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Generative conversational AI agent for managerial practices: The role of IQ dimensions, novelty seeking and ethical concerns

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ABSTRACT

This study aims to identify and empirically examine the influence of the main factors related to the content quality of generative conversational AI agents on decision-making efficiency. Additionally, this study explores the ramifications of decision-making efficiency facilitated by generative conversational AI agents in organisational innovation performance. This study proposes a model based on the information quality model as well as other factors, such as novelty seeking and ethical concerns. Data from this study was collected using online questionnaires from a purposive sample size of 228 employees in business organisations. Based on Structural Equation Modelling (SEM) analyses using AMOS, the results support the significant impact of information quality (intrinsic information quality, contextual information quality, representational information quality, and accessibility of information quality) on decision-making efficiency. The results also support the significant impact of novelty seeking and ethical concerns on decision-making efficiency. Decision-making efficiency was also found to have a significant positive impact on innovation performance. This empirical study makes a considerable contribution as it is among the first to expand the current understanding of the effective use of generative conversational AI agents in managerial practices (i.e. decision-making and innovation).

1. Introduction

Since their launch in late November of 2022, generative conversational artificial intelligence (AI) agents (i.e. ChatGPT and Google Bard) have garnered significant attention from people from diverse backgrounds and professional domains (Chavez et al., 2023; Dwivedi et al., 2023a; Dwivedi et al., 2023b; Kanitz et al., 2023; Yilmaz and Yilmaz, 2023). The increase in this phenomenon is due to the substantial surge in the user base of these smart systems. As of 18th of May 2023, Ruby (2023) reported that ChatGPT had surpassed 100 million users. Similarly, Google Bard, launched in March 2023, records approximately 30 million monthly visits (Sharma, 2023). This is in addition to the large amount of financial and human resources invested by high-tech organisations (e.g. Meta, OpenAI, Google, Microsoft, Amazon, and Jasper) in creating and improving generative conversational AI agents (Dwivedi et al., 2023a; Dwivedi et al., 2023b). According to Forbes (2023), Microsoft has invested approximately 10 billion US dollars into ChatGPT. This, in turn, creates new opportunities to obtain the information, knowledge, and experience that people need in various fields and from different backgrounds in a faster, timely, innovative, comprehensive, and customised manner (Chavez et al., 2023; Dwivedi et al., 2023a; Dwivedi et al., 2023b; Yilmaz and Yilmaz, 2023). Conceptually, generative conversational AI agents are defined as "computer-assisted systems that can generate text, images, audio, or videos" (Kanitz et al., 2023, p. 2).

The business sector was one of the most important sectors interested in benefiting from such emerging systems (Adiguzel et al., 2023; Dwivedi et al., 2023a; Dwivedi et al., 2023b; Hughes et al., 2016; Korzynski et al., 2023; Pan and Nishant, 2023; Richey et al., 2023). For example, approximately 49 % of business organisations in the USA have already started using ChatGPT, and approximately 30 of these organisations express their willingness to adopt it in the imminent future (Future of Commerce, 2023). Rational and highly efficient organisational decision-making largely relies on the quality and quantity of information available to employees. Historically, employees have adopted different sources (traditional or non-traditional) of information to make enhanced decisions at all organisational levels (Dwivedi et al., 2023a; Dwivedi et al., 2023b; Korzynski et al., 2023). However, there have always been concerns regarding the rationality and quality of such decisions owing to human barriers related to cognitive limitations, lack of information, and time pressure (Cristofaro, 2017; Dwivedi et al., 2023a; Dwivedi et al., 2023b; Kanitz et al., 2023).

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With emerging generative conversational AI agents, such as ChatGPT and Google Bard, a novel era of information generation and sources provides decision-makers with more interactivity, responsiveness, and accessibility (Kanitz et al., 2023). Therefore, employees at all organisational levels are actively engaged in the use of generative conversational AI agents (Korzynski et al., 2023). For example, a recent report published by Statista (2023a) in March indicated that 80 % of employees worldwide have had experience with ChatGPT at least once during their employment. This can be attributed to the ability of generative conversational AI agents to address key human barriers related to decision-making efficiency, such as cognitive limitations, lack of information, and time pressure, and, accordingly, enhance employees' productivity and quality of decisions (Dwivedi et al., 2023a; Dwivedi et al., 2023b; Kanitz et al., 2023; Mich and Garigliano, 2023; Yilmaz and Yilmaz, 2023).

The implications of generative conversational AI agents as credible sources of information seem to be among the most controversial issues on which academics and practitioners cannot agree (Dwivedi et al., 2023a; Dwivedi et al., 2023b). This is particularly noteworthy considering that integrating generative conversational AI agents into decision-making efficiency necessitates that employees divulge a substantial volume of confidential organisational information (Biswas, 2023a). In this respect, a new report published by Statista (2023b) indicated that 3 % of employees who have used ChatGPT have uploaded sensitive and confidential organisational information. Thus, there has not yet been a common consensus on the feasibility and validity of using generative conversational AI agents in business organisations for general decision-making efficiency in particular (Biswas, 2023a; Ivanov and Soliman, 2023). In their opinion paper, Dwivedi et al. (2023b, p. 2) documented that, "The technology (ChatGPT) presents opportunities, as well as, often ethical and legal, challenges, and has the potential for both positive and negative impacts for organisations, society, and individuals".

In other words, the availability of these contemporary technologies as credible sources of information and their use without controls may lead to disastrous results. Conversely, refusing to use these technologies and questioning their feasibility and usefulness deprives business organisations from catching up with development and benefiting from this rapid scientific advancement (Biswas, 2023a; Calvillo, 2023; Dwivedi et al., 2023b; Duan et al., 2019). There is also the question related to the conditions and standards that guarantee the safe and effective use of generative conversational AI agents.

Despite the growing interest in analysing issues related to this technology, whether by researchers or specialists, there is a noticeable scarcity of field and applied studies that examine the dimensions related to the use of such technology, especially in the business sector, and its impact on decision-making processes. This is in addition to the fact that most of these studies are opinion, conceptual, and systematic review papers, while no scientific or empirical study has been published on the use of such technologies in the business sector. This is because of the novelty of these technologies. Furthermore, it should be noted that most of these studies have exclusively focused on ChatGPT. Accordingly, we recognise the need to conduct an empirical study to validate the impact of generative conversational AI agents (ChatGPT and Google Bard) on decision-making efficiency. Remarkably, the business sector attaches great importance to the use of generative conversational AI agents. However, the implications of these technologies as credible sources of information seem to be one of the most controversial issues on which academics and practitioners cannot agree. Therefore, this study focuses on the adoption of generative conversational artificial intelligence agents within the business sector and from the perspective of decision makers.

This study aims to identify and empirically examine the impact of key factors related to the quality of content generated by generative conversational AI agents on decision-making efficiency. Furthermore, it investigates how decision-making efficiency, facilitated by generative conversational AI agents, would shape organisational innovation performance (Duan et al., 2019; Sifat, 2023).

This study is structured as follows: Section 2 provides an overview of generative conversational AI agent literature followed by a conceptual model in Section 3 (theoretical base, proposed model, and hypotheses). Sections 4, 5, 6, and 7 outline the methodology, results (i.e. demographic characteristics, descriptive statistics of the measurement items, structural equation modelling (SEM) including the measurement model and structural model), discussion (i.e. theoretical implications, practical implications, limitations, and future research directions), and conclusions, respectively.

