Interdisciplinary Journal of Information, Knowledge, and Management

An Official Publication of the Informing Science Institute InformingScience.org

IJIKM.org

Volume 18, 2023

The Influence of Big Data Management on Organizational Performance in Organizations: The Role of Electronic Records Management System Potentiality

Burkan Hawash*	Universiti Kebangsaan Malaysia, Bangi, Malaysia	burkan.hawash@yahoo.com
Muaadh Mukred	Universiti Kebangsaan Malaysia, Bangi, Malaysia	muaadh@ukm.edu.my
Umi Asma' Mokhtar	Universiti Kebangsaan Malaysia, Bangi, Malaysia	umimokhtar@ukm.edu.my
Mohammed Islam Nofal	University of Petra, Amman, Jordan	muhmmadnofal@uop.ed.jo

* Corresponding author

Abstract

Aim/Purpose	The use of digital technology, such as an electronic records management system (ERMS), has prompted widespread changes across organizations. The organization needs to support its operations with an automation system to improve production performance. This study investigates ERMS's potentiality to enhance organizational performance in the oil and gas industry.
Background	Oil and gas organizations generate enormous electronic records that lead to difficulties in managing them without any system or digitalization procedure. The need to use a system to manage big data and records affects information security and creates several problems. This study supports decision-makers in oil and gas organizations to use ERMS to enhance organizational performance.
Methodology	We used a quantitative method by integrating the typical partial least squares (SEM-PLS) approach, including measurement items, respondents' demographics, sampling and collection of data, and data analysis. The SEM-PLS approach uses a measurement and structural model assessment to analyze data.

Accepting Editor Ahmad Samed Al-Adwan │ Received: October 31, 2022 │ Revised: December 27, 2022, January 3, January 14, 2023 │ Accepted: January 14, 2023.

Cite as: Hawash, B., Mukred, M., Mokhtar, U. A., & Nofal, M. I. (2023). The Influence of big data management on organizational performance in organizations: The role of electronic records management system potentiality. *Interdisciplinary Journal of Information, Knowledge, and Management*, *18,* 59-86. https://doi.org/10.28945/5072

Contribution	This study contributes significantly to theory and practice by providing advancements in identity theory in the context of big data management and electronic records management. This study is a foundation for further research on the role of ERMS in operations performance and Big Data Management (BDM). This research makes a theoretical contribution by studying a theory-driven framework that may serve as an essential lens to evaluate the role of ERMS in performance and increase its potentiality in the future. This research also evaluated the combined impacts of general technology acceptance theory elements and identity theory in the context of ERMS to support data management.
Findings	This study provides an empirically tested model that helps organizations to adopt ERMS based on the influence of big data management. The current study's findings looked at the concerns of oil and gas organizations about integrating new technologies to support organizational performance. The results demonstrated that individual characteristics of users in oil and gas organizations, in conjunction with administrative features, are robust predictors of ERMS. The results show that ERMS potentiality significantly influences the organizational performance of oil and gas organizations. The research results fit the big ideas about how big data management and ERMS affect respondents to adopt new technologies.
Recommendations for Practitioners	This study contributes significantly to the theory and practice of ERMS potentiality and BDM by developing and validating a new framework for adopting ERMS to support the performance and production of oil and gas organizations. The current study adds a new framework to identity theory in the context of ERMS and BDM. It increases the perceived benefits of using ERMS in protecting the credibility and authenticity of electronic records in oil and gas organizations.
Recommendations for Researchers	This study serves as a foundation for future research into the function and influence of big data management on ERMS that support the organizational performance. Researchers can examine the framework of this study in other nations in the future, and they will be able to analyze this research framework to compare various results in other countries and expand ERMS generalizability and efficacy.
Impact on Society	ERMS and its impact on BDM is still a developing field, and readers of this article can assist in gaining a better understanding of the literature's dissemination of ERMS adoption in the oil and gas industry. This study presents an experimentally validated model of ERMS adoption with the effect of BDM in the oil and gas industry.
Future Research	In the future, researchers may be able to examine the impact of BDM and user technology fit as critical factors in adopting ERMS by using different theories or locations. Furthermore, researchers may include the moderating impact of demographical parameters such as age, gender, wealth, and experience into this study model to make it even more robust and comprehensive. In addition, future research may examine the significant direct correlations between human traits, organizational features, and individual perceptions of BDM that are directly related to ERMS potentiality and operational performance in the future.

Keywords	big data, big data management, ERMS potentiality, oil and gas, digital transformation, electronic records

INTRODUCTION

Digital transformation recently adds a new need to pursue research in information technology and telecommunications (ICT) and play a role in a rising trend in how organizations perform daily routine activities. Organizations are embracing Big Data Management (BDM) to reshape their business landscape and profit from better productivity, increased efficiency, and lower operational costs. The electronic records management system (ERMS) is considered new technology for oil and gas organizations that supports active services such as logistics, maintenance, and production departments that create many digital information and records to enhance daily activities and effectiveness (Gaglio et al., 2022; Hassanin & Hamada, 2022). ERMS is a tool that assists the organization in creating and protecting electronic records that contain data and complete service management to improve their operations. Applying ERMS with BDM will contribute to the protection of data in oil and gas organizations and support their performance, allowing firms to boost their production and profit. Furthermore, ERMS can improve operational efficiency and support decision-making that can improve business-related outcomes. ERMS, if implemented with BDM, will create a special connection with users and production growth (Dong et al., 2021; Park et al., 2020; Saffady, 2021; Y. Wang et al., 2021).

ERMS is influenced by BDM and produces a highly protective level in oil and gas organizations. The oil and gas organization uses manual procedures that cannot store and analyze such a tremendous volume of data to obtain information for making a decision (Hawash et al., 2022; Mukred et al., 2021; Mukred, Yusof, Noor, et al., 2019). During this era of the BDM technological revolution, the method for formulating strategy in services has changed, which encouraged enterprises to adopt an ERMS to fulfill the needs of optimistic strategy creation (Hawash, Mokhtar, & Yusof, 2021; Hawash, Mokhtar, Yusof, & Mukred, 2020; Hawash, Mokhtar, Yusof, et al., 2021; Hawash et al., 2022). Big data's impact on ERMS provides behavioral insights for organizations and users to get benefits of such digital systems for decision-making and supporting services that improve production. In the context of this study, ERMS refers to a novel technology or design that, to promote efficient production and services, may uncover previously concealed patterns in BDM and give valuable information about the behaviors of end users. Digital information related to user behavior is being created at impressive speeds due to the new transformation of technology (Hawash, Mokhtar, Yusof, Mukred, & Ali, 2020; Mohammadpoor & Torabi, 2020). The sources of data inputs in ERMS are digitally monitored and protected in the organization network, which it uses for supporting services. The input information that users create needs a system to manage it (Nguyen et al., 2020; Wanasinghe et al., 2020).

Therefore, this study proposes a framework to fulfill its aim by examining individual and organizational factors and theories that may contribute to a favorable impression of BDM in organizations. Furthermore, this study uses the innovation diffusion theory (IDT) and task-technology fit (TFF) to show how the BDM creates a technology fit perception between users to eventually influence the organizational performance and ERMS potentiality.

LITERATURE REVIEW

Over the years, it has become essential for oil and gas organizations to understand the data and records they have been using. They should have a track of what formats are being used and where they have been used so that they can, in turn, control or secure it. According to Ahmad and Mustafa (2022), records are essential elements in organizations and need to systematically control the organization from side creation of records, use, maintenance, and disposal. Besides, researchers (Asnawi et al., 2022a; Hawash, Mokhtar, Yusof, Mukred, & Ali, 2020; Mukred et al., 2016; Nguyen et al., 2020) believe that records management has a significant role in managing big data. The authors further mentioned that the technologies created today support the increase of big data rather than controlling it. Moreover, other researchers (Asnawi et al., 2022a, 2022b; Hawash, Mokhtar, Yusof, et al., 2021) also stated that good records management standards or practices could also be considered a method of handling big data (big data analytics). BDM is the method used to analyze vast data or information.

