use (PEU) and perceived usefulness (PU) were both positively related to the intention to adopt the BDA system ($\beta = 0.31$, $p < 0.01$; $\beta = 0.33$, $p < 0.01$, respectively), providing support for H6 and H7.

Furthermore, information quality and system quality together explained 48.5% of the variance in expected benefit ($R^2 = 0.485$). Perceived ease of use (PEU), perceived risk (PR), and perceived benefit (PB) explained 54.7% of the variance in perceived usefulness ($R^2 = 0.547$). Finally, perceived ease of use (PEU) and perceived usefulness (PU) jointly explained 28.5% of the variance in the intention to adopt the BDA system ($R^2 = 0.285$). The SEM analysis further indicated that the structural model exhibited a good fit to the data ($\chi^2(279) = 533.77$, CFI = 0.91, IFI = 0.91, TLI = 0.90, $\chi^2/df = 1.91$, RMSEA = 0.06).

5.3 FsQCA results

The fsQCA method was employed to identify all possible combinations of causal conditions leading to a specific outcome. This method identifies multiple causal patterns that precede the outcome [70]. The fsQCA procedure involves three steps to empirically identify configurations [61]. In the first step, all variables (dependent and independent) are calibrated and transformed into fuzzy variables. The 95th, 50th, and 5th percentiles of the raw data correspond to full membership, cross-over anchors, and full non-membership, respectively [70]. The second step consists of constructing a truth table with 2^k rows, where k is the number of conditions (six causal conditions in this study). In the third step, fsQCA applies thresholds for the minimum number of cases and the minimum consistency level to reduce the number of rows in the truth table [61], [71].

The measures of coverage and consistency are analogous to the coefficient of determination and the correlation coefficient, respectively. A higher consistency threshold yields higher final consistency in identifying the best combinations, but the corresponding coverage value decreases [72]. According to [71], a solution (model) is considered appropriate when consistency exceeds 0.75 and coverage ranges between 0.25 and 0.65. In this study, the minimum acceptable raw consistency for the model was set at 0.80, above the 0.75 threshold [70], [71] and the minimum acceptable solution frequency threshold was set at three [70].

The fsQCA method yields three possible solutions: complex, intermediate, and parsimonious. Intermediate solutions are considered superior to the other two, as they do not eliminate necessary conditions [70]. Following [61], intermediate solutions were employed (allowing each condition to be "present" or "absent") to explore the patterns leading to high levels of the outcome.

The derived intermediate solutions for each of the three models are presented in Table 4 (Appendix) and Table 5 (Appendix). Table 4 demonstrates that the models are appropriate, as all consistency and coverage values exceed the recommended thresholds suggested by previous studies [71], [72].

The intermediate solution for the first outcome condition reveals two pathways leading to high perceived benefit. The first pathway shows that high system quality leads to high perceived benefit. This pathway demonstrates high consistency (0.86) and accounts for a substantial proportion of cases with high perceived benefit (coverage = 0.86). The second pathway indicates that high information quality, in combination with high system quality, also leads to high perceived benefit. This pathway likewise exhibits high consistency (0.84) and explains the largest share of cases with high perceived benefit (coverage = 0.89). The overall solution demonstrates a consistency of 0.81 and a coverage of 0.93. Based on these findings, it can be concluded that a simple antecedent condition, namely the presence of both high system quality and high information quality, appears in one pathway and leads to high perceived benefit.

The derived solution for the antecedent conditions leading to high perceived usefulness indicates three pathways. The first pathway suggests that high perceived benefit, combined with low perceived risk, results in high perceived usefulness. This solution is consistent at 0.85 and has a coverage of 0.77. The second pathway shows that high perceived benefit, together with low perceived risk and high perceived ease of use, also leads to high perceived usefulness. This solution demonstrates high consistency at 0.90 and a coverage of 0.83. The third pathway reveals that high perceived benefit alone leads to high perceived usefulness, with a consistency of 0.86 and a coverage of 0.74. Taken together, the overall solution has a consistency of 0.82 and a coverage of 0.92. These findings indicate that the three antecedent conditions are necessary, and their combination is sufficient for achieving high perceived usefulness.