2. Literature review

Since its launch in November 2022, generative conversational AI agents have received considerable interest from researchers across different disciplines, including education (Hsu and Ching, 2023; Lo, 2023), medicine (Chavez et al., 2023; Tlili et al., 2023), food (Kasneci et al., 2023), tourism (i.e. Dwivedi et al., 2023a), knowledge management (Firat, 2023), academic research (Burger et al., 2023), climate change (Biswas, 2023b), and consumers and marketing (Paul et al., 2023). These studies are predominantly conceptual, opinion-based, and literature review papers (Dwivedi et al., 2021; Dwivedi et al., 2023b; Kasneci et al., 2023; Yilmaz and Yilmaz, 2023).

A wide range of themes and perspectives have been presented and discussed throughout the main body of generative conversational AI agents (Rese and Tränkner, 2024). In their opinion paper, Dwivedi et al. (2023b) presented insights gleaned from the contributions of 43 experts from diverse backgrounds and research domains, including management, hospitality and tourism, medicine, marketing, information systems, education, policy, computer science, publishing, and nursing. The authors discussed the key opportunities afforded by ChatGPT and underscored the need to develop appropriate capabilities and allocate efforts to effectively harness such latent opportunities. Issues related to the ethical and legal use of ChatGPT have also been discussed by Dwivedi et al. (2023b). In conclusion, Dwivedi et al. (2023b) highlighted several research areas (i.e. knowledge, education, academic research, ethics, social, and organisational digital transformation) that need to be fully addressed by future studies.

For example, in the hospitality and tourism context, Dwivedi et al. (2023b) scanned and analysed the current practices and challenges related to the adoption of generative conversational AI agents (i.e. ChatGPT). Based on a critical review of the main body of literature and scanning the best implications of generative conversational AI agents, Dwivedi et al. (2023b) concluded that the adoption of generative AI technologies is poised to revolutionise the hospitality and tourism sector, ushering in a profound era of transformation. This study sheds light on the inherent challenges that accompany the implementation of these cutting-edge technologies, as seen from the perspective of corporations, consumers, and governing bodies.

Gursoy et al. (2023) discussed ChatGPT usage by both customers and service providers in the hospitality and tourism sectors, arguing that customers could be disrupted by using ChatGPT, either in terms of obtaining the proper information required or even in conducting rational buying decisions. From a business perspective, Gursoy et al. (2023) highlighted the potential of ChatGPT to empower the hospitality and tourism sectors to tailor their products and services to align seamlessly with customer preferences and needs. This contributes to the ability of these organisations to design, produce, and exchange highly valued propositions with their target customers (i.e., Gursoy et al., 2023).

In the educational field, Hsu and Ching (2023) recently analysed the key potential and main concerns emerging over generative conversational AI agents. They concentrated on the ability of a generative conversational AI agent to create more informative, updated, and comprehensive learning content that would enhance learning and teaching experience and performance. According to Hsu and Ching

(2023), generative conversational AI agents would contribute considerably to learning and educational experience by empowering both teachers and students with more support in terms of task assessment, personalised learning content, and update feedback. Conversely, they discussed several concerns pertaining to the usage of generative conversational AI agents in this area, such as data accuracy and privacy. Ethical concerns, bias, and discrimination were also raised and identified as key challenges that would hinder the applicability of generative conversational AI agents.

In their exploratory study, Whalen and Mouza (2023) concluded that ChatGPT has several significant implications beneficial to both students and teachers. For example, ChatGPT could effectively support teachers in the education process, providing assessment tools and activities, improving learning content, and communicating with students and their parents. Whalen and Mouza (2023) focused on the potential of ChatGPT to enhance students' learning outcomes (i.e. problem solving, creative thinking, and innovation) while developing reading, writing, and comprehension skills. Kuhail et al. (2023) attributed this contribution to the learning experience to the high level of personalisation that both students and teachers would have by using ChatGPT. ChatGPT services are now available to everyone through the use of various devices 24/7 (Kuhail et al., 2023). This helps students and teachers obtain greater personalisation in terms of choosing the appropriate time and place, thus contributing to the convenience and efficiency of the learning process (Cooper, 2023; Ray, 2023; Ye et al., 2023).

Paul et al. (2023) have discussed the key capabilities of generative conversational AI agent for consumers and marketing in terms of enhancing the quality of customer service, personalised customer experience, improving contractual efficiency, and generating innovative ideas to build and craft promotional campaigns. Paul et al. (2023) also considered the dark side of using smart systems in marketing practices and customer experiences. Among the most significant drawbacks of using ChatGPT, apprehensions exist regarding consumer welfare, partiality, dissemination of incorrect information, absence of background information, concerns regarding privacy, ethical deliberations, and matters pertaining to security.

Korzynski et al. (2023) addressed the issue of using generative conversational AI agents from a management perspective by reviewing and analysing the most common models and theories in the management field, especially those related to decision-making efficiency (i.e. the rationality model), knowledge management, customer service (i.e. relationship marketing theory, theory of customer experience management), technology adoption (i.e. technology acceptance model), human resource management (i.e. human relations theory, human capital theory), and business administration (i.e. Max Weber's bureaucratic theory). Considering the generative AI revolution, Korzynski et al. (2023) focused on the importance of adapting such theories to make them more applicable to the context of generative AI systems. This requires initial testing of the validity and applicability of such theories in this context (Korzynski et al., 2023).

These studies provide insight regarding the key implications, opportunities, and challenges pertaining to generative conversational AI agents. However, a closer look at generative conversational AI agent studies and the main research databases (i.e. Google Scholar, Web of Science, Scopus, ScienceDirect, and Emerald Insight) reveals that most of these studies are opinion, conceptual, and systematic review papers, and no scientific and empirical studies have been published on the use of such technologies in the business sector. This is because of the novelty of these technologies. Furthermore, it should be noted that most of these studies have exclusively focused on ChatGPT. Accordingly, we recognise the need to conduct an empirical study to validate the impact of generative conversational AI agents (ChatGPT and Google Bard) on decision-making efficiency.

3. Conceptual model

Considering the transformative nature of generative conversational AI agents as heralding a new era of information, the key criteria for judging their success and effectiveness revolve around the credibility and quality of the content generated for users. In other words, the more quality and credibility users experience when using a generative conversational AI agent, the more efficient and effective they are in the decisions they make. According to Dwivedi et al. (2023a, 2023b), the role of generative conversational AI agents as trustworthy information sources appears to be a contentious topic for which scholars and industry experts have yet to reach a consensus. It is significant to note that the incorporation of generative conversational AI agents into decision-making processes requires employees to share a considerable amount of sensitive organisational data (Biswas, 2023a). Similarly, a recent report by Statista (2023b) revealed that 3 % of employees using ChatGPT have uploaded confidential company information.

Therefore, it is necessary to select a theoretical foundation which can cover the main features of the content created by generative conversational AI agents. After reviewing the main body of literature regarding information systems, it was noted that the information quality model proposed by Wang and Strong (1996) and validated by Lee et al. (2002) could provide a clear picture of the key standards and criteria of content that govern the effective and safe use of generative conversational AI agents in the decision-making process. The information quality model is one of the most inclusive perspectives covering the most important dimensions (i.e. accuracy, completeness, relevance, and timeliness) (i.e. Ghasemaghaei and Hassanein, 2015). This is in addition to the predictive validity of the information quality model, as approved by dominant studies in the related area of information systems (i.e. Ghasemaghaei and Calic, 2019). In line with Lee et al. (2002) and Wang and Strong (1996), four dimensions of information quality were considered in this study: generative conversational AI agent intrinsic information quality (GCAIAIIQ), generative conversational AI agent contextual information quality (GCAIACIQ), generative conversational AI agent representational information quality (GCAIARIQ), and generative conversational AI agent accessibility of information quality (GCAIAAIQ) (Fig. 1).