Facilities are often situated in hard-to-reach isolated places; for example, on-shore and off-shore, connected to the Internet and Local Area Networks. Managing and organizing these large data sets for sharing and interoperation is vital to any data management system. As the data quantities continue to expand, a greater emphasis on enhanced resources for storing and accessing data becomes essential. Multiple sensors generate multi-spatial and multi-temporal data, and this makes data management difficult (Cadei et al., 2018; J. Wang et al., 2022; R.-Y. Wang et al., 2021). In order to move the multi-dimensional data to a one-dimensional array for wireless transfer, practitioners must first determine how to arrange and map the multi-dimensional data. Another obstacle is keeping up with metadata and indexing maintenance. Data technology utility is dependent on the platform when selecting a computing platform. Generally, enterprises avoid complications and high costs associated with on-premises systems at the beginning of the implementation phase. Recent years have seen the introduction of many new BDM technologies (Hawash, Mokhtar, Yusof, Mukred, & Ali, 2020; Mukred, Yusof, & Alotaibi, 2019; Mukred et al., 2021; J. Wang et al., 2022). Big data management refers to the organization, administration, and governance of large volumes of unstructured and structured data. A high level of data quality and availability for business intelligence and big data analytics applications is the aim of big data management. Businesses, enterprises, and governments use big data management strategies to tackle the enormous and fast-expanding data that typically have hundreds of terabytes or even petabytes of data stored in various electronic records formats (Desai et al., 2021; J. Wang et al., 2022).

In this digital transformation period, daily users' data is a significant source of predictions about their activities, gathered from competitors and market stakeholders, which plays a significant role in building competitive strategies (Larrinaga et al., 2021). Other data storage and processing shortcomings include the inability to capture and store freshly generated and existing vast amounts of data and the incompatibility with ERMS (Oladejo & Hadžidedić, 2021; Papadopoulos et al., 2022). While BDM can evaluate large quantities and kinds of data from various sources, such as sensor network data, social media data, information captured from transactions, and survey data, it collects customer opinions about products, services, and organizations (Dou, 2020).

Accordingly, previous studies show that BDM can compensate for deficiencies of ERMS based on the primary goal of this study. A company must look at developing BDM as an alternative to ERMS to support production services potentiality. Based on this, the current study aims to evaluate how BDM positively affects operations performance and ERMS skills since no previous studies have been conducted that match this criterion (Aghimien et al., 2021; Ahmad & Mustafa, 2022; Mukred, Hawash, et al., 2022). Previous studies stated that oil and gas organization employees are essential entities in big data management, such as hardware, software, and other technical aspects. It is significant to note that employees play a critical role in data management as a whole, especially when dealing with big data issues like hardware, software, and other technical components (Bag et al., 2021; Dou, 2020; Mukred, Hawash, et al., 2022).

Oil organizations have involved users in implementing BDM and the subsequent use of ERMS to produce beneficial results for supporting services. Several previous studies indicate that BDM affects several levels of operational performance, such as field services and financial needs (Marciano et al., 2018; Sumbal et al., 2019). ERMS, when implemented with BDM, has significant impacts on managing huge data created by users in the organization to investigate diverse workplace variables that impact employee perceptions of BDM and, to encourage the impression of user technology fit, a time constraint must be introduced into the study (Mukred & Yusof, 2018). The majority of the literature points to the fact that several organizations have rejected SFA due to the system's shortcomings, and these weaknesses allow an unwarranted impression of the system in the minds of consumers (Dou, 2020). As a result, a wrong impression of the system becomes entrenched in the customers' minds, promoting a job and professional mismatch between the new system and the operations. Based on identity theory, a favorable view of technology fosters the perception of work and career fit for employees, which eventually becomes the cause for improvements in the performance of organization operations and ERMS potentiality, as well as reductions in employee income (Andreou et al., 2022; Hawash, Mokhtar, Yusof, Mukred, & Ali, 2020).

Problem Statement

The growing volume of electronic records and big data created by oil and gas organizations in developing countries is problematic and affects their performance because they are still managed manually (Hawash, Mokhtar, & Yusof, 2021). It is critical to have an effective electronic records management system for managing big data to overcome challenges in big data created by users. According to Hawash et al. (2022), it is critical to address a few essential factors while developing a solution for handling big data, such as data governance, information quality, manipulation, and integration. Furthermore, Andreou et al. (2022) emphasized that today's big data difficulties are not only technical but also data related. As a result, having proper information or data processing might be an ideal solution to the efficiency and effectiveness of data integration that supports the performance of oil and gas organizations. Therefore, in this study, ERMS potentiality is measured to support the managing of big data and support organizational performance.

Challenges of Digital Transformation

Many authors have dealt with issues of Digital Transformation (DT) in different industries and organizations due to the DT venture being a complex project. For DT to be successful, a new business model must be reviewed, and a clear and compelling vision of what the company will be like. Sivarajah et al. (2020) argue that even if new and old technologies may be used, there are a few major problems that need to be overcome regarding management and staff, not just the technical issues. The obstacles are organized into the following implementation phases: start-up issues (lack of motivation, guidelines, reputation, and uncertain business circumstances), execution issues (missing skills, culture issues, and ineffective IT) (Ahmad & Mustafa, 2022), and governance concerns (uncertain strategy, logistics, and information technology issues). A study by Kraus et al. (2021) stated that the creative and analytical techniques offered by ERMS to manage huge data are considered critical issues to be addressed in the process of reconfiguring customer value and will be the monetization of new offers and establishing operational requirements in order to improve the company's operations. In contrast to some authors, the greatest challenge is not only to identify new technologies but also how to use them in an existing business model, taking into account the increase in the number of additional costs that accompany the new tools and infrastructure, without getting stuck in the so-called productivity paradox (Kraus et al., 2021). Highlighting the data has tremendous value in Industry 4.0, as for traditional manufacturing firms, one of the greatest problems is creating a clear idea of the value that DT delivers (Han & Trimi, 2022). Additionally, organizations should learn how to deal with massive amounts of data and information. While Agostini and Filippini (2019) stated that the greatest challenge to digitization is user issues related to the implementation of new technologies such as ERMS, as an additional challenge, they cite a lack of elasticity in the current IT infrastructure, namely with respect to collecting and processing unstructured data from multiple sources. Conversely, studies on non-profit organizations (Ashaari et al., 2021; Singh et al., 2019) identified organizational, strategic, and managerial challenges alongside digitization efforts, and a crucial difficulty of digitization is the transformation of an organization's culture, as it is impossible to ensure digitization success by engaging new IT staff and experts. The three primary problems, or difficulties to DT success, are called 'isolated thinking,' 'lack of knowledge management,' and 'underestimation of digitalization.'

DEVELOPMENT OF HYPOTHESES AND FRAMEWORK

We developed hypotheses to test the effect of factors on the ERMS potentiality to support organizational performance in organizations. This study formulated hypotheses based on theories and a literature review. The framework was integrated based on IDT and TTF theories and contains two dimensions that bear important factors.

ORGANIZATION DIMENSION

Previous studies in the field of big data and ERMS adoption have identified several organizational factors that have a substantial influence on system perception. These factors would also affect BDM perception. Organizational factors in this study include all the factors that have a strong influence on users' perceptions (Lai et al., 2018; Rafique et al., 2020; Shamim et al., 2019). Although user involvement is the user's emotional condition that can describe the system's significance, user participation contributes to increased performance. According to the behavioral theory of information system success and technology perception model, user behavior and employee participation cement a solid link. Users' level of engagement and involvement has been shown to affect how users evaluate a system significantly. The more users participate and get involved, the greater their impression of BDM (Dubey et al., 2019; Papadopoulos et al., 2022).

Top management support is a critical factor for the successful adoption of new technologies in an organization. The support of top management can influence the adoption of technology in several ways such as setting the strategic direction, setting the strategic direction for the organization, and determining which technologies will be adopted. Furthermore, communicate the importance and benefits of new technologies to employees, which can help to build support and buy-in (Colwell, 2020; Mukred, Hawash, et al., 2022). In conclusion, the factors we have stated that are influencing personnel views of BDM and perception are compatibility (COM), user involvement (UI), user participation (UP), and top management support (TMS). This dimension contains four factors associated with individual perception of BDM and lead to state four hypotheses.

H1: Compatibility (COM) is positively associated with the individual perception of BDM.

H2: User involvement (UI) is positively associated with the individual perception of BDM.

H3: User participation (UP) is positively associated with the individual perception of BDM.

H4: Top management support is positively associated with the individual perception of BDM.

