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Examining Factors Influencing the Acceptance of Big Data Analytics in Healthcare

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Abstract

This study investigated the factors influencing the acceptance of big data analytics in healthcare. Big data analytics can improve many aspects of healthcare, including diagnostics, service provision, and patient outcomes. A cross-sectional online survey administered to N = 132 professionals working in the U.S. healthcare industry used regression analysis to determine the extent of the predictive relationships between the variables. The findings support previous research linking big data analytics to performance improvements in healthcare by highlighting performance expectancy's significance as a predictor of behavioral intentions. The mixed results suggest that the Unified Theory of Acceptance and Use of Technology (UTAUT) has limited explanatory power when studying big data analytics adoption in healthcare settings. Future research should focus on developing a theory that explains big data analytics acceptance and use based on information security risks, implementation costs, and user aversion to technology.

Keywords: Big Data Analytics, health care, UTAUT, performance expectancy

1. INTRODUCTION

Healthcare is making increasing use of big data analytics (Nazir et al., 2020). Big data analytics and innovative tools like electronic health records and centralized client-server architecture advance the delivery of healthcare services and improve patient outcomes (Galetsi et al., 2020). Applying big data analytics technologies in healthcare depends on healthcare practitioners' acceptance of these technologies (Aljarboa & Miah, 2020). Healthcare practitioners play a crucial role in adopting, implementing, and institutionalizing new technologies (Brock & Khan, 2019). Increasing healthcare practitioners' behavioral intentions to accept big data analytics increases the benefits of implementations.

This study investigated how factors associated with the Unified Theory of Acceptance and Use of Technology (UTAUT) influence big data analytics acceptance in healthcare settings i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions.

2. THEORETICAL FRAMEWORK

This research relied on the UTAUT as the theoretical framework. Venkatesh et al. (2003) developed the UTAUT to show the factors influencing an individual's behavioral intention to

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accept and use new technology. The UTAUT model identifies four main factors influencing the acceptance of technology: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Performance expectancy refers to an individual's level of trust in the ability of a system to help improve their performance. Effort expectancy refers to the potential user's evaluation of the ease of using and interacting with the new technology (Susanto et al., 2020). People's perceptions regarding whether or not the individual should accept and use a certain technology constitute social influence. Facilitating conditions refer to the objective environmental factors influencing an individual to accept and use new technology (Ayaz & Yanartas, 2020). These four factors were adopted as the study's independent variables, while the behavioral intention to accept big data analytics was the dependent variable.

In the UTAUT mode, the influence of the four independent variables (R1, R2, R3, and R4) on the dependent variables is moderated by age, gender, experience, and voluntariness of use. Additionally, the model includes use behavior as a dependent variable influenced by behavioral intention and facilitating conditions. The present study's theoretical model deviates slightly from the original UTAUT by eliminating the moderating variables from the model and focusing exclusively on behavioral intention. Figure 1 depicts the study's theoretical model adapted from the UTAUT.

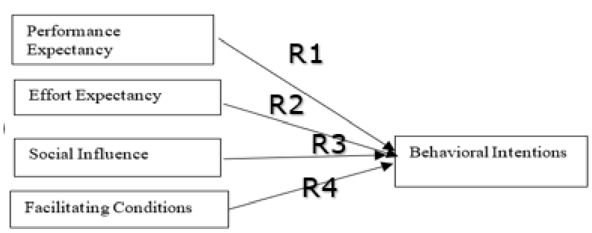

Figure 1 Research Model

The current state of the healthcare industry is shaped by the need to manage costs, increase quality, increase productivity, and function effectively in the face of complexity. The stakeholders in the industry, including payers, providers, managed healthcare organizations, pharmaceuticals, and patients, have needs that become more complicated over time. Healthcare organizations are expected to find ways of addressing current challenges, such as increased charges, inefficiency in delivery systems, increased rates of medication and medical error, and reliance on inaccurate information for decision-making (Zhu & Chen, 2021). One essential and promising solution to such challenges involves adopting information technology (IT), an enabler of healthcare transformation (Zhu & Chen, 2021). Integrating IT into healthcare operations is crucial in collecting, analyzing, and interpreting information to improve decision-making (Zhu & Chen, 2021). Healthcare organizations also risk losing competitiveness when they fail to proactively recognize the need for IT and carefully evaluate their potential contribution to healthcare operations.