3.1. Qualitative interviews

To provide an accurate picture of the applicability of the information quality model as a theoretical base of this study's model, as well as to assess if other aspects should be considered in this study's model, 20 exploratory interviews were conducted with employees involved in decision-making processes and with experience using generative conversational AI agents. It is also worth mentioning that the interviewed employees were selected from different departments and backgrounds (i.e. IT, HR, finance, marketing, operations, etc.) and from different levels in the organisations (i.e. chief executive officers, department heads, and operational or first-line management).

The main objective of these exploratory interviews was to determine the most important and related constructs from the perspective of decision makers in Saudi Arabia. Notably, most interviewed employees were assured that generative conversational AI agents (ChatGPT and Google Bard) are highly innovative and smart sources of information in recent times. For example, one interviewee stated:

> “I believe that ChatGPT represents a breakthrough in the world of information, which will lead to a radical change in the nature of organisations' work in general and the decision-making mechanisms in particular”.

Interviewed employees also reported that generative conversational AI agents (ChatGPT and Google Bard) would contribute to employee decision-making efficiency compared to traditional methods in this respect. They attributed such privileges of generative conversational AI agents (ChatGPT and Google Bard) to the value-added by using such

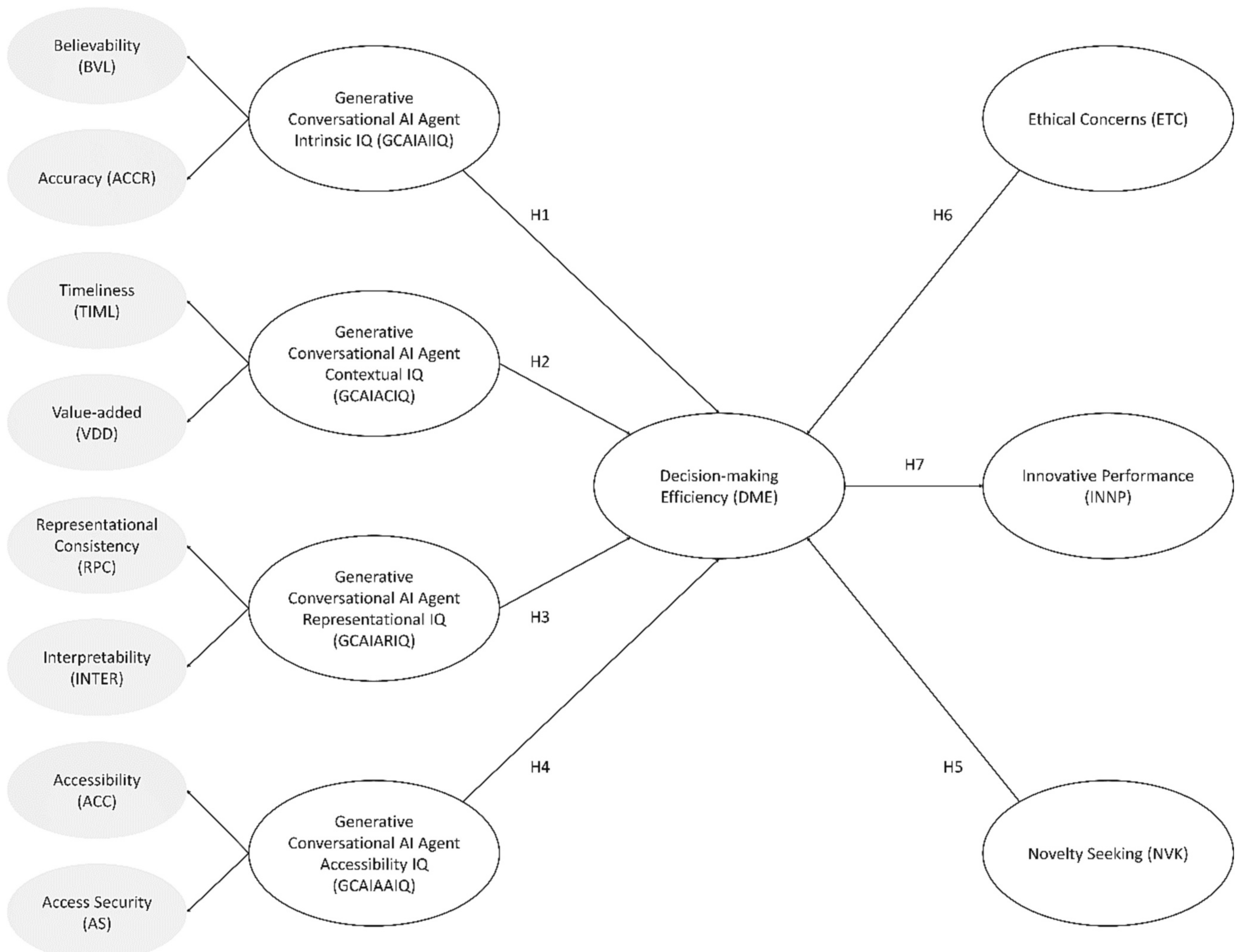

Fig. 1. Conceptual model.
(Source: adapted from Jarupathirun (2007); Lee et al. (2002); Mardani et al. (2018); Wang and Strong (1996)).

smart systems to employees' knowledge and exposure. This demonstrates the importance of including decision-making efficiency as a key component of the model. Samples of the content provided by the interviewed participants are presented below:

> "Since the launch of these systems, I usually use them, and I find that they are able to provide a lot of comprehensive information that increases my knowledge and awareness of the issue in which I must take a decision, and this has helped me a lot during the past months to form a better perception of the problems that must be solved and provided me with information that was not available to me before about these problems, which improved the quality of the decisions that I made".

> "I am amazed at the speed of this system's response to my questions and its ability to provide a large amount of information in a very short time".

The credibility of the content provided by generative conversational AI agents (ChatGPT and Google Bard) was also one of the main issues reported by the interviewees. In this regard, they reported that reliance on generative conversational AI agents (ChatGPT and Google Bard) in the decision-making process is not absolute but is greatly affected by the accuracy and trustworthiness of the information provided by these systems. According to the information quality model, intrinsic information quality aspects (accuracy and believability) address the concerns reported by the interviewees. Samples of the content provided by the interviewed participants are presented below:

> "Despite the ability of these systems, ChatGPT and Google Bard, to provide a huge amount of information that we need in decision-making, there is an urgent need to ensure the validity of this information and its degree of accuracy and credibility before adopting it in the decision-making process".

> "One of the most important criteria that I warn to take into account when using these systems is the credibility and accuracy of the generated content".

Among the most important positive aspects emphasised by the interviewees was the clear and flexible structure in the process of presenting information with a high level of customisation. This is in addition to what was mentioned by a large number of interviewees regarding the consistency of presenting ideas in a logical and convincing manner, as this makes it easy for decision makers to interpret them later. These aspects have been explicitly documented in the information quality model in terms of representational consistency and interpretability. A sample of quotes from interviews regarding this are listed below.