INDIVIDUAL DIMENSION

The individual dimension is important in the study of technology adoption because it focuses on the behavior and characteristics of individuals in relation to the adoption and use of technology. Factors such as individual characteristics, attitudes, beliefs, and prior experiences are considered significant in the individual dimension of technology adoption. For example, an individual's perceived ease of use, perceived usefulness, and level of computer self-efficacy can all impact their decision to adopt new technologies. Additionally, demographic factors such as age, education, and income can also play a role in technology adoption (Hawash et al., 2022; Mukred et al., 2021; Mukred, Yusof, et al., 2022). It is observed that digital technology alters the individual dimension of the innovation process, allowing for a set of heterogeneous actors to become active engagers in the adoption process. A review of previous research revealed a lack of focus on the roles these different actors play in the digital innovation process, as well as the mechanisms by which digital technology facilitates actor engagement, calling for research to shed some light on this topic (Allataifeh & Moghavvemi, 2021; Yang et al., 2021). In this study, traits connected with the perception of BDM and ERMS expected outcomes, and which help one in one's adoption of BDM are classified as individual traits. In this study, we examined three individual characteristics: self-efficacy, complexity, and social norms. Innovation diffusion theory has shown a clear connection between self-efficacy and being playful, as well as producing an accurate picture of positive purpose by the user (Shahbaz, Gao, Zhai, Shahzad, & Khan, 2021; Shahbaz, Gao, Zhai, Shahzad, Luqman, & Zahid, 2021; Wook et al., 2021).

Theoretical support for the hypothesis of planned behavior can be found in the relationship between social norms and users' subjective evaluations of the system. The level at which users are capable of accomplishing a task with technology or a system is referred to as computer self-efficiency. A large majority of operations teams have merely a cursory knowledge of technology. One of the reasons why employees do not like the system is because of a lack of confidence in their own abilities. For the sake of brevity, the phrase 'computer complexity' will be used to describe an individual's response time to computer-related tasks. We have shown that fun computer use has the potential to alter adoption and the public perception of technology (Kodapanakkal et al., 2022). BDM is also a computer-based technology, and this mentality of using computer-based technologies is referred to as complexity. BDM indicates that users of the organization must have the spirit and ability to use a computer in order to operate BDM. Research and concepts done before have proven that a user's willingness to experiment with a number of complex computer-based technologies is crucial (Shahbaz, Gao, Zhai, Shahzad, & Khan, 2021).

It is imperative to explore the significance of playful behavior in this study's context. In past research, people with strong computer fun qualities also tend to be excited about using a system, allowing them to have a good perspective on the system. The more people respond to a social norm, the more technology is accepted in the workplace. Because of this, employees are discouraged from using new technologies, as they believe it will lead to social isolation. The perceived value of a product depends to a large extent on whether consumers conform to social or subjective norms. Additionally, many academic sources show that the things mentioned here have a big impact on the perception of various systems in various industries (Kodapanakkal et al., 2022; Semantha et al., 2021). However, the findings in this study predicted that these factors influence individual perception towards new technology such as BDM. Therefore, this dimension has three factors linked with the individual's perception of BDM which leads to state three hypotheses.

H5: Self-efficacy (SE) is positively associated with the individual's perception of BDM.

H6: Playfulness (P) is positively associated with the individual's perception of BDM.

H7: Social norms (SN) is positively associated with the individual's perception of BDM.

Individuals' Perception (IP)

Individual perception, also known as the individual level of analysis, is an important aspect in the study of various disciplines, such as sociology, psychology, and political science. It focuses on the characteristics and behavior of individuals and how they interact with their environment. Factors such as personality, motivation, and cognition are considered significant in the individual dimension. Additionally, this dimension also examines how individuals differ from one another, and how these differences may impact their behavior and interactions Many researchers have conducted studies to investigate the degree to which users adopt new technologies (Hawash et al., 2022; Mnif et al., 2021; Mukred, Yusof, et al., 2022). It is the task of the Human Resources Department to cultivate a good employee view of the company's systems because that will increase the likelihood that these systems will be adopted and used (Sodero et al., 2019). This paper focuses on user perception rather than on the organization. It is important to think about visibility, compatibility, and complexity when it comes to how employees see the system and whether they want to embrace it (Jöhnk et al., 2021). In other words, the extent to which a system is well-matched with previously accepted standards, beliefs, values, and prior experience is known as compatibility. Complexity is how much a company user expects it will take to use the system. The perception of a system could be the visibility that shows how a user perceives or sees a system (Mukred, Yusof, Mokhtar, et al., 2021).

According to the innovation diffusion theory, users' views about the system or technology can be positive or negative, and those views improve operations performance. Other than that, this theory explains why and how individuals who have a good fit with their job tasks and the technologies they employ do better. Therefore, the researchers proposed a correlation between the perception of BDM and the fit between users and technology as well. We can see this clearly from the academic literature, which describes how an employee's view of different systems influences their fit with their job and professional requirements. Furthermore, both the system and the requirements that the individual perceives connected with the job and profession have a relationship with the individual's perspective of the system (Hewavitharana et al., 2021; Shahbaz, Gao, Zhai, Shahzad, & Khan, 2021).

We assume that each individual will have a different impression of BDM and the perception of user-technology. Recent studies have shown that when employees perceive the system to be beneficial, they have more optimistic expectations about operations employees' ability to meet their job and professional-related expectations. Based on that perception, the following hypothesis can be assumed:

H8: Individuals' perception (IP) is positively associated with user-technology fit.

User Technology Fit (UTF)

Oil and gas organizations perform distinct roles in their workplace activities. According to the paradigm, employees go through several roles and employ them to achieve the expected outcomes (hopes and expectations). For example, users perceive several positions, such as professional and organizational leader. In the professional identity, the user reflects the participant's involvement in production activities, whereas in the organizational identity, the leader reflects better involvement in managerial functions. An activity completed in one role may not be consistent with the expectations of another role (Shahbaz, Gao, Zhai, Shahzad, & Khan, 2021).

It is significant to discover how any given system might influence these roles. It can be observed from earlier research that an individual's expectations can either enhance or diminish his or her skill set based on society's normative expectations. Increasing competency will occur when building up and increasing skills, relationships, and knowledge are implemented. When it minimizes or has no influence on current skills, relations, or information, it causes a drop in capability; when it rises or has an influence on existing skills, relations, or information, it has a positive or negative impact on the job's acceptability (Arkorful et al., 2022; Sayaf et al., 2022). To reduce the strain of everyday duties such as receiving and answering emails and electronically communicating with users, BDM is applied to support production. The organizational users and management would likely see the system negatively if they needed more time to meet physically with each. Thus, the new system must be well-received by the users before use, so organizations should examine how it aligns with their jobs and professions. Being reliable with users' jobs and their occupations indicates the grade to which BDM boosts users' long-term career possibilities (Antón-Sancho & Sánchez-Calvo, 2022; Sayaf et al., 2022). Thus, perception of user-technology fit positively impacts prospects and confidences that eventually bring optimistic outcomes, such as system adoption, resulting in increased operations performance in terms of ERMS and production potentiality. Conversely, an absence of user-technology fit would negatively affect prospects and confidence that are resulting in adverse outcomes, such as decreased ERMS and production potentiality (Chueh & Huang, 2023; Sodero et al., 2019). This study assumes two hypotheses to show the relationship between user technology fit with the ERMS and operations performance.

H9: User-technology fit is positively associated with ERMS potentiality.

H10: User technology fit is positively associated with organization operations performance.

ERMS POTENTIALITY

ERMS is an automated tool that supports an organization's workflow processes and helps them produce, manage, use, store, and dispose of their records. Moreover, this software can improve the ability to revise electronic documents and build daily work to track day-to-day operations in case of a lawsuit. ERMS will let an organization keep its electronic records in one location while helping to increase productivity by providing features to help managers plan their workflow. ERMS is capable of dealing with various sorts of files, including emails, word-processing documents, spreadsheets, PDFs, scanned photos, and more (Gandomi & Haider, 2015; Semantha et al., 2021).

ERMS is available on organization workstations or as a web application via its web browser. Dragging, copying, pasting, and saving are simple ways to implement these methods, allowing the ERMS system to be easily accessed by the user base. There is no need to go anywhere — navigating folders and electronic information is incredibly easy (Hawash, Abuzawayda, et al., 2020; Hawash, Mokhtar, Yusof, & Mukred, 2020; Hawash et al., 2019; Hawash et al., 2022).