IT integration in healthcare focuses on adopting a wide range of new technologies. One is telemedicine, which involves delivering healthcare services online. Unlike in the past, when patients would be required to visit hospitals upon the appearance of disease symptoms for diagnosis and treatment, telemedicine allows the exchange of clinical information between physicians and patients regardless of location using modern technologies (Han & Lee, 2021). Telemedicine combines various technologies to facilitate the non-face-to-face exchange of medical information. Another critical technology is mHealth, which involves the application of wearable devices and related applications in healthcare. Wearable devices are deployed to monitor a patient's activity levels, sleep patterns, and heart rate to help inform the prevention and treatment decisions made by the physician (Han & Lee, 2021). Healthcare organizations adopt these data-driven technologies to reduce costs, improve quality, foster productivity, and increase patient safety. These new technologies increase the digitization of health care.

Big data has emerged as one of the most famous developments in the public and private sectors. It is characterized by the data's high volume, velocity, variety, value, and veracity (Chasupa & Paireekreng, 2021). Big data refers to data that cannot be stored, processed, and computed using conventional data analysis techniques but requires advanced tools and methods. On the other hand, big data analytics involves collecting, organizing, and analyzing massive amounts of data to aid the discovery of patterns and other valuable insights. It encompasses the techniques and technologies to allow the disclosure of hidden insights from large datasets (Chasupa & Paireekreng, 2021). Big data analytics offers unique opportunities that can be exploited by society. Big data possesses the potential to change how the world, people, and organizations do things due to its role in increasing awareness and providing more profound insight.

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Galetsi et al. (2020) notes that the healthcare industry is data intensive utilizing dynamic interactive platforms with innovative tools and technologies like electronic health records with centralized client-server architecture to improve patient outcomes and overall healthcare operations. Further Galetsi et al. (2020) observes that the industry captures and manages large volumes of data from various sources, such as laboratory information, library systems, and electronic health records. Big data analytics in healthcare is characterized by the deployment of methods that enable the analysis of large amounts of electronic data relating to the delivery of care to patients (Zhan, 2019). Such data cannot be captured and analyzed using traditional techniques. Big data analytics in healthcare and medicine allows large and complex heterogeneous data to be integrated and analyzed, including telemedicine, biomedical, and electronic (Batko & Ślęzak, 2022). The application of big data analytics helps improve patient health by supporting long-term prediction about the health status of patients and informs the implementation of the proper therapeutic procedures.

Batko and Ślęzak (2022) noted that adopting big data analytics improves healthcare organizations' quality of care. The role played by big data analytics should cause the management and employees in these organizations to readily accept the deployment of big data analytics techniques to support their actions and decisions. However, accepting big data analytics techniques and tools in healthcare organizations still faces challenges, just like accepting other technologies. It is not uncommon for employees to resist and even oppose big data analytics deployment for personal and organizational reasons. For instance, employees will accept or reject a new technology depending on whether they possess the knowledge and skills required to utilize it (Lagzian & Pourbagheri, 2022). Individual, organizational, and social factors can influence the acceptance of new technology. Individual factors include individual innovation, knowledge, training, and previous experience. Organizational factors that influence technology acceptance include information security, supporting mechanisms, and the quality of the systems. Social factors include trust and available infrastructure.

3. CONTRIBUTION OF THIS RESEARCH

Most of the previous UTAUT studies reviewed either focused on the acceptance of technology at the organizational level or mixed the variables for organizations and individuals. Whereas, the current study explores individuals' evaluation that influences the acceptance of big data analytics in healthcare organizations. Employees play a crucial role in the acceptance of new technologies. No technology can ever be successfully implemented and diffused without the support and willingness of employees. Efforts made by the organization to introduce new technology, including introducing big data analytics in a healthcare organization, will not produce the required results without the acceptance of employees (Panari et al., 2021). This study explores the individual-level factors influencing an employee's behavioral intention to accept new technology.

Much of the existing literature focused on specific job roles rather than taking a general approach to adopting big data analytics in healthcare. For instance, Cabrera-Sánchez and Villarejo-Ramos (2019) only collected data from the selected companies' CEOs and managers of departments. Managers' views may not represent those of all other employees in these organizations. Alternatively, Brock and Khan (2019) relied on the data collected from students enrolled in an IT program, who may not represent the view of all students in the university. Lastly, Ajimoko (2019) collected data from IT professionals, whose views may not represent those held by other professionals in the organization because IT professionals may focus more on the technical attributes of the technology. The present study sought to address these limitations by collecting a general sample of healthcare professionals to improve generalizability.