> "One of the things that positively affected my opinion and made these systems more effective in the process of collecting information is the consistent and smooth format in the process of displaying

information, as I, as a user, can choose the appropriate display model (i.e. text; points; paragraph; tables) for the information I want".

"When I use ChatGPT, I feel like I am speaking with human rather than machine as the replied content on my questions and inquiries are really understandable and presented in more conscious manner".

However, most interviewees expressed their concerns towards issues related to the ethical and secure use of technologies using generative conversational AI agents. They stressed the need for these technologies to be governed by an ethical framework and reference that prevents misuse and considers a high degree of organisational information confidentiality and security. Therefore, this study recognises the importance of considering the ethical aspects associated with using generative conversational AI agents (Paul et al., 2023; Yilmaz and Yilmaz, 2023). In this respect, Dwivedi et al. (2023b) stressed that one of the most important issues to consider is the discovery of ethical and legal issues regarding the use of generative conversational AI agents in different settings. Therefore, this study considers the role of ethical concerns, along with information quality dimensions, in decision-making efficiency. A sample of quotes from the interviews that highlighted the importance of ethical concerns is listed below.

"Despite my conviction that these systems are effective means that facilitate the decision-making process and save a lot of time and effort, there are ethical considerations such as bias, fairness, transparency, and interpretability".

"One of my primary concerns about using these systems is their capability to store sensitive regulatory data during interactions. As a result, it becomes crucial to address important considerations regarding data privacy. Ensuring that user data is handled securely and in strict compliance with relevant data protection laws is of utmost importance".

The majority of interviewees reported that generative conversational AI agents (ChatGPT and Google Bard) are technological breakthroughs that cannot be overlooked, and organisations and individuals must keep pace with these changes and fluctuations in the world of information technology. As a contemporary and highly evolved technology, there is also a need to consider issues related to innovativeness and novelty seeking from the user's perspective (Paul et al., 2023). The importance of such factors becomes evident when a new technology (e.g. ChatGPT and Google Bard) is introduced, particularly if it has been released for more than eight months, and is shrouded in ambiguity and risk. In this regard, Dwivedi et al. (2023b, p. 38) questioned the role of novelty: "What does it mean for society when so many people turn to ChatGPT to gather their information for them, or equally so many people are in fear of this novel technology". Therefore, novelty seeking is proposed in this study as a key predictor of decision-making efficiency. Finally, this study examines the impact of decision-making efficiency empowered by generative conversational AI agents on innovation performance. A sample of quotes from the interviews that emphasised the importance of novelty seeking is listed below:

"Generative conversational AI agents (ChatGPT and Google Bard) represent contemporary and non-traditional systems in the process of obtaining information, processing it, and using it in various fields of life. Using such smart systems personally make me feel that I am a person capable of acquiring what is new and different."

"The use of this technology in the decision-making process is an essential part of the personal development of my technical skills and knowledge as it presents a new ideas and experiences".

3.2. Generative conversational AI intrinsic information quality (GCAIAIIQ)

According to Wang and Strong (1996, p. 19), intrinsic information quality "Denotes that data have quality in their own right". Intrinsic quality has been operationalised as a multi-dimensional construct comprising aspects related to believability, accuracy, reputation, and objectivity (Bliemel and Hassanein, 2007; Ghasemaghaei and Hassanein, 2019; Herrera-viedma et al., 2006; Lee et al., 2002; Seppänen and Virrantaus, 2015; Widiyanto et al., 2016). Intrinsic information quality has commonly been approved as the most significant factor compared to other dimensions of information quality (Lee et al., 2002; Seppänen and Virrantaus, 2015). This can be attributed to the critical aspects within intrinsic information quality. For instance, accuracy is one of the primary intrinsic information criteria that not only influences informational value, but also enhances the credibility of utilising such information in the decision-making process (Kim et al., 2017). In other words, the extent to which the collected data are accurately and correctly reflected in their original state, as they were from their original sources without any distortion or modification, guarantees that such information has zero errors (Barcellos et al., 2022). Indeed, the accuracy of the answers and information provided by generative conversational AI agents remains questionable, as users have raised concerns that generative conversational AI agents can produce false or non-existent information in response to claims. "ChatGPT hallucinations" is a term to describe problems with a chatbot that generates scientifically reasonable answers but is empirically imprecise (Hsu and Ching, 2023; Sallam, 2023; Surameery and Shakor, 2023). To address this weakness, Microsoft integrated GPT-4 technology into its Bing search engine to maintain the strength of the generative conversational AI agent with the support of updated web search information. Meanwhile, Google has provided a convenient button linked to Google's search engine after users' queries on Bard, encouraging users to explore further through more Internet searches.

Another crucial dimension of intrinsic information is believability, which pertains to the credibility and trustworthiness of information (Aladwani and Dwivedi, 2018; Chen and Tseng, 2011). Regarding generative conversational AI agents, believability (trust) in the data generated is one of the most important criteria that should be matched to effectively and efficiently use it in the decision-making process (Chen and Tseng, 2011; Dwivedi et al., 2023a; Erdem and Ozen, 2003). Remarkably, the level of trust seems to consistently increase when using generative conversational AI agents. This trend is identified through the increasing number of users, which reached approximately 100 million (Ruby, 2023) on 18th of May 2023. Furthermore, according to a recent report published by Statista (2023a), approximately 26.5 % of ChatGPT users expressed trust and believability in the content generated by such systems.

The significant influence of intrinsic information quality has been supported by many studies in information systems such as Bliemel and Hassanein (2007), Chae et al. (2002), Chen and Tseng (2011), Ghasemaghaei and Hassanein (2019), Herrera-Viedma et al. (2006), and Widiyanto et al. (2016). Houhamdi and Athamena (2019) showed that intrinsic information quality has a significant impact on decision-making quality. Similarly, Ge and Helfert (2013) confirmed intrinsic information quality (accuracy) as a key predictor of decision-making quality in the supply chain area. Thus, this study proposes the following hypothesis:

H1. Generative conversational AI agent intrinsic information quality will positively impact the decision-making efficiency.

3.3. Generative conversational AI agent contextual information quality (GCAIACIQ)

Wang and Strong (1996, p. 19) operationalised contextual information quality as "the requirement that data quality must be considered within the context of the task at hand; that is, data must be relevant, timely, complete, and appropriate in terms of amount so as to add value" (Ge and Helfert, 2013; Houhamdi and Athamena, 2019). According to this dimension, the judgment of the quality of information must consider the nature of the objective based on this information (Kim et al., 2017; Lee et al., 2002; Seppänen and Virrantaus, 2015). Therefore, the high level of contextual quality of information produced by generative conversational AI agents is governed by the extent to which the data can inform highly efficient decision-making (Chen and Tseng, 2011; Ghasemaghaei et al., 2018; Saha et al., 2012).

In practical terms, the successful execution of these tasks, which involve highly efficient decision-making, predominantly relies on the usefulness (value-added) and recency of the information utilised (Cheung et al., 2008; Dwivedi et al., 2023b; Filieri and McLeay, 2014; Kim et al., 2017; Xie et al., 2016). Timeliness was considered one of the most important challenges faced by ChatGPT which was trained mainly on information and data collected before 2021. This is reflected in the usefulness and feasibility of using this information to make decisions that address contemporary problems in 2023 and beyond (Dwivedi et al., 2023b; Hsu and Ching, 2023; Sallam, 2023; Seppänen and Virrantaus, 2015; Temsah et al., 2023).