It is crucial to have consistent record retention standards across a firm. An ERMS's users can choose a retention policy for each folder and pre-define it. Furthermore, highly effective records-level security means users have absolute authority over who can access, edit, or upload records (Y. Wang et al., 2021; Zhang et al., 2021). An ERMS supports the retrieval process of electronic records from where they are stored based on accepted principles. ERMS developed from early computerized practices for the management of hard-copy records. Previous studies indicate that ERMS enables the organization to store, retrieve, and disseminate information and make it secure. This system could protect information and guarantees its backup during any emergency. In some instances, ERMS seems more efficient in terms of fast access process for records and arranging information for business continuity needs. ERMS enhances the role of protecting records, minimizes records broadcast delays, endorses the pursuit of records, and enlarges the lifecycle of records. Furthermore, ERMS minimizes records misplacement-related issues and ensures business continuity in organizations (Mukred et al., 2016; Mukred, Yusof, & Alotaibi, 2019; Mukred, Yusof, Noor, et al., 2019; Wahid et al., 2022). Therefore, the ERMS capability supports the operations performance. We hypothesized the following:

H11: ERMS potentiality is positively associated with operations performance.

OPERATIONS PERFORMANCE

It has been noted that it has become difficult for companies to maintain track of the data and records coming from these areas. The drilling and production activities in the business have evolved into a sector that places a significant emphasis on collecting and maintaining vast amounts of data and records. Big Data has a variety of applications in the industry. The applications include the analysis of records and data, the development of reservoir classification, and imitation, in addition to reducing drilling time while simultaneously raising the safety of drilling, improving the performance of operations, optimizing the management of petrochemical assets, enhancing shipping and transportation, and enhancing occupational safety. Although there has been a recent uptick in interest in using ERMS to support BDM in the oil and gas sector, there are still many obstacles to overcome, which need to be improved in business support and understanding of Big Data (Mohammadpoor & Torabi, 2020).

BDM and ERMS have many features shared by numerous sectors of the business (for example, exploration, drilling, and production) that are explicit. Seismic data capture is a process to explore and produce a mass of data needed to create 2D and 3D representations of the subsurface layers. Narrow-azimuth towed streaming is used for offshore seismic research to individual perception of the underlying geology by utilizing acquired data. Data might range in size and format because sensors and recording devices vary in type. The final data can come in various formats: images, audio, video, or plain text. Structured, semi-structured, and unstructured data all have many ways of being classified (Hawash et al., 2022).

CONCEPTUAL FRAMEWORK

In prior studies in the literature on information systems (IS) and information technology (IT), the association between the adoption of a new system or technology and users' perception (UP) is considered by many researchers as a topic of argument. Many theories predict the user's perception regarding specific system adoption or implementation, such as the innovation diffusion theory (IDT), task-technology fit (TTF), technology perception model (TAM), social identity theory, self-efficacy theory (SET), and the theory of planned behavior (TPB). Therefore, we combined two suitable IS theories to construct the conceptual framework: IDT includes the factors of IDT and TTF to test the user perception of new technology. Thus, we predict the UP regarding the adoption of a BDM-ERMS. In the field of BDM adoption, the study by S. L. Wang and Lin (2019), through empirical examination, has combined IDT and TTF on the user's intention to accept BDM and stated that combining more than one theory provides better results than either theory individually. The impact of combined IDT and TTT needs to be included in the literature on BDM perception, and the inspiration for the current study is to fill this gap. Therefore, the conceptual framework in this study was integrated by combining IDT and TTF theories and contains 11 hypotheses to measure the relationships between factors and UP. Figure 1 shows the related hypotheses and theories that we have chosen to construct the study framework.

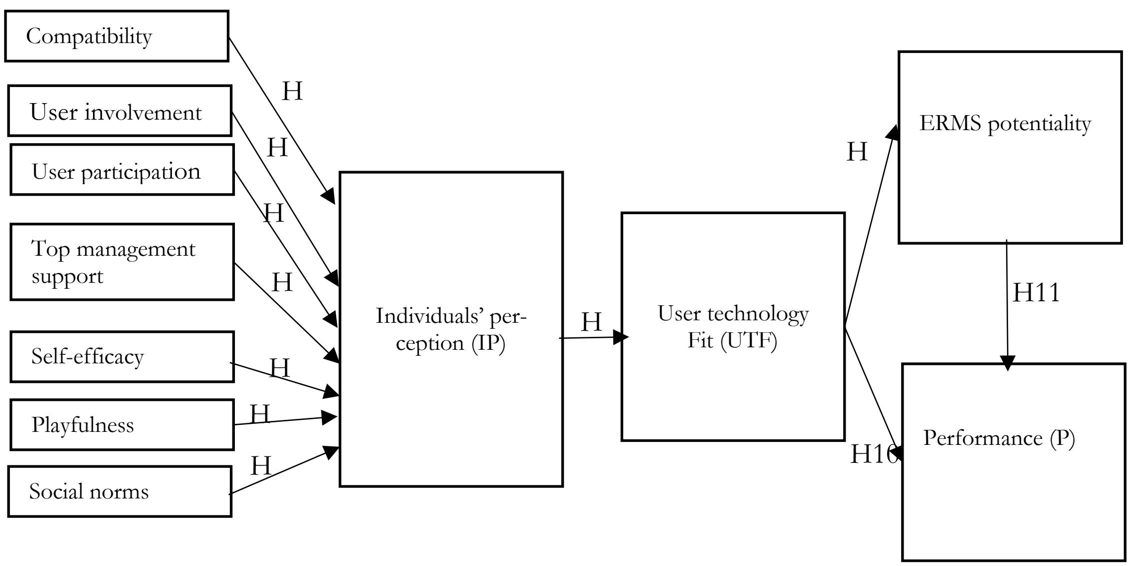

Figure 1. Conceptual framework

METHOD

We applied a quantitative method by integrating the typical SEM-PLS (partial least squares) approach, including measurement items, respondents' demographics, sampling and collection of data, and data analysis. The SEM-PLS method uses a measurement model and structural model assessment to analyze data.

STEPS TO ANALYZE DATA

This study used Smart-PLS to analyze data through the PLS Algorithm test and bootstrapping test. First, we prepared the data in the form of indicators to be uploaded into the PLS software. We also defined individual initial outer weights for every indicator in the PLS path model through Smarts. Second, we constructed the framework in the PLS and indicators that can ease the testing model. An algorithm test was applied to test the measurement model, and convergent validity was determined by analyzing factor loading, Cronbach's alpha, composite reliability (CR), and the extracted average variance (AVE). Next, we examined the association between constructs based on standardized routes, we ran bootstrapping test in Smart PLS, and the path coefficient, as well as the t-values and p-values, were determined. Figure 2 shows the steps used in analyzing data using Smart PLS.

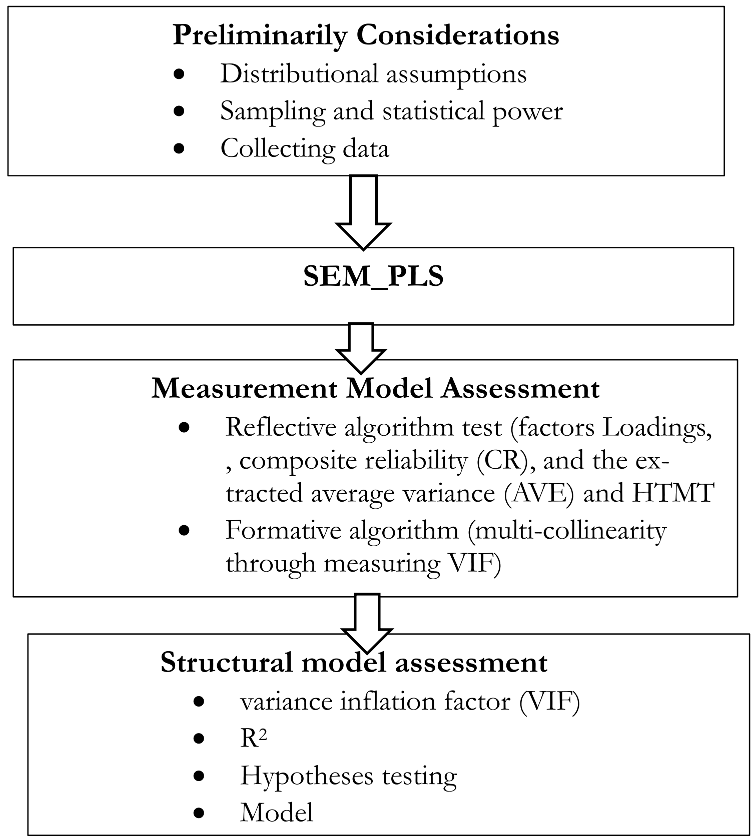

Figure 2. Steps of data analysis (adopted from Ferrell et al., 2019)

MEASUREMENT ITEMS

The measuring items used in this study adapt to those used in previous research. They are relevant to the current study setting, including a total of 53 items in the questionnaire when the survey was done. A seven-point Likert scale was used to score the final questionnaire items, with 1 being strongly disagree and 7 being strongly agree. When it comes to surveying instrumentation, the 7-point Likert scale is the most often employed (Anjaria, 2022; Yamashita, 2022). In order to test the questionnaire's validity, an additional pilot study was conducted with 45 respondents from the target population whose names are not involved in the study analysis. Afterward, three academics who are seasoned professionals in survey tools, were enlisted to help develop the questionnaire further after it had been debated throughout the pilot test period. According to the findings, the instrument was valid, as Cronbach's alpha scores for all components ranged from 0.789 to 0.966, which is significantly higher than the threshold value (Hair et al., 2019). Furthermore, there is no problem with factor loading in any of the factors of the instrument. Items that were used in the questionnaire to collect data are addressed in the Appendix.