Finally, the model regarding the antecedent conditions that lead to the intention to adopt BDA systems identifies two pathways. The first pathway indicates that high perceived usefulness, together with high perceived ease of use, results in a positive intention to adopt BDA systems (consistency = 0.83; coverage = 0.84). The second pathway shows that high perceived usefulness alone also leads to a positive intention to adopt BDA systems (consistency = 0.90; coverage = 0.79). Overall, the solution demonstrates high consistency (0.91) and high coverage (0.83). These results highlight that high perceived usefulness, which appears in all pathways, is the only simple antecedent condition that is necessary, although not sufficient, for the intention to adopt BDA systems.

5.4 Integration of SEM and fsQCA Findings

Combining SEM and fsQCA enhanced robustness by uniting relational and configurational perspectives. SEM showed that system and information quality raise expected benefit, a finding that fsQCA confirmed by mapping pathways to high benefit. Both methods highlighted the positive role of perceived benefit and the negative role of risk in shaping usefulness. On ease of use, SEM found no direct effect, but fsQCA showed it matters when paired with high benefit and low risk. Finally, both approaches converged on perceived usefulness as the key driver of adoption intention: SEM showed its strong effect, while fsQCA identified it as necessary in all pathways. Together, they reinforce each other, with SEM clarifying effect strengths and fsQCA capturing alternative causal paths, thus increasing validity and explanatory power.

6 Discussion and Implications

6.1 Discussion

The findings show the proposed model applies to BDA systems. This study extends TAM by adding system quality, information quality, perceived benefit, and perceived risk [1], [29], contributing to IT adoption literature. The first hypothesis—that information quality positively affects perceived benefit—was confirmed. Users who view BDA information as high quality are more likely to see performance and productivity gains. These results align with big data literature stressing the role of information quality for organizational outcomes [1], [4], [17], [32], [55]. The second hypothesis suggested that system quality positively influences perceived benefit, which the results supported. They also showed a positive effect on perceived usefulness. System quality helps users explore BDA's functions, access information, and see its value [1], supporting benefit formation [24]. Hence, system and information quality are key to understanding BDA benefits. Since BDA aims to process large data for decision-making [8], quality in both areas is vital [32]. These findings align with earlier studies [1], [32], [55], showing firms adopt BDA to improve performance by providing timely information. The third hypothesis proposed that perceived benefit positively affects perceived usefulness. The findings supported this effect, demonstrating that perceived benefit is a key determinant of the usefulness of BDA [1]. When senior managers perceive the benefits of BDA systems, their approval of such systems increases. This result is consistent with the findings of [55] and [1]. The fourth hypothesis examined the negative effect of perceived risk on perceived usefulness. The findings revealed that perceived risk is negatively associated with the perceived usefulness of BDA systems and exerts a strong inhibitory effect on perceived benefit. These results highlight the critical role of perceived risk in shaping users' intention to adopt BDA systems. Indeed, the negative relationship between risk and usefulness in the adoption of new technologies has been documented in prior studies [21], [54]. The fifth and sixth hypotheses examined the positive effects of perceived ease of use on perceived usefulness and intention to adopt BDA systems. The findings confirmed that perceived ease of use positively influences the intention to adopt BDA systems, which is consistent with [1]. However, perceived ease of use was not significantly related to perceived usefulness. This finding is consistent with [1] but contradicts several prior studies [29]. According to these results, ease of use does not foster a positive perception of the usefulness of BDA systems, possibly because users are more concerned with how the system supports business processes. Therefore, efforts to simplify BDA systems do not necessarily lead users to perceive them as more useful. Finally, perceived usefulness was found to have a positive effect on the adoption of BDA systems. This finding is consistent with several prior studies [1], [29], [59]. The results indicate that managers believe the usefulness of BDA systems increases their intention to adopt them. In other words, managers who perceived BDA systems as beneficial expressed stronger intentions to use them more frequently.