Value-added is another dimension of contextual information quality pertaining to the degree to which users of generative conversational AI agents can benefit from the information provided by these applications to make more informed decisions (Kim et al., 2017). Generative conversational AI agents offer a high level of convenience, enabling decision makers to use them around the clock, regardless of their location, and with increased effectiveness and efficiency (Kohnke et al., 2023). Thus, this study proposes the following hypothesis:

H2. Generative conversational AI agent contextual information quality will positively impact the decision-making efficiency.

3.4. Generative conversational AI representational information quality (GCAIARIQ)

In line with Wang and Strong (1996, p. 21), representational information quality covers “aspects related to the format of the data (concise and consistent representation) and meaning of data (interpretability and ease of understanding)”. Two critical sub-dimensions (interpretability and representational consistency) reflect representational information quality and the efficiency and effectiveness of using this information in the decision-making process (Chae et al., 2002; Ghasemaghaei and Hassanein, 2019; Seppänen and Virrantaus, 2015). The quality of representational information focuses on the technical features of information structures (Ghasemaghaei et al., 2018). Hence, the concept of generative conversational AI agent representational information quality (GCAIARIQ) involves evaluating the interpretability and consistent representation of information provided by the generative conversational AI agent (Seppänen and Virrantaus, 2015). Thus, this study proposes the following hypothesis:

H3. Generative conversational AI agent representational information quality will positively impact the decision-making efficiency.

3.5. Generative conversational AI agent accessibility of information quality (GCAIAAIQ)

Accessibility can refer to the extent to which a user can conveniently and securely access the required data (Ghasemaghaei and Hassanein, 2019; Lee et al., 2002; Wang and Strong, 1996). Technically, accessibility of information quality is primarily related to the features and functionalities of applications that enable convenient and safe information access (Seppänen and Virrantaus, 2015). A new report conducted by corporate IT and cybersecurity decision makers at the beginning of 2023 revealed that in various countries, 53 % of the surveyed sample believed that hackers may infiltrate ChatGPT to generate phishing emails that seem credible and legitimate (Statista, 2023c). This, in turn, makes issues related to accessibility and security the focus of attention for both users and generative application developers (Bozkurt and Sharma, 2023; Lomas, 2023; Ray, 2023). Generative AI service providers have been keen to enhance technical features related to ease of navigation and security to create a unique and positive user experience (Baidoo-Anu and Owusu Ansah, 2023; Bozkurt and Sharma, 2023). According to a report by Statista (2023b), the latest version of ChatGPT has shown a significant reduction (82 %) in the response rate to requests for unauthorised content. This reflects positively on ChatGPT4 users' experience, as this version has demonstrated a remarkable reduction (89 %) in producing malicious content compared to previous versions (Statista, 2023c). Thus, this study proposes the following hypothesis:

H4. Generative conversational AI agent accessibility of information quality will positively impact the decision-making efficiency.

3.6. Novelty seeking (NVK)

Conceptually, Hirschman (1980) and Jang and Feng (2007) defined novelty seeking as the degree to which a person exhibits curiosity and motivation to try new things. Correia et al. (2008) operationalised novelty seeking as an individual and psychological trait that can predict a person's tendency to adopt what is new (i.e. generative conversational AI agents). In this respect, Dabholkar and Bagozzi (2002) addressed novelty seeking as a quality that predicts a person's readiness to try new systems. Borhan et al. (2019) argued that individuals with a high tendency to seek novelty are more likely to be intrinsically motivated to adopt new systems and search for new stimuli. As discussed earlier, generative conversational AI agents have been recently introduced (November 2022), and therefore, it is as an emerging AI system that has been commonly attributed with innovativeness (Dwivedi et al., 2023b; Elmustapha et al., 2018; Javaid et al., 2023). Therefore, this study considers novelty seeking as an external factor to be examined alongside information quality dimensions. Decision makers who enjoy a high level of novelty seeking are expected to use generative conversational AI agents effectively and successfully in their endeavours to make informative decisions. Thus, this study proposes the following hypothesis:

H5. Novelty seeking will positively impact the decision-making efficiency.

3.7. Ethical concerns (ETC)

According to Koroma et al. (2022, p. 3), “ethical concerns comprise of regulations on the conduct of transactions which include; legal implications of smart contracts, personal data, investing money through virtual assets, and the advent of disruptive technology”. The implications of generative conversational AI agents as credible sources of information are among the most controversial issues for academics and practitioners (Hsu and Ching, 2023; Koroma et al., 2022). This is because of the ongoing arguments concerning the ethical and legal dimensions of the correct and safe use of generative conversational AI agents (Sallam, 2023; Treiblmaier and Sillaber, 2021). This leads to questioning the extent to which ethical and accountability issues may affect the effective use of such technologies (Hsu and Ching, 2023; Jain et al., 2023; Stahl and Eke, 2024; Treiblmaier and Sillaber, 2021; Rahimi and Abadi, 2023). Hsu and Ching (2023) found that ethical concerns typically emerge when generative systems are manipulated to harm individuals and society by creating unreliable content and spreading negative publicity. Technically, a generative system is based on trained data, some of which are obtained from the Internet. Therefore, any type of bias, inaccuracy, or deception in the trained data is more likely to result in concerns that generative systems could unintentionally perpetuate and share misinformation (Ray, 2023). These problems may make decision makers reluctant to use generative conversational AI agents because they are exposed to ethical and legal questions if the information generated from this system is biased and distorted. Furthermore, using generative conversational AI agents could require users to disclose sensitive and confidential organisational data, which creates concerns about information privacy and security (Ray, 2023). In this respect, a new report published by Statista (2023b) suggested that 3 % of employees who have used ChatGPT have uploaded sensitive and confidential organisational information. Sallam (2023) highlighted the need for cooperation among all stakeholders to develop an ethical and legal framework that guarantees the safe and correct use of generative conversational AI agents. Thus, this study proposes the following hypothesis:

H6. Ethical concerns will negatively impact decision-making efficiency.

3.8. Decision-making efficiency (DME)

In line with Ghasemaghaei et al. (2018), decision-making performance is defined as the extent to which decision makers are able to make high-quality and efficient decisions. In other words, a high-performance decision-making process should yield accurate, precise, and reliable decision outcomes with less time and effort (Gilbert-Saad et al., 2023; Jarupathirun, 2007; Shamim et al., 2020). It has been widely argued that emerging systems (AI; big data analytics, chatbots, machine learning, and generative AI systems) have considerably expanded the information sources available to decision makers (Aringhieri et al., 2016; Deveci et al., 2023; Issa et al., 2022; Li et al., 2022; Mikalef and Gupta, 2021; Youn and Jin, 2021; Xuan, 2022; Wilson and Daugherty, 2018). This is in addition to the ability of such smart systems to empower decision makers with high levels of sensing and analytical capabilities that help them make highly rational and accurate decisions (Aringhieri et al., 2016; Duan et al., 2019; Gilbert-Saad et al., 2023; Youn and Jin, 2021). This, in turn, positively reflects an organisation's innovativeness and creativity (Duan et al., 2019; Wilson and Daugherty, 2018). Thus, high-quality and efficient decision-making performance helps business organisations speedily recognise and fully utilise potential innovative opportunities, and accordingly, accelerate the process of continuous improvement of all activities and functions at all levels within the organisation, which enhances the culture of creativity and innovativeness (Aydiner et al., 2019; Bag et al., 2021; Pietronudo et al., 2022). Furthermore, high-quality and efficient decisions foster the ability of such organisations to develop and launch new products and services for the target market (Aydiner et al., 2019; Bag et al., 2021; Ravichandran et al., 2005; Yalcin et al., 2022). Further, a high-performance decision-making process comprises a high-quality risk-benefit analysis of the available options for decision makers. Thus, business organisations will be better able to avoid costly wrong decisions while creating an environment that is more risk-bearing and innovation-enhancing (Abubakar et al., 2019; Aven, 2009; Keding and Meissner, 2021; Lăzăroiu et al., 2020). In light of the above discussion, this study proposes the following hypothesis:

H7. Decision-making efficiency will positively impact innovation performance.