SAMPLING AND DATA COLLECTION METHOD

This study's population consists of users working in the Yemen sector, including IT staff, managers, supervisors, officers, engineers, and technicians. By involving those users, the results of this study will show a comprehensive and clear picture of ERMS adoption in the sector in Yemen. The probability sampling technique has been used to check the personnel's opinions in the oil and gas sector. We conducted an online study through a questionnaire sent to respondents, which should be a relatively large sample; at least 402 respondents should be selected to be the target set for this study with consideration of the complexity of the study and the significance of the opinions that would be gathered from this sample. The sample number was calculated through a mathematical equation called the Equation for sampling, designed as a calculator on the website (http://www.raosoft.com/samplesize.html).

The calculation was made to target the exact number needed for answering the questionnaire. Data was collected using an online questionnaire delivered in person and to the group from October 2020 to April 2021 to users of two companies in Yemen. Only 392 answers were received from the distributed questionnaires and considered eligible for further analysis. The response rate was high because the researcher dropped and collected the questionnaire personally. In order to obtain sufficient responses, 450 valid questionnaires were sent to respondents in the fields and at the company's headquarters. Moreover, the study sample was chosen from the sites and headquarters of the companies based on their knowledge of records management, qualifications, and work experience.

Respondents' Demographic Characteristics

The demographics of the respondents are summarized in Table 1, which indicates that 87.8% are male and 12.2% are female. Most participants are highly educated, with 82.1% holding a bachelor's degree, 12.5% holding postgraduate degrees, and 5.4% holding a diploma. As a result, our volunteers were youthful and well-educated. Additionally, the study used gender, age, and education as control factors, and all these characteristics are statistically insignificant.

Table 1. Respondents' demographic

Characteristic	Item	Frequency	Percentage
Gender	M	353	87.8
	F	49	12.2%
	Total	402	100%
Age	22-32 Years	50	12.4%
	33-43 Years	183	45.5%
	44-54 Years	157	39.1%
	55+ Years	12	3.00%
	Total	402	100%
Level of education	Diploma	21	5.3%
	Bachelor	322	80.0%
	Post-graduate degree	59	14.7%
	Total	402	100%
Computer knowledge	Moderate	142	35.3%
	Poor	10	2.5%
	Very Good	250	62.2%
	Total	402	100%

Results and Analysis

PLS-SEM has been applied as a data analysis technique for this study based on the data set's objective, design, and character. The PLS-SEM method is talented at achieving factors analysis, testing hypotheses, and generating best statistical power values (Hair et al., 2019). The SEM-PLS approach was helpful if the study's aim involved exploration and theory development. We used the PLS-SEM technique to test the hypotheses with the integration of Smart-PLS v3. Thus, PLS-SEM has many significant features for analysis and is considered an accurate technique to measure the conceptual framework from the prediction viewpoint. As demonstrated in previous research, a consistent PLS method enables the modification of reflective construct correlations. Therefore, this study applied a consistent PLS algorithm. Thus, the development of a complete SEM model involves a combination of measurement and structured models, and the results are discussed below.

MEASUREMENT MODEL

The study evaluated the measurement model using the SEM-PLS approach to assess its content, convergent, and discriminant validity. The instrument's content validity is established by a review of existing literature and a pilot study. Convergent validity was determined by analyzing factor loading, Cronbach's alpha, composite reliability (CR), and the extracted average variance (AVE). The results are summarized in Table 2, which indicates that all items have factor loadings of more than 0.7, which is acceptable. Cronbach's alpha, AVE, and CR have cut-off values of 0.70, 0.50, and 0.70, respectively (Ferrell et al., 2019; Hair et al., 2019). Cronbach's alpha, AVE, and CR all exceed the cut-off values. Therefore, the results show that there is no issue of convergent validity.

Table 2. Items loading and Cronbach's alpha

Constructs	Items	Loadings	Cronbach's alpha	CR	AVE
Compatibility (com)	com1	0.957	0.960	0.968	0.811
	com2	0.826			
	com3	0.936			
	com4	0.855			
	com5	0.827			
	com6	0.939			
	com7	0.953			
User involvement (UI)	ui1	0.795	0.956	0.967	0.853
	ui2	0.940			
	ui3	0.957			
	ui4	0.951			
	ui5	0.964			
User participation (UP)	up1	0.795	0.958	0.931	0.889
	up2	0.940			
	up3	0.957			
	up4	0.951			
	up5	0.964			
Top Management Support	tms1	0.840	0.901	0.931	0.772
	tms2	0.892			
	tms3	0.920			
	tms4	0.860			
Self-efficacy (SE)	se1	0.873	0.873	0.922	0.798
	se2	0.926			
	se3	0.880			
Playfulness (PU)	pu1	0.723	0.860	0.882	0.556
	pu2	0.777			
	pu3	0.722			
	pu4	0.734			
	pu5	0.747			
	pu6	0.769			

Constructs	Items	Load-ings	Cronbach's alpha	CR	AVE
Social norms (SN)	sn1 sn2 sn3	0.865 0.895 0.892	0.840	0.915	0.781
Individuals' perception (IP)	ip1 ip2 ip3 ip4 ip5 ip6	0.812 0.799 0.872 0.826 0.795 0.823	0.903	0.926	0.675
User Technology fit (UTF)	utf1 utf2 utf3 utf4 utf5	0.795 0.940 0.957 0.951 0.964	0.888	0.918	
ERMS	erms1 erms2 erms3 erms4	0.727 0.931 0.956 0.945	0.912	0.941	0.691
Performance (P)	p1 p2 p3 p4 p5	0.781 0.726 0.802 0.828 0.734	0.833	0.926	0.601

Three strategies were used to establish discriminant validity, as suggested by Ferrell et al. (2019), Hair et al. (2017), and Hair et al. (2019). The initial technique, as outlined by Ferrell et al. (2019) and Fornell and Larcker (1981), was the correlation between factor correlations and the square root of AVE. This is the optimal technique for item loadings of all associated variables that are greater than those of other latent variables, indicating that there is no problem with DV. The ratio criterion of HTMT was developed to characterize the sensitivity of the cross-loadings and Fornell-Larcker techniques. The HTMT is a method for estimating the correlation between factors, or in other words, the upper border. HTMT should be less than 1 to make a clear distinction between two variables (Hair et al., 2017). In Table 3 and Table 4, the maximum result is 0.665, which is less than the threshold value, confirming the lack of discriminant validity in this investigation. All the results demonstrate that there were no issues with content, convergence, or discriminant validity in this investigation, hence approving the use of the data for the structural model.