Most of the literature reviewed focused on accepting technology as a broader topic. For instance, Barkoczi and Lobontiu (2020) only investigated the factors influencing the acceptance of technologies in the telecommunications sector, specifically mobile computing. The study did not focus on any single technology, which was like research by Skoumpopoulou and Wong (2019), who only sought to understand the factors influencing the acceptance of new technologies in the workplace. It is important to note that employees will respond differently to different technologies. The behavioral intention to accept varies across technologies. Second, most of the studies reviewed focused on the workplace in general or other industries other than the healthcare industry. For instance, Cabrera-Sánchez and Villarejo-Ramos (2019) only explored the acceptance of big data analytics in companies, while Farias and Resende (2020) focused on

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technology acceptance in institutions of higher learning. After investigating the moderating role of resistance to change in adopting big data analytics in healthcare, Shahbaz et al. (2019) recommended further research on big data analytics adoption in healthcare. The healthcare industry differs from other industries regarding the technologies and workforce.

4. RESEARCH METHODS AND FINDINGS

This study addressed a gap in the literature regarding big data analytics adoption in the U.S. healthcare industry. The study examined four research questions: (1) To what extent does performance expectancy explain U.S. healthcare professionals' behavioral intentions to accept big data analytics in research-based healthcare organizations? (2) To what extent does effort expectancy explain U.S. healthcare professionals' behavioral intentions to accept big data analytics in research-based healthcare organizations? (3) To what extent does social influence explain U.S. healthcare professionals' behavioral intentions to accept big data analytics in research-based healthcare organizations? (4) To what extent do facilitating conditions explain U.S. healthcare professionals' behavioral intentions to accept big data analytics in research-based healthcare organizations? The UTAUT survey items are shown in Table 1.

Survey data were collected from healthcare professionals working in research-based healthcare organizations. This study focused on participants working at research-based healthcare organizations in the United States. Research-based healthcare organizations were selected as the research setting because these institutions generate and use vast amounts of data (Singh et al., 2018). A third-party survey provider called Pollfish facilitated participant selection and data collection. Power analysis using Gpower3 for regression indicated that a sample size of 120 was needed. Using Pollfish enabled affordable, timely, and anonymous data collection via random sampling.

The demographics for the respondents and sample size are shown in Table 2. The five UTAUT constructs had Cronbach Alpha scores of .70 or more demonstrating acceptable reliability. The constructs were not multicollinear.

Constructs and Survey Items from Venkatesh et al. (2003)
Performance Expectancy

If I use big data analytics…
1. I will increase my effectiveness on the job.
2. I will spend less time on routine job tasks.
3. I will increase the quality of output of my job.
4. I will increase the quantity of output for the same amount of effort.
5. My coworkers will perceive me as competent.
6. I will increase my chances of obtaining a promotion.
7. I will increase my chances of getting a raise.

Effort Expectancy
1. Learning to operate big data analytics would be easy for me.
2. I would find it easy to get big data analytics to do what I want it to do.
3. My interaction with big data analytics would be clear and understandable.
4. I would find big data analytics to be flexible to interact with.
5. It would be easy for me to become skillful at using big data analytics.
6. I would find big data analytics easy to use.

Social Influence
1. I use big data analytics because of the proportion of coworkers who use it.
2. The senior management of this business has been helpful in the use of big data analytics.
3. My supervisor is very supportive of the use of the system for my job.
4. In general, the organization has supported the use of big data analytics.

Behavioral Intentions
1. I have control over using big data analytics.
2. I have the resources necessary to use big data analytics.
3. I have the knowledge necessary to use big data analytics.
4. Given the resources, opportunities, and knowledge it takes to use big data analytics, it would be easy for me to use big data analytics.
5. Big data analytics is not compatible with other systems I use.

Facilitating Conditions
1. Guidance was available to me in the selection of big data analytics.
2. Specialized instruction concerning big data analytics was available to me.
3. A specific person (or group) is available for assistance with big data analytics difficulties.

Table 1 – Survey Items

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	Percentage
Age	
18 to 24	85%
Over 54	15%
Gender	
Females	53%
Males	47%
Years of Work Experience	
<= 10 years	74%
> 10 years	26%

N = 132
Gpower3 recommended 120 sample size
22 million Healthcare Professionals in US
Table 2: Demographics

Analysis of the UTAUT constructs revealed that they were normally distributed. Also, they demonstrated a high degree of internal reliability, as shown in Table 3 of the descriptive statistics.