6.2 Theoretical Implications

The findings of this study contribute to the literature on TAM and the adoption of BDA systems in several ways. First, the study develops a new conceptual model that provides fresh insights into a relatively new field. Using this conceptual model, an integrated framework for BDA system adoption was developed, grounded in the TAM. Second, research on the adoption of BDA systems remains limited, with existing studies often focusing on a single perspective, such as financial or economic, or emphasizing only the TAM model. This study is among the first to propose a model that incorporates TAM along with additional antecedents, including system and information quality, perceived risk, and perceived benefit, in explaining BDA system adoption. The findings will help advance adoption theory and guide future research on BDA. Furthermore, the study incorporates information quality, system quality, perceived risk, and perceived benefit into the model to explain their effects on BDA system adoption. The results contribute to the technology acceptance literature by advancing understanding of information quality, system quality, perceived risk, and perceived benefit, and by providing a foundation for further research.

6.3 Managerial implications

This study has several practical contributions in addition to its theoretical contributions. From a managerial perspective, the findings have important implications for business managers, policymakers, and BDA vendors. The results indicate that perceived ease of use and perceived usefulness are significant determinants of BDA system adoption. Aligning system functions with required tasks, as well as ensuring that systems are perceived as useful and easy to use, is therefore critical.

The findings provide valuable insights for business executives seeking to create value from BDA by identifying and addressing problems related to BDA systems. Managers aiming to capture value from BDA should pay particular attention to ease of use, usefulness, expected benefit, perceived risk, and system and information quality as key strategic factors for enhancing adoption intentions.

6.4 Limitations and future research direction

This study offers useful insights into how system and information quality affect perceived benefit, risk, usefulness, ease of use, and ultimately BDA adoption. While it has theoretical and practical value, several limitations remain. First, the focus on firms may not reflect industry differences; future research could include cross-industry comparisons. Second, its cross-sectional design restricts causal inference; longitudinal studies may provide a clearer view of adoption dynamics. Third, since the study was conducted in Turkey, results may not generalize broadly; testing the model in other contexts could enhance applicability. Adding variables such as management support, organizational culture, or readiness might also strengthen the model.

Finally, future research could also extend beyond adoption intention to examine realized business performance outcomes of BDA implementation, thereby offering a more holistic understanding of its organizational impact.

6.5 Conclusion

Grounded in the Technology Acceptance Model (TAM), this study systematically investigated six factors influencing the adoption of BDA systems and integrated them into a comprehensive adoption framework. The findings provide robust preliminary evidence supporting the viability and explanatory power of the proposed research model in the context of BDA systems. The study tested the TAM framework in the specific context of BDA adoption and confirmed its utility. It extends the TAM by incorporating perceived benefit, perceived risk, and two critical external factors, system quality and information quality, thereby strengthening the model’s explanatory capacity. The results confirm that the TAM framework, when expanded with these additional constructs, is appropriate for explaining the adoption of BDA systems in Turkish firms.

This study contributes to the information systems literature by advancing the understanding of expected benefit and by emphasizing the pivotal role of external factors such as information quality and system quality. Overall, the study significantly strengthens our understanding of the drivers influencing firms’ adoption of BDA systems. It establishes a solid foundation for future research on big data adoption and offers actionable insights for subsequent empirical investigations. By extending the big data literature, the results of this study will inform and guide future research on BDA adoption, both conceptually and empirically.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed to the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or the Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