4. Methodology

This study used a quantitative research approach, as it is more deductive and theoretical (Maier et al., 2023). Online questionnaires were distributed to a purposive sample of 400 employees from various business organisations in Saudi Arabia. The selected participants were required to be involved in decision-making processes and have experience with generative conversational AI agents. In this respect, it is important to mention that the potential implications of generative conversational AI agents are vast, spanning various contexts and user perspectives, including employees, customers, researchers, marketers, students, academics, and healthcare professionals (Jeyaraj et al., 2023). However, this study specifically focuses on employees engaged in decision-making processes who also have experience with generative conversational AI agents. This focus is justified, given that the primary domain of the current study is business organisations. The central aim of this study is to empirically examine the influence of key factors related to the content quality of generative conversational AI agents on decision-making efficiency. Employees across various hierarchical levels were best suited for furnishing the empirical data required for this research. The data collection process commenced June 1st, 2023, and ended June 30th, 2023. In total, 228 participants completed the questionnaire, with a response rate of 57 %.

All dimensions of information quality (GCAIAIIQ, GCAIACIQ, GCAIARIQ, and GCAIAAIQ) were treated as multidimensional, as proposed by Lee et al. (2002) and Wang and Strong (1996). GCAIAIIQ was measured using two factors (believability and accuracy), GCAIACIQ was measured using two sub-dimensions (value-added and timeliness), GCAIARIQ was measured using two factors (interpretability and presentational consistency), and two sub-dimensions (accessibility and access security) were considered to reflect GCAIAAIQ.

As demonstrated in Appendix A, the believability, timeliness, and accuracy measurement items were adapted from Lee et al. (2002) and Shamala et al. (2017). Value-added was measured using three items derived from Rasool et al. (2020). Furthermore, the four scale items proposed by Lee et al. (2002) and validated by Shamala et al. (2017) were used to measure representational consistency. The three items suggested by Lee et al. (2002) were adapted to measure interpretability, access security, and accessibility. The ethical concern measurement items were derived from Koroma et al. (2022) and Wang et al. (2023), whereas the scale items from Dabholkar and Bagozzi (2002) were used to test novelty seeking. Decision-making efficiency was tested based on scale items proposed by Jarupathirun (2007) and later validated by Ghasemaghaei et al. (2018). Finally, Mardani et al.'s (2018) scale was used to measure innovation performance.

A seven-point Likert scale ranging from strongly disagree to strongly agree was adopted to measure the degree of the respondents' agreement with these items. The questionnaire was also validated by experts in related areas to ensure adequacy and clarity of all scale items. The experts are professors in information systems, as well as in AI and conversational agents. The experts supported all scale items to reflect the latent constructs to be measured. A pilot study with a small sample size (25 respondents) was conducted to ensure that all items were understandable and applicable over the related areas of the decision-making process. Cronbach's alpha values for all constructs were tested and found to be above 0.70, as recommended by Nunnally (1978).

5. Results

5.1. Demographic characteristics

Of the 400 questionnaires allocated, 228 (57 % response rate) were returned and deemed valid for the current study. As seen in Table 1, the vast majority of respondents were male (65 %). As for the respondents' age distribution, the age categories 31–40 (32.46 %) and 41–50 (33.77 %) represented the majority of the sample. More than half of the respondents (62.72 %) had a bachelor's degree, followed by those who had a master's degree (19.74 %) and diploma (10.53 %). Approximately 22.81 % of the current sample worked in marketing, 20.61 % in HR, and 17.11 % worked in the operations area. Regarding the economic sector, the largest portion of the sample was from the wholesale and retail trade sectors (19.31 %), followed by the manufacturing and industrial sectors (15.35 %). Regarding experience with generative conversational AI agents, 32.02 % of the total sample had been using generative conversational AI agents for 3–4 months, and approximately 25 % had an experience of 4–5 months. Finally, ChatGPT appeared to be the most preferred and commonly used generative conversational AI agent (57.02 %), whereas approximately 42.98 % of the sample preferred Google Bard.

Table 1
Demographic characteristics.

Demographic profile	Number of respondents (*N* = 228)	Percentage (%)
Gender		
Male	148	65 %
Female	80	35 %
Total	228	100 %
Age		
18–30	46	20.18 %
31–40	74	32.46 %
41–50	77	33.77 %
51–60	26	11.40 %
61–65	4	1.75 %
65+	1	0.44 %
Total	228	100 %
Education Level		
High school	5	2.19 %
Diploma	24	10.53 %
Bachelor	143	62.72 %
Master	45	19.74 %
PhD	11	4.82 %
Total	228	100 %
Job field		
IT	20	8.77 %
HR	47	20.61 %
Finance	36	15.79 %
Marketing	52	22.81 %
Operation	39	17.11 %
Other	34	14.91 %
Total	228	100 %
Economic sector		
Wholesale and retail trade	14	19.31 %
Finance and insurance	26	11.40 %
Information and communication	44	6.14 %
Manufacturing and industrials	34	15.35 %
Construction	13	5.70 %
Transportation and storage	16	7.02 %
Accommodation and food service	19	14.91 %
Education	35	8.33 %
Health and social care	21	9.21 %
Other	6	2.63 %
Total	228	100 %
Generative Conversational AI Agent Experience		
<1 month	16	7.02 %
2–3 months	48	21.05 %
3–4 months	73	32.02 %
4–5 months	57	25 %
Since it has been launched in November 2022	34	14.91 %
Total	228	100 %
Preferred generative conversational AI agent		
ChatGPT	130	57.02 %
Google Bard	98	42.98 %
Total	228	100 %

Table 2
Descriptive statistics of the measurement items.