Construct/Item	*M (SD)*	*α*
Performance expectancy	5.61 (.989)	.73
Effort expectancy	5.45 (1.041)	.75
Social influence	5.38 (1.030)	.78
Facilitating conditions	5.56 (0.951)	.74
Behavioral intentions	5.74 (1.022)	.72

Table 3 Descriptive Statistics, Reliability

Research Question 1 addressed the relationship between performance expectancy and participants' behavioral intentions to adopt big data in U.S. research-focused healthcare organizations. In this study, performance expectancy referred to the participants' belief that big data analytics would facilitate enhanced performance for healthcare professionals working in research-focused organizations (Susanto et al., 2020). Behavioral intention refers to the participants' inclination to use big data analytics in the future (Handoko, 2019). The linear regression model analysis indicated that the relationship between performance expectancy and behavioral intentions was significant (β = 0.368, *t*(127) = 3.968, *p* = .000175). The significant finding was indicated by the *p*-value being lower than .05, the threshold for significance used in this study. The β value reflected a positive relationship between the variables. In support of Research Question 1, the positive β value meant that behavioral intentions increased when performance expectancy increased. This implies that doctors, nurses, and healthcare researchers who believed that using big data analytics would improve their work performance were more likely to use the technology than healthcare professionals who did not believe big data analytics would improve performance. The positive significant relationship between performance expectancy and behavioral intention was not unexpected. Working with big data is complicated because these datasets cannot easily be gathered, stored, managed, or analyzed using traditional database software tools (Sun et al., 2019). Cuzzocrea (2020) noted that big data analytics allows users to discover patterns, trends, and previously unidentified correlations. These discoveries often improve healthcare outcomes, supporting the link between performance expectancy and behavioral intention.

Research Question 2 addressed the relationship between effort expectancy and participants' behavioral intentions to adopt big data in U.S. research-focused healthcare organizations. Effort expectancy referred to the participants' belief that big data analytics would be easy to use (Yohanes et al., 2020). In the original UTAUT model, the expectation that a technology is easy to use was assumed to have a significant positive influence on users' behavioral intentions to accept and use that technology (Venkatesh et al., 2003). The linear regression analysis indicated that the relationship between effort expectancy and behavioral intentions was nonsignificant (β = 0.019, *t*(127) = 0.204, *p* = .838). The finding for Research Question 2 did not support the assumed relationship between effort expectancy and behavioral intentions in the UTAUT model. It is possible that ease of use is not closely associated with big data analytics because of the complexity of the technology (Sun et al., 2019).

Research Question 3 addressed the relationship between social influence and participants' behavioral intentions to adopt big data in U.S. research-focused healthcare organizations. Social influence refers to subjective norms and social factors in users' working environments that influence their attitudes toward using technology (Vallerie et al., 2021). Venkatesh et al.'s (2003) original UTAUT model assumed a positive link between social influence and the behavioral intention to adopt a technology. Linear regression model analysis indicated that the relationship between social influence and behavioral intentions was nonsignificant (β = 0.008, *t*(127) = 0.089, *p* = .930). The actual relationship between social influence and behavioral intention did not support Venkatesh et al.'s (2003) UTAUT model or the study's theoretical framework. Social influence has significantly influenced big

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data analytics use in some settings (Cabrera-Sánchez & Villarejo-Ramos, 2019). However, Queiroz and Pereira (2019) found that social influence was not always a driver of technology adoption among professionals. The present study's data analysis illustrated that social influence was not a significant driver of U.S. healthcare professionals' behavioral intentions to use big data analytics in research-focused organizations.

Research Questions	Regression Results
RQ1: To what extent does performance expectancy explain U.S. healthcare professionals' behavioral intentions to accept big data analytics in research-based healthcare organizations?	β = 0.368, t(127) = 3.968, p = .000175***
RQ2: To what extent does effort expectancy explain U.S. healthcare professionals' behavioral intentions to accept big data analytics in research-based healthcare organizations?	β = 0.019, t(127) = 0.204, p = .838
RQ3: To what extent does social influence explain U.S. healthcare professionals' behavioral intentions to accept big data analytics in research-based healthcare organizations? (	β = 0.008, t(127) = 0.089, p = .930
RQ4: To what extent do facilitating conditions explain U.S. healthcare professionals' behavioral intentions to accept big data analytics in research-based healthcare organizations?	β = 0.398, t(127) = 4.193, p = .000088***