APPENDİX

Table 1. Reliability and Validity Results

Construct	Items	Loadings	t-value	Cronbach's □	AVE	CR
	PU1	0.814**	-			
Perceived Usefulness (PU)	PU2	0.877**	13.855	0.844	0.660	0.853
	PU3	0.740**	11.290			
	PEU1	0.768**	-			
Perceived Ease of Use (PEU)	PEU2	0.754**	10.541	0.828	0.627	0.834
	PEU3	0.850**	11.237			
	PR1	0.691**	-			
Perceived Risk (PR)	PR2	0.797**	9.066	0.779	0.550	0.785
	PR3	0.733**	8.811			
	PB1	0.749**	-			
Perceived Benefit (PB)	PB2	0.723**	10.142	0.828	0.564	0.837
	PB3	0.845**	11.827			
	PB4	0.678**	9.334			
	COMP1	0.781**	-			
Completeness (COMP)	COMP2	0.834**	12.361	0.825	0.617	0.828
	COMP3	0.739**	10.779			
	FOR1	0.695**	-			
Format (FOR)	FOR2	0.669**	7.558	0.725	0.501	0.750
	FOR3	0.757**	8.628			
	CUR1	0.840**	-			
Currency (CUR)	CUR2	0.861**	14.658	0.880	0.719	0.885
	CUR3	0.843**	14.019			
	ACC1	0.861**	-			
Accuracy (ACC)	ACC2	0.697**	11.071	0.831	0.654	0.849
	ACC2	0.858**	15.243			
	SR1	0.842**	-			
System Reliability (SR)	SR2	0.894**	15.568	0.849	0.653	0.848
	SR3	0.671**	10.467			
	SA1	0.740**	-			
System Adaptability (SA)	SA2	0.719**	10.046	0.808	0.585	0.808
	SA3	0.831**	11.382			
	SI1	0.908**	-			
System Integration (SI)	SI2	0.906**	20.356	0.923	0.800	0.923
	SI3	0.869**	18.839			
	SP1	0.969**	-			
System Privacy (SP)	SP2	0.878**	20.663	0.899	0.757	0.902
	SP3	0.749**	14.361			
	SRT1	0.834**	-			
System Response Time (SRT)	SRT2	0.877**	14.965	0.884	0.712	0.881
	SRT3	0.820**	13.997			
	IA1	0.802**	-			
Intention to Adopt BDA (IA)	IA2	0.781**	11.794	0.825	0.618	0.829
	IA3	0.769**	11.097			

**p<0.01

Source: created by the authors

Table 2. Correlations, descriptive statistics, and convergent validity

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. PU	(0.81)													
2. PEU	0.33**	(0.79)												
3. PR	-0.31**	-0.49**	(0.74)											
4. COMP	0.33**	0.44**	-0.47**	(0.78)										
5. FOR	0.37**	0.29**	-0.34**	0.51**	(0.70)									
6. CUR	0.39**	0.46**	-0.46**	0.60**	0.48**	(0.84)								
7. ACC	0.25**	0.45**	-0.40**	0.60**	0.53**	0.61**	(0.80)							
8. SR	0.41**	0.33**	-0.43**	0.55**	0.47**	0.48**	0.52**	(0.80)						
9. SA	0.45**	0.37**	-0.34**	0.46**	0.46**	0.41**	0.45**	0.57**	(0.76)					
10. SI	0.36**	0.30**	-0.31**	0.36**	0.38**	0.40**	0.34**	0.55**	0.70**	(0.89)				
11. SP	0.41**	0.34**	-0.38**	0.39**	0.33**	0.45**	0.41**	0.57**	0.57**	0.53**	(0.84)			
12. SRT	0.34**	0.45**	-0.41**	0.51**	0.45**	0.47**	0.43**	0.55**	0.57**	0.61**	0.54**	(0.87)		
13. PB	0.57**	0.49**	-0.38**	0.45**	0.44**	0.41**	0.42**	0.48**	0.52**	0.39**	0.40**	0.47**	(0.75)	
14. IA	0.32**	0.33**	-0.35**	0.43**	0.29**	0.50**	0.44**	0.42**	0.43**	0.46**	0.45**	0.37**	0.45**	(0.78)
Mean	4.33	3.80	2.11	3.85	4.07	4.02	3.99	4.10	4.12	3.99	4.10	3.95	4.13	4.22
Std. Dev.	0.57	0.71	0.70	0.64	0.58	0.64	0.63	0.59	0.57	0.74	0.73	0.68	0.59	0.65