Table 3. Heterotrait-Monotrait Ratio

	COM	ERMS	IP	P	PU	SE	SN	TMS	UI	UP	UTF
COM	0.900										
ERMS	0.481	0.895									
IP	0.512	0.610	0.822								
P	0.429	0.515	0.578	0.775							
PU	0.472	0.527	0.553	0.559	0.746						
SE	0.404	0.403	0.480	0.440	0.463	0.893					
SN	0.475	0.514	0.561	0.450	0.446	0.398	0.884				
TMS	0.417	0.467	0.527	0.536	0.454	0.453	0.398	0.879			
UI	0.428	0.454	0.435	0.376	0.421	0.365	0.396	0.333	0.924		

	COM	ERMS	IP	P	PU	SE	SN	TMS	UI	UP	UTF
UP	0.413	0.442	0.508	0.454	0.479	0.471	0.367	0.467	0.454	0.943	
UTF	0.442	0.561	0.678	0.514	0.489	0.349	0.476	0.438	0.417	0.448	0.831

Table 4. Fornell-Larcker criteria

	COM	ERMS	IP	P	PU	SE	SN	TMS	UI	UP	UTF
COM	0.601										
ERMS	0.513	0.520									
IP	0.549	0.671	0.541								
P	0.482	0.589	0.662	0.518							
PU	0.524	0.601	0.632	0.668	0.462						
SE	0.440	0.450	0.539	0.513	0.537	0.357					
SN	0.520	0.579	0.633	0.531	0.523	0.459	0.413				
TMS	0.447	0.515	0.581	0.617	0.520	0.509	0.452	0.535			
UI	0.445	0.483	0.466	0.418	0.466	0.399	0.436	0.358	0.427		
UP	0.431	0.471	0.544	0.504	0.534	0.516	0.403	0.501	0.472	0.425	
UTF	0.477	0.622	0.756	0.593	0.566	0.394	0.544	0.488	0.450	0.485	0.437

Multi-Collinearity Test

The variance inflation factor (VIF) was used to evaluate the multi-collinearity of the formative indicators. VIF values of 5 or above indicate critical collinearity issues among the indicators of formatively measured constructs (Hair et al., 2019). We used SMART PLS to test the multi-collinearity based on the reference (Hair et al., 2019), which determined the values that affect the collinearity. Therefore, the results show that there are no collinearity problems between the independent constructs in this study, as illustrated in Table 5.

Table 5. Collinearity statistic (VIF)

Factors	VIF
COM	1.597
ERMS	1.460
IP	1.0
P	1.120
PU	1.683
SE	1.555
SN	1.511
TMS	1.543
UI	1.464
UP	1.653
UTF	1.460

According to the results in Table 5, the VIF values are less than 5, which results in no collinearity between factors. This method bias test proposed by Hair et al. (2019) constructed on the complete collinearity test process, succeeds in identifying a standard method that does not bias the regression results.

STRUCTURAL MODEL

In order to examine the association between constructs based on standardized routes, Smart PLS3 was used. The path coefficient and the t-values and p-values are shown in Table 6. In Table 6, the model is found to explain 39.9% of the variance in operations performance, 33.5% of the variance in ERMS potentiality, 46.0% of the variance in user technology fit, and 52.7% of the variance in individuals' perception.

Table 6. Hypotheses

Hypotheses	Path Coefficient	T-Value	P-Values	Results
COM -> IP	0.123	2.924	0.004	Accepted
ERMS -> P	0.331	6.127	0.000	Accepted
IP -> UTF	0.678	14.477	0.000	Accepted
PU -> IP	0.176	4.502	0.000	Accepted
SE -> IP	0.087	2.111	0.035	Accepted
SN -> IP	0.248	5.930	0.000	Accepted
TMS -> IP	0.176	4.042	0.000	Accepted
UI -> IP	0.060	1.352	0.177	Rejected
UP -> IP	0.132	2.834	0.005	Accepted
UTF -> ERMS	0.561	10.414	0.000	Accepted
UTF -> P	0.328	6.811	0.000	Supported

The organizational dimension factors (Compatibility), user participation (UP), and top management support (TMS) have a significant positive connection with the exception of the relationships between H1, H4, H3, and user involvement (UI) has an insignificant positive connection with individuals' perception (IP) of BDM. Thus, H1, H3, and H4 are accepted but H2 is not accepted. Hypotheses H1, H3, and H4 are supported because we tested the hypothesized relationship between dependent and independent factors based on the p-values and t-statistics at a significance level of 0.05, the statistics values for Compatibility (t-value = 2.924, p = 0.004), top management support (TMS) (t-value = 4.042, p-value = 0.000), and user participation (UP) (2.834, p-value = 0.005). Conversely, UI statistical values are t-value = 1.352, p = 0.177 which appear higher than the standard statistical values. Therefore, three factors of organizational dimension have significantly influenced the individuals' perception and one factor has insignificantly influenced the Individuals' Perception (IP) of BDM.

The individual dimension factors (self-efficacy (SE), playfulness (PU), and social norms (SN)) have shown a significant positive connection with IP of BDM because t-value and p-value are significant. Thus, SE statistical values are t-value = 2.111, p = 0.035), PU statistical values are t-value = 4.502, p = 0.000) and the relationship between SN and IP are significant because the values are significant (t-value = 5.930, p = 0.000). Therefore, H5, H6, and H7 are supported and the individual dimension factors influencing the IP of BDM.

On the other hand, the relationship between individuals' perception and user technology fit (UTF) is positive and significant as per the values of t-value and p-value which are t-value = 14.477, p = 0.000, thus hypothesis H8 is supported. Furthermore, UTF supports the ERMs potentiality and performance where the H9 and H10 have statistically significant values, H9 values are t-value = 10.414, p = 0.000 and H10 values are t-value = 6.811, p =0.000. Therefore, H9 and H10 are supported. The ERMS potentiality supports the operation performance (P) based on the statistical values of H11 which are t-value = 6.127, p = 0.000, which show a significant relationship between ERMS and performance. Therefore, the suggested research framework has been accepted on the basis of all of the findings. Furthermore, the PLS predict test was carried out in order to validate the predictive accuracy of the model in the research and we took into account the root mean square error (R^2). The values for R^2 derived from dependent components were rather optimistic, ranging from 0.315 to 0.527, according to what is seen in Figure 3 As a result, the R^2 values determined using the statistical test were significant.

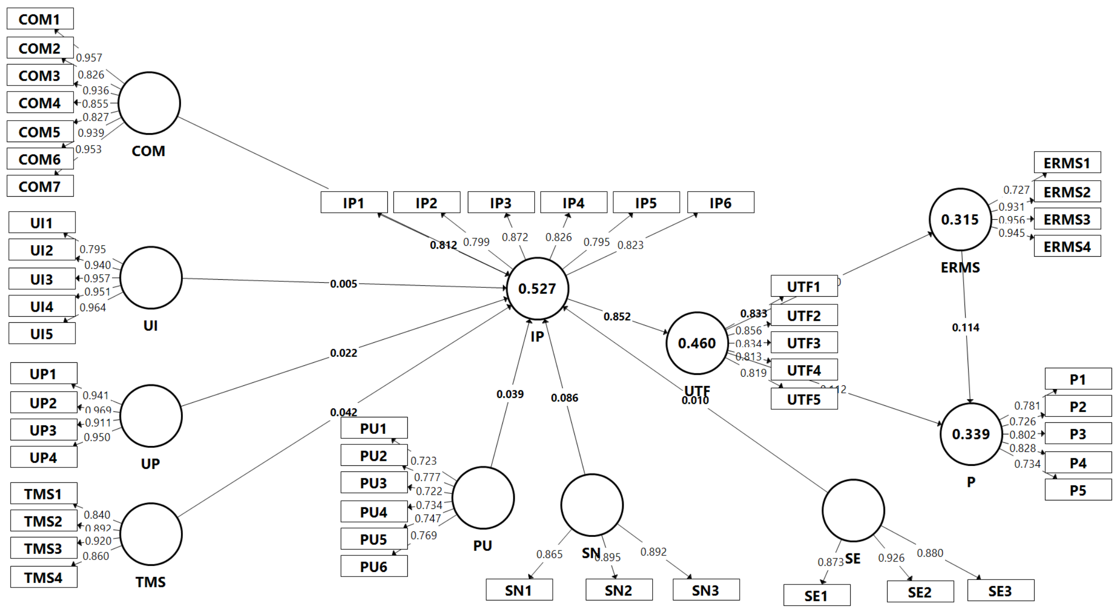

Figure 3. ERMS and BDM framework

DISCUSSION

The current study's findings looked at the particular concerns of oil organizations about integrating new technologies to support operations and production performance. The overall findings of this study demonstrated that individual characteristics of users of oil and gas organizations, in conjunction with organizational features, are robust predictors of IP of BDM. The measuring of individual perception appears to be a strong predictor of user technology fit. The findings of this study are summarized as: the research results fit with the big ideas about how people adopt new technologies that have been put forward.