Table 4 Regression Results

Research Question 4 addressed the relationship between facilitating conditions and participants' behavioral intentions to adopt big data in U.S. research-focused healthcare organizations. Facilitating conditions referred to objective factors within the work environment that supported participants' use of big data analytics (Handoko, 2019). Examples include specialized software, organizational training programs, or onsite technical support. Linear regression analysis indicated that the relationship between facilitating conditions and behavioral intentions was significant (β = 0.398, t(127) = 4.193, p = .000088). The positive β value meant that behavioral intentions increased when participants had greater access to technology support structures. Doctors, nurses, and healthcare researchers who felt they had the support tools and infrastructure necessary to use big data analytics were more likely to use the technology than healthcare professionals who lacked the necessary infrastructure. The positive significant relationship between facilitating conditions and behavioral intentions was expected based on Venkatesh et al.'s (2003) original UTAUT model. Researchers like Lutfi et al. (2022) have noted that complexity can significantly affect technology adoption and use, and Sun et al. (2019) highlighted the complex nature of big data analytics. Using big data analytics in healthcare specifically involves analyzing and integrating large and complex datasets (Batko & Ślęzak, 2022). The present study's findings regarding the significant relationship between facilitating conditions and behavioral intentions to use big data analytics support both the UTAUT model and existing research on the topic.

These findings are summarized in Table 4. Here are the research questions and regression results for each hypothesis.

5. SUMMARY, DISCUSSION, AND IMPLICATIONS

In the healthcare industry, big data analytics advance the delivery of healthcare services and improve patient outcomes (Zhu & Chen, 2021). Recent studies have illustrated the many benefits of adopting and implementing big data analytics in healthcare settings (Nazir et al., 2020). However, the effective use of new technologies depends heavily on user acceptance (Aljarboa & Miah, 2020), and realizing the benefits of big data analytics relies on the successful implementation of the analytics techniques and tools as well as support from all organizational members (Alghamdi & Alsubait, 2021). Big data analytics use in healthcare organizations is evolving (Shahbaz et al., 2019). Characterized by high volume, velocity, variety, value, and veracity, big data requires advanced analytic tools and methods (Chasupa & Paireekreng, 2021). Resistance to change is a leading cause of failed big data analytics implementations in healthcare settings (Zhang et al., 2021). Healthcare employees can be unwilling to accept new technologies, even after organizations have begun implementing them (Shahbaz et al., 2019). Healthcare organizations can use adoption

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models to support big data analytics implementations by identifying the most critical factors affecting acceptance and addressing them before introducing additional tools and techniques (Shahbaz et al., 2019).

Employees play a crucial role in adopting new technologies, and it is only possible to institutionalize big data analytics with the support of technology users (Boldosova, 2019). Establishing users' behavioral intentions to accept big data analytics before implementing these tools improves project success (Shahbaz et al., 2019). Attempting to implement big data analytics without gaining the support and willingness of employees leads to implementation failure (Brock & Khan, 2019). This study relied on Venkatesh et al.'s (2003) unified theory of acceptance and use of technology (UTAUT) model as a theoretical framework. The UTAUT constructs include performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intentions. The study aimed to determine how performance expectancy, effort expectancy, social influence, and facilitating conditions influence healthcare professionals' behavioral intentions to accept big data analytics techniques and tools.

This study was significant because its findings could be used to improve the acceptance of big data analytics in healthcare. A literature gap exists concerning the acceptance of technology in healthcare, including big data analytics (Alghamdi & Alsubait, 2021; Batko & Ślęzak, 2022). Technology managers and other healthcare organizations can refer to this study's recommendations when formulating policies and best practices that foster big data analytics acceptance among organizational staff (Lambay & Mohideen, 2020).

Healthcare organizations can benefit from several types of big data analytics, including descriptive, predictive, prescriptive, and diagnostic analytics (Fang et al., 2021; Kaur et al., 2021). Each analytics type can potentially support healthcare professionals' and healthcare organizations' performance. For example, Fang et al. (2021) used prescriptive analytics to illustrate how big data analytics could improve clinical decision-making. Hoque and Rahman (2020) developed a predictive analytics tool to support chronic disease prediction through machine learning techniques. As a result, they could predict patients' likelihood of developing health complications such as hypertension and heart disease more accurately than without prescriptive analytics.