Notes: Diagonals show the square root of AVE. **p<0.01

Source: created by the authors

Table 3. SEM Results of Research Model

Hypothesis	Structural Path	Unstandardized estimate	Standard Error	Standardized estimate	t-Value	P-value
H1	IQ → PB	0.276	0.134	0.286*	2.060	0.040
H2	SQ → PB	0.415	0.135	0.446**	3.074	0.002
H3	PB → PU	0.568	0.139	0.466**	4.086	0.000
H4	PR → PU	-0.445	0.083	-0.493**	-5.361	0.002
H5	PEU → PU	-0.163	0.113	-0.145	-1.442	0.149
H6	PEU → IA	0.335	0.091	0.310**	3.681	0.000
H7	PU → IA	0.326	0.081	0.339**	4.025	0.000
Control Variables	Size →IA	-0.0003	0.013	-0.002	-0.026	0.980
	Industry →IA	0.004	0.008	0.035	0.516	0.606
	Experience →IA	-0.045	0.078	-0.04	-0.575	0.565

*p<0.05;**p<0.01

Source: created by the authors

Table 4. Intermediate solution for outcome conditions

Solutions	Raw coverage	Unique coverage	Consistency
Perceived benefit results			
Model: f_PB = f(f_SysQ, f_InfQ)			
f_SysQ	0.865758	0.0390787	0.867746
f_InfQ*f_SysQ	0.892051	0.0653723	0.841315
Solution coverage: 0.93113; solution consistency: 0.807954			
Frequency cut-off: 4; consistency cut-off: 0.806354			
Perceived usefulness results			
Model: f_PU = f(f_PEU, f_PB, f_PR)			
f_Benefit*~f_Risk	0.775879	0.0515954	0.85403
f_Benefit*~f_Risk*f_PEU	0.837534	0.0724715	0.902343
f_Benefit	0.748945	0.0114655	0.868431
Solution coverage: 0.921795; solution consistency: 0.820449			
Frequency cut-off: 3; consistency cut-off: 0.820449			
Intention to adopt BDA systems results			
Model: f_IA = f(f_PU, f_PEU)			
f_PU*f_PEU	0.844673	0.140676	0.834929
f_PU	0.792774	0.088776	0.905674
Solution coverage: 0.933449; solution consistency: 0.816819			
Frequency cutoff: 19; consistency cutoff: 0.850525			

Source: created by the authors

Table 5. Final configurations for high levels of the outcome

Solutions and pathways for a high membership score in the outcome conditions

	Outcome conditions									
	Perceived Benefit			**Perceived Usefulness**				**Intention to Adopt the BDA System**		
Antecedent Condition	**1st**	**2nd**	**Conclusion**	**1st**	**2nd**	**3rd**	**Conclusion**	**1st**	**2nd**	**Conclusion**
System Quality	●	●	● (H1√)							
Information Quality		●	Ø (H2¢)							
Perceived Benefit				●	●	●	● (H3√)			
Perceived Risk				○	○		Ø (H4¢)			
Perceived ease of use					●		Ø (H5¢)	●		Ø (H6¢)
Perceived usefulness								●	●	● (H7√)

Notes: Black circles and white circles show very high presence of a condition and very low presence (i.e., absence) of a condition, respectively. Large black (white) circles are a core-necessary condition of presence (absence). "Ø" indicates a not necessary condition. Blank spaces in a link indicate "don't care. "√" shows that the respective result presented in our study is supported, "¢" shows that the respective result is conditionally supported, and "x" shows that the respective result is not supported.

Source: created by the authors