Construct	Item	Mean	Std. Deviation	Skewness	Kurtosis
TIML	TIML1	5.90	1.281	−1.417	2.249
	TIML2	5.73	1.281	−1.329	1.762
	TIML3	5.92	1.205	−1.222	1.624
	TIML4	5.69	1.353	−1.040	0.793
	TIML5	5.78	1.302	−1.080	1.123
	TIML6	5.65	1.295	−1.229	1.380
	Average	5.78	1.286		
VDD	VDD1	5.95	1.180	−0.911	0.629
	VDD2	5.69	1.463	−1.002	0.631
	VDD3	5.99	1.198	−0.973	0.706
	Average	5.88	1.280		
BVL	BVL1	6.08	1.246	−1.496	1.976
	BVL2	6.07	1.276	−1.558	2.403
	BVL3	5.84	1.462	−1.581	2.537
	BVL4	5.88	1.215	−0.744	−0.024
	BVL5	5.70	1.216	−1.056	0.803
	Average	5.91	1.283		
ACCR	ACCR1	5.77	1.297	−0.801	0.163
	ACCR2	5.70	1.267	−0.915	0.519
	ACCR3	5.72	1.261	−0.976	0.897
	ACCR4	5.74	1.263	−0.962	0.704
	ACCR5	5.82	1.182	−1.114	1.101
	Average	5.75	1.254		
INTER	INTER1	5.62	1.281	−0.810	0.337
	INTER2	5.71	1.272	−1.097	1.434
	INTER3	5.76	1.196	−0.842	0.408
	Average	5.70	1.250		
RPC	RPC1	5.68	1.313	−1.060	1.060
	RPC2	5.58	1.367	−0.832	0.364
	RPC3	5.53	1.349	−0.530	−0.484
	RPC4	5.48	1.290	−0.852	0.406
	Average	5.57	1.330		
ACC	ACC1	5.82	1.213	−1.512	2.625
	ACC2	5.80	1.342	−1.168	1.018
	ACC3	5.93	1.267	−1.069	0.953
	Average	5.85	1.274		
AS	AS1	5.80	1.300	−1.088	0.584
	AS2	5.73	1.277	−0.967	0.620
	AS3	5.89	1.181	−0.947	0.229
	Average	5.81	1.253		
DME	DME1	5.84	1.239	−1.165	1.457
	DME2	5.62	1.266	−0.916	0.426
	DME3	5.70	1.245	−1.006	1.134
	DME4	5.81	1.189	−0.901	0.778
	DME5	5.70	1.252	−0.878	0.749
	DME6	5.79	1.238	−0.950	0.376
	Average	5.74	1.238		
INNP	INNP1	5.65	1.285	−0.884	0.345
	INNP2	5.56	1.278	−0.885	0.398
	INNP3	5.58	1.384	−0.901	0.716
	INNP4	5.81	1.196	−0.845	0.429
	Average	5.65	1.286		
ETC	ETC1	2.94	1.262	−1.129	1.082
	ETC2	2.74	1.302	−1.217	1.424
	ETC3	2.97	1.192	−1.217	1.615
	ETC4	2.74	1.351	−1.308	1.670
	Average	2.84	1.277		
NVK	NVK1	5.83	1.280		
	NVK2	5.69	1.293	−1.293	1.536
	NVK3	5.98	1.188	−1.312	1.786
	NVK4	5.69	1.485	−0.987	0.808
	Average	5.80	1.312		

5.2. Descriptive statistics of the measurement items

As presented in Table 2, all scale items were positively rated by the sample respondents, with mean values not less than five, except for ETC. For example, six items used to measure the TIML had a mean value of 5.78 (standard deviation (SD) = 1.286). The three items used to measure VDD were also highly rated by the respondents, with a mean value of 5.88 (SD = 1.280). A mean value of 5.91 (SD = 1.283) was also accounted for the five scale items considered to measure BVL, whereas a mean value of 5.75 (SD = 1.254) was reported for ACCR. The three items adapted to measure INTER recorded a mean value of 5.70 (SD = 1.250), whereas the four items used to test RPC had a mean value of 5.57 (SD = 1.330). The three ACC items accounted for a mean value of 5.85 (SD = 1.274). The NVK items were also positively rated by the respondents, with a mean value of 5.80 (SD = 1.312). However, the respondents expressed interest in ethical issues, as the four items used to test ETC accounted for a mean value of 2.84 (SD = 1.277). In addition, the six items adopted to test the DME recorded a mean value of 5.74 (SD = 1.238). Finally, with a mean value of 5.65 (SD = 1.286), four items of the INNP were highly estimated by the sample participants.

A normality test was performed for all the scale items using skewness kurtosis. This step was conducted to ensure that the collected data were normally distributed and free from violations of normality (Byrne, 2010; Hair et al., 2010; Kline, 2005). The threshold value considered for skewness should be between −3 and 3, whereas the threshold value for kurtosis should be <8 (Byrne, 2010; Hair et al., 2010; Kline, 2005; West et al., 1995). As seen in Table 2, all skewness values yielded from the current scale items were between −3 to 3 and kurtosis values <8, which in turn, indicates that the data for all scale items is normally distributed (Byrne, 2010; Hair et al., 2010; Kline, 2005; West et al., 1995). Furthermore, the Mahalanobis-D squared distance (D2) was tested to determine the outlier cases. Any case (observation) with a *p*-value <0.001 was considered an outlier. Approximately 20 cases were found to have a p-value <0.001 and were treated as outliers. Given that the current sample size was adequate and the generalisability of the results could be negatively affected by removing these 20 cases, a decision was made to retain these cases in the current study data and subsequently include them in additional analyses in SEM (Hair et al., 2010; Tabachnick and Fidell, 2007).

5.3. Structural equation modelling (SEM)

5.3.1. Measurement model

As reported in the methodology section, the information quality aspects of GCAIAIIQ, GCAIACIQ, GCAIARIQ, and GCAIAAIQ were proposed and tested as multi-dimensional constructs. As seen in Table 5, BLV and ACCR significantly loaded on GCAIAIIQ with regression weight values of 0.926 and 0.973, respectively. TIML and VDD loaded significantly on GCAIACIQ, with regression weight values of 0.980 and 0.768, respectively. Likewise, the GCAIARIQ sub-dimensions INTER and RPC had high standardised regression weight values of 0.994 and 0.950, respectively. High regression weight values were also accounted for by the GCAIAAIQ dimensions with AS (0.969) and ACC (0.981). It is also worth mentioning that various fit indices such as CMIN/DF, GFI, AGFI, NFI, CFI, and RMSEA were used to assess the goodness of fit of the measurement model. All yielded fit indices were found with their threshold values: CMIN/DF = 2.547, GFI = 0.914, AGFI = 0.867, NFI = 0.944, CFI = 0.958, and RMSEA = 0.057 (Anderson and Gerbing, 1988; Byrne, 2010; Bagozzi and Yi, 1988).

Criteria pertaining to construct validity, average variance extracted (AVE), and reliability (composite reliability) were matched for the main latent constructs (Anderson and Gerbing, 1988; Hair et al., 2010; Nunnally, 1978). As shown in Table 3, the CR values for all the constructs were >0.70, as suggested by Fornell and Larcker (1981) and Hair et al. (2010). The highest CR value (0.975) was accounted for by GCAIAAIQ, whereas the lowest CR value (0.799) was recorded for NVK. Likewise, all Cronbach's Alpha (α) values were close to the CR values accounted for latent constructs. For example, GCAIAAIQ exhibited the highest Cronbach's Alpha (α) (0.971), followed by GCAIARIQ (0.969). The lowest Cronbach's Alpha (α) was observed for NVK (0.796). Additionally, AVE values exhibited values higher than 0.50 (Fornell and Larcker, 1981; Hair et al., 2010). GCAIAAIQ had the highest AVE value of 0.951, whereas NVK had the lowest AVE value of 0.501.

As seen in Table 5, all scale items used to measure information quality dimensions have a factor loading (standardised regression weight value) higher than 0.50 (Hair et al., 2010). Discriminant validity criteria were attained, as shown in Table 4, with all inter-correlation values below 0.85, as recommended by Kline (2005). Furthermore, the squared root of the AVE values for all latent constructs was higher than the inter-correlation values accounted for by the corresponding constructs (Fornell and Larcker, 1981) (see Table 4).

Table 3
Constructs' reliability and validity.