The findings for Research Question 1 aligned with both theoretical and scholarly research. The UTAUT model assumes a positive relationship exists between performance expectancy and technology acceptance (Venkatesh et al., 2003). Research shows that big data analytics improves physicians' performance in predicting, preventing, and treating diseases (Fang et al., 2021). The present study's findings regarding performance expectancy align with and support these findings, suggesting that more research-based healthcare organizations should consider implementing big data analytics, especially if their goal is to improve performance.

Research Question 2 addressed the relationship between effort expectancy and participants' behavioral intentions to adopt big data in U.S. research-focused healthcare organizations. Effort expectancy refers to the ease or difficulty users associate with a technology (Yohanes et al., 2020). Specifically, effort expectancy refers to the potential user's evaluation of the ease of using and interacting with the new technology (Susanto et al., 2020). The UTAUT assumes effort expectancy will influence technology adoption (Venkatesh et al., 2003). Thus, it was expected that participants who perceived big data analytics as easy to use would be significantly more likely to use the technology than participants who perceived it as harder to use.

The nonsignificant relationship between effort expectancy and the behavioral intention to adopt big data analytics did not support the study's theoretical framework. Evaluating a system's effort expectancy depends on the ease of use, design of the interface, ease of learning, and flexibility (Ayaz & Yanartas, 2020). Some studies have shown that the influence of effort expectancy on behavioral intention to use a technology decline in continuous and long-term use (Ayaz & Yanartas, 2020). The present study focused on healthcare professionals working in research-focused organizations. Such organizations would be more likely to have used big data analytics compared to rural clinics or other organizations primarily focused on patient care. Thus, their employees would have more familiarity with the technology, and it would seem easier to use.

Another similar explanation for the lack of a significant relationship between effort expectancy and the behavioral intention to adopt big data analytics in research-based healthcare organizations could be the combination of familiarity and voluntariness of use. As previously noted, researchers have found that effort

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expectancy influences users' behavioral intentions to use technology less over time (Ayaz & Yanartas, 2020). Effort expectancy has been known to significantly influence behavioral intentions in both mandatory and voluntary usage contexts, but this influence may only be significant the first time the technology is used (Ayaz & Yanartas, 2020). The influence of effort expectancy becomes insignificant when the system is used for a long time (Ayaz & Yanartas, 2020). Thus, it is possible that participants working in research-based healthcare organizations already had sufficient experience working with big data analytics (i.e., the ease of use of the technology) was not a concern.

Complex technologies can be harder to use, and in this way, complexity can significantly influence technology adoption. Lutfi et al.(2022) reported that more complex technologies have lower adoption and acceptance than easy-to-use technologies. Batko and Ślęzak (2022) observed that big data analytics use in healthcare involves analyzing and integrating large and complex datasets. While the complexity of big data analytics use might seem like it would negatively affect behavioral intentions in the form of effort expectancy, the present study's findings did not support this conclusion. Rather, the findings suggest that other factors influence big data analytics adoption in this context. Researchers should look for other frameworks that might more accurately explain the drivers of big data analytics use in the U.S. healthcare industry.

Research Question 3 addressed the relationship between social influence and participants' behavioral intentions to adopt big data in U.S. research-focused healthcare organizations. Social influence refers to the effects that subjective norms and interpersonal factors have in working environments that influence users' attitudes toward using technology (Vallerie et al., 2021). In the present study, social influence described the influence of peers' and colleagues' attitudes and opinions that potentially affected U.S. healthcare professionals' intentions regarding the use of big data analytics in research-focused organizations.

The nonsignificant relationship between social influence and big data analytics did not support the study's theoretical framework. The UTAUT model assumes social influence will have a significant positive effect on technology adoption (Venkatesh et al., 2003). However, in the present study's context, this assumption was not validated. Participants were not significantly influenced by the opinions of their peers and colleagues. Despite contradicting the study's theoretical framework, the lack of a significant predictive relationship between social influence and behavioral intention to use big data analytics is not completely unexpected. Subjective norms and interpersonal factors can cause individuals to adopt technologies or adjust their technology use (Vallerie et al., 2021). However, the peer pressure associated with social influence is not typically perceived as a main driver of complex technologies like big data analytics (Queiroz & Pereira, 2019).