The findings have confirmed that users' technology fit influences ERMS potentiality, and ERMS enhances organizational performance. All relationships between individual characteristics (self-efficacy, playfulness, and social norms) and individual perceptions of BDM characteristics (relative advantage, individual perception, visibility, compatibility, complexity, and result demonstrability) have statistically significant relationships with each other, with the exception of the relationships between playfulness and individual perception, social norms and visibility, social n norms and compatibility, and social n norms and result demonstrability. A person's sense of self-efficacy is the most powerful individual feature that might impact his or her impression of BDM, impacting ERMS adoption in oil and gas organizations. Playfulness is not related to the picture of the BDM since, as playfulness grows, the ease with which the user sees the ERMS increases as well, indicating that playfulness does not have a significant relationship with individual perception.

Playfulness has an effect on the compatibility, complexity, and relative benefit of a system in research. According to Venkatesh et al. (2022), social norms are a significant predictor of individual perception because social norms can increase or decrease the individual perception of any technology or system, which in turn increases or decreases difficulty in the minds of users and eventually motivates users to accept or reject new technology as a result. The trend in past studies, which has shown that social norms have a substantial association with individual perception and complexity, is likewise supported by our findings as well. Because self-efficacy is the most significant predictor of an individual's view, firms should pay greater attention to self-efficacy in their decision-making processes. Individual perceptions of BDM are predicted by two of the most important factors of individual perceptions of BDM: playfulness and social norms.

The oil and gas organizations also believe that these aspects contribute to the development of a more favorable impression of BDM. Apart from the relationships between voluntariness and relative advantage and complexity (which are significant), the relationships between organizational characteristics (user involvement, user participation, and management support) and individual perceptions of BDM characteristics (such as relative advantage, individual perception, visibility, compatibility, complexity, and result demonstrability) are significant. However, the relationships between voluntariness and visibility, individual perception, and complexity are not significant. The perception is widespread, and this study contributes to the development of the same belief that voluntariness will improve the individual perception and compatibility of BDM in the minds of users, user involvement and participation will also improve the compatibility between the needs of users and the BDM, and management which will have an important impact on the visibility, individual perception, and complexity of BDM.

In addition, these findings are consistent with prior research which found that every organizational attribute should have a statistically significant link with at least one element of user perception of technology or the system. According to the findings of this research, oil and gas firms should priorities management support and user engagement as organizational elements in order to improve the perception of BDM among consumers and the perception of professionals to implement ERMS. Furthermore, all factors of the oil and gas of ERMS have statistically significant relationships with job fit and professional fit, with the exception of individual perception and compatibility with job fit, and result demonstrability with profession fit, which have both statistically significant relationships with job fit. Previous research and the identity theory have already shown that relative advantage is the most important predictor of job and career fit.

In conclusion, a relative advantage is the sole factor that influences user-technology fit. The findings of this research also demonstrate that relative advantage has a statistically significant positive association with both job fit and professional fit. Conclusions Organizations in the oil and gas industry should consider all components of innovation diffusion theory in order to foster a feeling of work and profession fit in their personnel, but they should pay particular attention to the relative advantage and complexity factors of BDM. The findings of the research supported our hypothesis that both user-technology fit criteria are significant predictors of ERMS skills, which in turn improve operations success in the long run. The results of this study attempt to solve the particular difficulties faced by the operations team that needs technology such as ERMS to enhance the continuity of business. Individual characteristics (self-efficacy, playfulness, and social norms) and organizational characteristics (volunteerism, user involvement, user participation, management support) as well as innovation diffusion theory (IDT), and factors (relative advantage, visibility, individual perception, compatibility, complexity, result demonstrability) are all positive predictors of individual perception of BDM, according to the findings of empirical data analysis. If oil and gas companies wish to implement BDM in their businesses, they need to concentrate on aspects such as individual, organizational, and IDT issues, among others.

This research found that individual perceptions of BDM lead to a user-technology fit, which is supported by the findings. Therefore, if employees of organizations believe that BDM has a comparative benefit over other systems or technologies, and if BDM has a positive perception, is more visible, more well-matched with the user's job needs, reduces the difficulty, and has better certainty of results, then they will feel more job fit and professional match. Companies that want to instill employee confidence in user-technology fit should pay close attention to these factors, particularly comparative benefit and complexity. According to the findings of this study and previous works, these are the two most significant concepts that influence user-technology fit. By getting the user-technology fit right, employees will have a better idea of how BDM can help them better meet their work and professional needs.

Work fit and professional fit benefit ERMS skills and operations effectiveness. This study suggests that the operations believe ERMS will enable them to build a better connection with their clients and boost operational productivity. Furthermore, customer relationship management (ERMS) skills have a favorable impact on operations effectiveness. For this reason, oil and gas organizations should concentrate on the factors that influence individual, organizational, and IDT perceptions of BDM, the adoption of BDM in organizations, and the perceptions of job and professional fit in organizations. Therefore, it will ultimately increase operations performance and ERMS potential for oil and gas organizations.

THEORETICAL AND PRACTICAL IMPLICATIONS

This study makes a significant contribution to both theory and practice. First, it contributes to the advancement of identity theory in the context of big data management and ERMS. This study serves as a foundation for further research on the role of business development managers in operations performance and ERMS skills. This research makes a theoretical contribution by studying a theory-driven framework that may serve as an essential lens through which to evaluate the role of BDM in performance and increases in ERMS potentiality in the future. This research also evaluated the combined impacts of general technology acceptance theory elements and identity theory in the context of BDA, which is a topic that has been understudied in the BDA literature until now. The research also makes a contribution to theory by combining the identity theory with the innovation diffusion theory, as well as individual and organizational characteristics, in the setting of business development agencies. Furthermore, this work contributes to theory by investigating the role of BDM in performance and ERMS potentiality, which may prove to be a useful lens for technologically improving performance and ERMS potentiality in the future. Also, this study serves as a foundation for future research into the function and influence of business development managers (BDMs) in performance and the potentiality of enterprise resource planning systems (ERMS). In addition to making a theoretical contribution, this work makes a practical contribution from a variety of angles. First and foremost, this research presents an experimentally verified model that may be used to aid in the adoption of business development management (BDM) in enterprises. This research also helps oil and gas companies realize that the favorable view of the performance toward BDM, as well as the user-technology fit, are the most critical elements in the adoption of BDM and the resultant improvement in operations performance and ERMS potentiality. Understanding of BDM implementation in particular, as well as user acceptance of technology in general, was gained via the usage of the model. This research also provides a foundation for companies to begin implementing business development management (BDM) to support operations and enterprise resource management systems (ERMS) in order to reap the benefits of BDA while also effectively countering the challenges of operations performance and ERMS potentiality.

CONCLUSION

Organizations such as oil and gas companies need to equip their operations with new technology, such as ERMS, to improve production and operations performance. Thus, the main objective of this study is the impact of big data management on adopting new records management systems in oil and gas originations. This study gives an excellent platform for further expanding the investigation of BDM in operations and ERMS skills. The research indicated that user traits, organizational features, and innovation diffusion theory elements (relative advantage, visibility, individual perception, compatibility, complexity, and outcomes demonstrability) might establish a good view of ERMS in the staff's mind. A good view of BDM will drive the operations towards ERMS acceptability in an organization.

The current study also emphasized that using ERMS will boost the feeling of work and career fit in the mind of the users. The research revealed that a good impression of BDM produces a user-technology fit belief in the new technology that can improve the operations performance. This positive perception improves the performance and ERMS potentiality in organizations.

LIMITATIONS

In addition to the contributions of this work, we identify several limitations, and on the basis of these limitations, some future lines of research are offered. First and foremost, the data acquired for this study from Yemeni oil and gas firms, as well as the conclusions drawn from this research, may differ when viewed in a cross-cultural setting. Research in the future might pay more attention to the multicultural setting in order to improve the generalizability of the model. Furthermore, longitudinal research should be prioritized in future studies in order to enhance the findings. As a second point, since the data was gathered in a developing country, the findings of this study may vary from those obtained in developed countries. Consequently, researchers will be able to test this model in developed nations in the future, and they will be able to analyze this research model to compare various countries and expand its generalizability and efficacy. Despite the fact that the study findings explain improvements in both performance and ERMS potentiality, there are other factors that may have an influence on these two dependent variables, such as role conflict and role ambiguity, that should be considered. In the future, researchers will be able to examine these two variables in addition to the model that has been provided. Furthermore, researchers may include the moderating impact of demographical parameters such as age, gender, wealth, and experience into this study model in order to make it even more robust and comprehensive. In addition, future studies may be undertaken after the implementation of BDM, and the perception of BDM in the operations performance after the implementation of BDM can then be explored. Future research may examine the significant direct correlations between human traits, organizational features, and individual perceptions of BDM that are directly related to ERMS potentiality and operational performance in the future.