Cabrera-Sánchez and Villarejo-Ramos (2019) used the UTAUT model to study big data analytics adoption among CEOs and managers and found that social influence had a positive effect on the intention to use the technology. However, they also reported that social influence was less likely to influence behavioral intention than factors like performance expectancy and facilitating conditions. In similar research, Queiroz and Pereira (2019) used the UTAUT model to examine big data analytics among Brazilian supply chain managers. Queiroz and Pereira found that social influence did not affect behavioral intentions in their population. The competitive nature of healthcare research may make social influence less of a concern when deciding whether to implement big data analytics in support of a research program.

Factors more likely to influence big data analytics adoption could include relative advantage, job fit, and organizational readiness (Lutfi et al., 2022). Relative advantage would be more relevant in environments where organizations are competing for market share or where competition is high for resources. Job fit may be more relevant in this research since healthcare researchers often deal with complex datasets that require specialized analysis tools. Many scholars have noted that big data analytics offers many benefits in the healthcare industry (Nazir et al., 2020; Shahbaz et al., 2019). These benefits can only be realized if the technologies are adopted, which relies on healthcare practitioners' acceptance of big data analytics (Aljarboa & Miah, 2020).

The lack of a significant relationship for Research Question 3 suggests that the original UTAUT model is not the most effective theoretical model when studying big data analytics in research-based healthcare settings. U.S. healthcare organizations seeking to understand their employees' intentions regarding big data analytics use should consider job fit, competitive advantage, and providing the necessary support infrastructure for the technologies to be effective. Support infrastructure is linked to facilitating

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conditions, the final variable examined as part of the UTAUT model. The following section addresses the results of the linear regression analysis regarding facilitating conditions.

Research Question 4 addressed the relationship between facilitating conditions and participants' behavioral intentions to adopt big data in U.S. research-focused healthcare organizations. Facilitating conditions referred to objective factors within the work environment that supported participants' use of big data analytics (Handoko, 2019). Examples include specialized software, organizational training programs, or onsite technical support. Vanduhe, Nat, & Hasan (2020) noted that training was essential to improve technology acceptance and use because it creates a sense of self-competence among users. Facilitating conditions also reflect organizational readiness (Lutfi et al., 2022). Organizations without appropriate support have less successful technology implementations because the lack of support undermines performance and increases difficulty using the technology (Lutfi et al., 2022).

The significant relationship between facilitating conditions and behavioral intention to use big data analytics supported the UTAUT model as the study's theoretical framework. Facilitating conditions refer to objective factors like infrastructure, technical support, or institutional knowledge that make using complicated technology easier (Handoko, 2019). As noted previously, complexity can significantly influence technology adoption (Lutfi et al., 2022). Jadhav (2021) reported that the more complex a technology is to understand and use, the lower the adoption rate. Additionally, big data analytics in healthcare involves analyzing and integrating large and complex datasets (Batko & Ślęzak, 2022). These observations support the importance of organizational infrastructures that aid users in adopting technologies. This perspective highlights the inherent links between effort expectancy and facilitating conditions in the context of this study, as facilitating conditions can reduce the difficulties healthcare professionals face when using technologies like big data analytics.

The literature also suggests a link between facilitating conditions and performance expectancy. As previously noted, the large datasets associated with big data analytics are not easily gathered, stored, managed, or analyzed with traditional tools (Sun et al., 2019). Big data analytics uses technology to improve data processing and, by extension, patient outcomes (Philip et al., 2022). These considerations suggest an implicit link between facilitating conditions and the ability to improve job performance (i.e., performance expectancy) when adopting new technology. Thus, the study's findings related to facilitating conditions support the importance of performance expectancy but undercut the potential negative effects associated with effort expectancy.

6. LIMITATIONS OF THE STUDY

This study had some limitations that must be addressed when evaluating the findings. One limitation was associated with the decision to limit the target population to participants who worked at research-based healthcare organizations in the United States. Research-based healthcare organizations were selected because these facilities generate and use vast amounts of data (Singh et al., 2018). Thus, big data analytics represents an effective way to analyze, evaluate, and manage data. The selection of the target population excluded individuals working at similar organizations in other countries and individuals working in different types of U.S. healthcare organizations. As a result, the findings should not be generalized to populations outside the United States or employees working in different types of healthcare organizations like rural hospitals or small clinics.

The study used an acceptable quantitative approach to data collection and analysis. However, the choice of methodology did limit the study's scope. Using a closed-ended survey instrument meant that participants did not have the opportunity to share personal insights or attitudes regarding their experiences with big data analytics. This limitation meant that the study could not account for individual differences between respondents, but the methods aligned with the positivist research paradigm (Alharahsheh & Pius, 2020).

Another limitation related to the research design was the decision to conduct a correlation study rather than an experimental or quasi-experimental study. Experimental and quasi-experimental research designs were eliminated because of the difficulty of obtaining access to individuals willing to participate in a study that required control groups and interventions. However, because the variables were not manipulated and the study did not include any intervention between groups, the findings only represent relationships or correlations between the variables. Thus, while changes in performance expectancy and facilitating

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conditions were significantly correlated with changes in behavioral intentions to use big data analytics, the changes in the independent variables cannot be said to have caused the changes in participants' behavioral intentions.

A final limitation resulted from selecting the UTAUT as a theoretical framework. The UTAUT is a common model for understanding technology adoption (Al-Fahim et al., 2021). However, focusing exclusively on UTAUT variables means that other factors contributing to big data analytics adoption and use could not be analyzed. Cost benefits, efficiency, security, and organizational culture are all considerations that could influence big data analytics adoption in healthcare settings (Han & Lee, 2021). This limitation could be addressed through the development of a modified UTAUT model. The following section discusses the study's implications for future research.

7. IMPLICATIONS FOR FUTURE STUDY

The study's findings have implications for many stakeholders. Professionals in the healthcare industry can use the study's results to examine their perceptions, attitudes, and experiences using big data analytics in healthcare settings. While this study focused on research-based organizations, the literature identified the clinical benefits of using big data analytics (see Alghamdi & Alsubait, 2021; Philip et al., 2022). Thus, the present study's findings are likely generalizable to clinical settings. The findings and literature suggest that utilizing the benefits of big data analytics would improve outcomes for practitioners, healthcare organizations, and patients through cost reductions, improved diagnostics, and greater access to care.
Healthcare systems and data security regulations vary dramatically from country to country. These differences may influence the use of big data analytics in specific settings, limiting the study's generalizability to other settings. Conducting additional studies comparing the adoption and use of big data analytics in national healthcare systems would provide insights into national differences in healthcare provision. Specifically, differences could be explored between the use of big data analytics in countries with nationally funded healthcare systems (e.g., Canada, the United Kingdom) and countries with private healthcare systems (e.g., the United States, Switzerland).

Big data analytics is an emerging technology characterized by high levels of technical complexity (Lutfi et al., 2022). The present study's quantitative approach and use of closed-ended survey questions did not allow participants to share individual perceptions of big data analytics. Conducting a qualitative study of the barriers to big data analytics adoption would highlight the main obstacles
individuals face as they implement new and complex technologies.

Designing an experimental or quasi-experimental study to examine individual attitudes toward big data analytics would allow researchers to determine causal relationships between variables. Additionally, longitudinal research could be conducted to determine how behavioral intentions to use big data analytics changed over time. Some researchers have noted that factors like effort expectancy lose significance over time (Ayaz & Yanartas, 2020; Yohanes et al., 2020). Documenting these changes would contribute to discussing the UTAUT's efficacy in similar research settings.

Finally, only two constructs associated with the UTAUT were significant: performance expectancy and facilitating conditions. The significance of performance expectancy and facilitation conditions suggests that the UTAUT may not be the most effective theoretical framework when studying big data analytics adoption. Future research could focus on developing a theory that explains big data analytics acceptance and use based on information security risks, implementation costs, and user aversion to technology. Focusing on potential barriers would allow organizations to improve their chances of successfully using or implementing big data analytics.

8. SUMMARY

This study explored factors influencing user acceptance of big data analytics in research-based healthcare organizations in the United States. The study aimed to determine whether four independent variables associated with the UTAUT (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) were significant predictors of the behavioral intention to adopt big data analytics. The linear regression analysis indicated that performance expectancy and facilitating conditions were significantly associated with behavioral intentions. Effort expectancy and social influence were not significant predictors.

This study's findings supported previous research linking big data analytics to performance improvements in healthcare and other industries.

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Additionally, the study supported the importance of organizational systems to facilitate the use of these complex technologies. As organizations become more dependent on data and technological advances, the importance of big data analytics tools will continue to increase. Recognizing how big data analytics can help healthcare professionals and research-focused organizations improve patient outcomes is important to effectively use these technologies. Future research should focus on identifying barriers to big data analytics adoption.

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