ACKNOWLEDGMENT

This work was supported by grant code: GUP-2022-061.

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APPENDIX. QUESTIONNAIRE ITEMS

Factors	Items	Questions
Compatibility (com)	com1	I found ERMS compatible with my work in managing electronic records.
	com2	ERMS increases my intention to manage records and big data.
	com3	ERMS helps me to support the work processes without conflict
	com4	I believe ERMS is consistent with Oil and Gas records.
	com5	I believe ERMS is friendly with managing huge records.
	com6	I believe ERMS is consistent with the existing values of records in my organization
	com7	I think ERMS fits into my work style.
User involvement (UI)	ui1	I consider that the use of ERMS to be relevant to me.
	ui2	I consider that the use of ERMS to be significant for managing records in my organization.
	ui3	I deliberate that the use of ERMS helps me organized my job.
	ui4	I reflect that adopting ERMS is suitable for my job.
	ui5	I found that ERMS will enhance my overall experience
User participation (UP)	up1	I played an important role in the adopting of ERMS based on BDM influence.
	up2	I felt my opinion was adequately considered during the process of design and/or development of the ERMS based on BDM influence.
	up3	I participated in the adopting of ERMS based on BDM influence.
	up4	I shared my concerns about ERMS adoption based on BDM influence.
	up5	I played an important role in the decision of ERM adoption in my organization.
Top management support	tms1	I believe top management will provide adequate support to adopt ERMS.
	tms2	Top management is important for me to understand the change when ERMS is adopted.
	tms3	I think top management will enable ERMS adoption faster.
	tms4	Top management will help me understand the impacts of BDM on adopting ERMS.

Factors	**Items**	**Questions**
Self-efficacy (SE)	se1 se2 se3	I could complete the job using the ERMS if there was no one around to tell me what to do. I could complete the job using the ERMS if I had a lot of time to complete the job for which the big data was provided. I could complete the job using the ERMS if I had only the user manuals for reference.
Playfulness (PU)	pu1 pu2 pu3 pu4 pu5 pu6	I feel myself as Natural when I am interacting with ERMS. I feel myself as imaginative when I am cooperating with ERMS. I feel myself as Flexible when I am interacting with ERMS. I feel myself easy to manage records when I am interacting with ERMS. I feel myself as Playful when I am interacting with computers to use ERMS. I feel myself as original when I am interacting with ERMS.
Social norms (SN)	sn1 sn2 sn3	People whose opinions I value, prefer me to use ERMS in my work. At work, my colleagues who are important to me think that I should use ERMS. At work, my superiors think that I should use ERMS.
Individuals' perception (IP)	ip1 ip2 ip3 ip4 ip5 ip6	Individuals are influencing my behavior to use ERMS. I think ERMS used by other business firms will encourage me to use it for my business dealings. People have changed my behavior about the usefulness of ERMS. People increase my attention to use ERMS in my workplace. My leaders influence my intention to use ERMS. Individuals have ability to change my mind in using ERMS in my workplace.
User Technology fit (UTF)	utf1 utf2 utf3 utf4 utf5	Using ERMS increases the level of challenge in my career. Adopting the ERMS increases the flexibility of changing jobs. Using the ERMS increases the amount of variety in my career. Using the ERMS increases the opportunity for more meaningful work. Using the BDA increases the opportunity to gain job security.
ERMS Potentiality	erms1 erms2 erms3 erms4	I believe that ERMS potentiality support my job. I believe the use of ERMS will control the effective daily transactions. I believe ERMS will achieve regulatory compliance in the business. I believe ERMS will enable the recovery of critical records to guarantee continuity of operations
Performance (P)	p1 p2 p3 p4 p5	Utilization of ERMS improves the performance of my organization. Utilization of ERMS improves the operational performance. Adopting ERMS increases the integration that improve organizational performance Applying ERMS in my workplace will increase the efficiency of processes within an organization which contributes to the improvement of overall performance. ERMS adoption increases work productivity that helps in improving organizational performance.

AUTHORS

Burkan Hawash has a Ph.D. in Information Science from Universiti Kebangsaan Malaysia's Faculty of Information Science and Technology. His research interests include information system management, electronic records management, and information security. Burkan has worked in TOTAL E&P for 10 years as Telecom Supervisor. Burkan is an expert in data analysis through SmartPLS, SPSS, and R Programming. Burkan interest in archives, records management, digital transformation, and research. He possesses a Master's degree in Information Security Management and a Bachelor's degree in Telecommunication Engineering. He is working as Telecom Supervisor, Petromasilah Petroleum Company in Yemen (2015-present). He has managed and installed Voice over IP network in TOTAL Company in Yemen. Recently has been a researcher with good skills in electronic records management systems, Digital Transformation (DT), and Big Data and Internet of Things (IoT). He started publishing in DT and is ready to build skills in transformation with the latest digital tools, technologies, and solutions across cloud, connectivity, cyber-security, and smart services.

Muaadh Mukred is currently an Associate Fellow at the Cyber Security Center in the Information Science and Technology Faculty, University Kebangsaan Malaysia (UKM), Malaysia. He is also an academic staff at Sana'a Community College (SCC), Sana'a, Yemen. Muaadh has served as a post-doctoral researcher at the Cyber Security Research Center in the Information Science and Technology Faculty. Previously, he served as a lecturer at the Computer Science Department at Sana'a Community College for over eight years. Muaadh completed his first degree in Computer Science at AL-Mustansiriyah University in 2002. Muaadh joined the industry for more than five years, working in Computer Science, data analysis, and programming, in addition to his permanent positions at Sana'a Community College. Afterward, Muaadh moved to Malaysia after getting a scholarship and did his Master's degree in Computer Science from the University of Technology of Malaysia in 2009. Muaadh joined SCC again in 2011, where he started a new position as Head of the Higher Professional Education Division and served as a Lecturer. In 2013, Muaadh got another scholarship and moved to Malaysia, where he was awarded a PhD from the UKM with an outstanding researcher award as one of the best students in his batch. He has published several scientific/research papers in well-known international journals and conferences. Muaadh was involved in some research grant projects, some in artificial intelligence and machine learning, and others in analyzing and architecting big data. He has recently been engaged as an academic partner with research projects funded by some universities in Europe, Malaysia, and the Middle East. He has supervised Ph.D. and Master students and other undergraduate final-year projects. Muaadh also has been invited as an external examiner for many Ph.D. and Master's students and served as a reviewer for many high-impact journals. His current research interests include big data analytics, natural language processing, technology adoption, and cybersecurity.

Umi Asma' Mokhtar is a Senior Lecturer in Information Science at Universiti Kebangsaan Malaysia's Faculty of Information Science and Technology. In 2012, she was awarded the Oliver Wendell Holmes Travel Award by the Society of American Archivists. Her areas of interest in research include electronic records management, function-based classification, information policy, and information security. Her articles have appeared in international and national periodicals, such as the International Journal of Information Management and the Records Management Journal. She is currently the Malaysian Team's lead researcher for the InterPARES Trust AI project.

Mohammed Islam Nofal is an Assistance Professor of Philosophy/Information Science and Technology/Business Intelligence. He obtained his undergraduate degree in Computer Science at Zarqa Private University in 2005. His Master's degree was in Information technology at Utara University Malaysia in 2009, under the supervision of Professor Norshuhada Shiratuddin. Nofal received his Ph.D. in Information Science and Technology/Business Intelligence at Malaysian National University in 2016 under the supervision of Professor Zawiyah Mohammad Yusof. After brief stints as Lecturer at Amman Arab University, he was appointed to the Department of Management of Information Systems in the Business School at Amman Al Ahliyya University in 2019 as an Assistant Professor. After that, Nofal was appointed to the Department of Business Intelligence and Data Analytics, Faculty of Administrative and Financial Sciences at Petra University in 2022 as an Assistant Professor. Nofal has made many scholarly contributions. He has important research in several different fields, including information systems, business intelligence and data analysis, e-government, human resources, network system, e-learning, social media, multimedia, problem-based learning, and decision support system. He has participated in many international scientific conferences, was a keynote speaker several times, and held several seminars in several universities and departments. He contributed to many discussions of Master's theses and was a reviewer for them, and he was a reviewer for many research papers in several scientific journals. Nofal participated in many academic and management committees, and was a member of AACSB Eligibility Application Committee, Libraries Committee, Community Service, Committee Quality, Committee, Study Plans Committee, Websites Improvement Committee.