	CR	Cronbach's Alpha (α)	AVE
ETC	0.871	0.870	0.629
GCAIACIQ	0.872	0.871	0.775
GCAIAIIQ	0.949	0.945	0.902
GCAIARIQ	0.972	0.969	0.945
GCAIAAIQ	0.975	0.971	0.951
DME	0.930	0.929	0.690
INNP	0.919	0.917	0.740
NVK	0.799	0.796	0.501

5.3.2. Structural model

The results of the second stage of the SEM analyses supported both the structural model goodness of fit and model predictive validity. For example, all fit indices (i.e. CMIN/DF = 2.976, GFI = 0.908, AGFI = 0.854, NFI = 0.907, CFI = 0.951, and RMSEA = 0.061) of the structural model were within the recommended level, which in turn supported the conceptual model's goodness of fit (Anderson and Gerbing, 1988; Bagozzi and Yi, 1988; Byrne, 2010). Furthermore, the current model accounted for 76 % and 68 % of the variance in DME and INNP, respectively. As seen in Fig. 2 and Table 6, path coefficient analyses have also supported the significant impact of GCAIACIQ ($\gamma = 0.502$, $p < 0.008$), GCAIAIIQ ($\gamma = 0.593$, $p < 0.000$), GCAIARIQ ($\gamma = 0.181$, $p < 0.031$), GCAIAAIQ ($\gamma = 0.329$, $p < 0.000$) on DME. The external factors ETC ($\gamma = -0.132$, $p < 0.035$) and NVK ($\gamma = 0.122$, $p < 0.041$) are also supported to have a significant impact on DME. Finally, a strong and significant relationship was confirmed between DME and INNP ($\gamma = 0.502$, $p < 0.000$) (see Table 6).

6. Discussion

Aligning with what was suggested and proposed in the conceptual model (Section 3), the empirical results support the selection of the information quality model as the theoretical base for this study. Initially, the model adequately fit the observed data, as all structural model fit indices were within their threshold levels. This study's model also accounted for a large portion of the variance in DME and INNP. This supports the validity and applicability of the information quality model in related areas of generative conversational AI agents. The empirical part of this study supports the ability of the information quality model (Wang and Strong, 1996) to cover the key standards and criteria of content that govern the effective and safe use of generative conversational AI agents in decision-making processes.

Path-coefficient analyses supported the significant impact of four dimensions of information quality–GCAIAIIQ, GCAIACIQ, GCAIARIQ, and GCAIAAIQ–on DME. In this respect, GCAIAIIQ was the most important and strongest predictor of DME, with a regression weight value of 0.593. These results clearly imply that decision makers who use generative conversational AI agents are concerned about the believability (credibility) and accuracy of the content provided by generative conversational AI agents. The higher the accuracy and credibility of the content provided by the generative conversational AI agent, the higher the effectiveness and quality of the decisions made. In this respect, it is worth indicating that updated versions of ChatGPT and Google Bard have been linked to their search engines to improve their technical strength in providing users with more credible and accurate information, as seen in ChatGPT4 and PaLM2 (Hsu and Ching, 2023).

As shown in Table 6, GCAIACIQ was the second strongest factor influencing DME, with a retrogression weight value of 0.502. This relationship indicates that users place significant emphasis on contextual quality (TIML and VDD) regarding the content created by a generative conversational AI agent. A high level of timeliness and value-added captured in the content of generative conversational AI agents leads users to make efficient business decisions. Practically, generative conversational AI agents provide decision makers with a high level of convenience, which in turn reflects the extent of the usability and timeliness of such systems (Kohnke et al., 2023). In addition to the adequacy and relevance of information, this accelerates the value perceived when using such applications (Chang and Kidman, 2023). In

Table 4
Discriminant validity.

	ETC	GCAIACIQ	GCAIAIIQ	GCAIARIQ	GCAIAAIQ	DME	INNP	NVK
ETC	**0.793**							
GCAIACIQ	−0.784	**0.880**						
GCAIAIIQ	−0.724	0.799	**0.950**					
GCAIARIQ	−0.753	0.774	0.801	**0.972**				
GCAIAAIQ	−0.781	0.805	0.818	0.717	**0.975**			
DME	−0.770	0.811	0.792	0.784	0.768	**0.831**		
INNP	−0.672	0.775	0.797	0.778	0.752	0.766	**0.860**	
NVK	−0.668	0.682	0.665	0.656	0.654	0.602	0.640	**0.708**

The square root of AVE values (diagonal) are in bold.

Table 5
Standardised regression weights.

			Estimate
TIML	<—	GCAIACIQ	0.980
VDD	<—	GCAIACIQ	0.768
BLV	<—	GCAIAIIQ	0.926
ACCR	<—	GCAIAIIQ	0.973
INTER	<—	GCAIARIQ	0.994
RPC	<—	GCAIARIQ	0.950
ACC	<—	GCAIAAIQ	0.981
AS	<—	GCAIAAIQ	0.969
TIML1	<—	TIML	0.860
TIML2	<—	TIML	0.863
TIML3	<—	TIML	0.823
TIML4	<—	TIML	0.731
TIML5	<—	TIML	0.797
TIML6	<—	TIML	0.699
VDD1	<—	VDD	0.829
VDD2	<—	VDD	0.661
VDD3	<—	VDD	0.781
BVL1	<—	BLV	0.791
BVL2	<—	BLV	0.772
BVL3	<—	BLV	0.797
BLV4	<—	BLV	0.849
BLV5	<—	BLV	0.827
ACCR1	<—	ACCR	0.795
ACCR2	<—	ACCR	0.825
ACCR3	<—	ACCR	0.853
ACCR4	<—	ACCR	0.774
ACCR5	<—	ACCR	0.828
INTER1	<—	INTER	0.810
INTER2	<—	INTER	0.839
INTER3	<—	INTER	0.832
RPC1	<—	RPC	0.847
RPC2	<—	RPC	0.775
RPC3	<—	RPC	0.708
RPC4	<—	RPC	0.867
ACC1	<—	ACC	0.825
ACC2	<—	ACC	0.843
ACC3	<—	ACC	0.841
AS1	<—	AS	0.770
AS2	<—	AS	0.852
AS3	<—	AS	0.872
DME1	<—	DME	0.841
DME2	<—	DME	0.832
DME3	<—	DME	0.881
DME4	<—	DME	0.813
DME5	<—	DME	0.834
DME6	<—	DME	0.781
INNP1	<—	INNP	0.901
INNP2	<—	INNP	0.896
INNP3	<—	INNP	0.827
INNP4	<—	INNP	0.812
ETC1	<—	ETC	0.816
ETC2	<—	ETC	0.837
ETC3	<—	ETC	0.806
ETC4	<—	ETC	0.705
NVK1	<—	NVK	0.782
NVK2	<—	NVK	0.745
NVK3	<—	NVK	0.705
NVK4	<—	NVK	0.583

Table 6
Hypotheses testing.

			Standardised estimate	Critical ratio	P
DME	<—	GCAIARIQ	0.181	2.158	0.031
DME	<—	GCAIACIQ	0.502	2.637	0.008
DME	<—	GCAIAIIQ	0.593	4.177	***
DME	<—	GCAIAAIQ	0.329	3.570	***
DME	<—	ETC	−0.132	−2.315	0.035
DME	<—	NVK	0.122	2.103	0.041
INNP	<—	DME	0.767	14.161	***

fact, GCAIACIQ has been commonly reported in the literature on information quality and systems as playing a crucial role in predicting either the usage of new systems or enhancing the quality and efficiency of the decision-making process (Barcellos et al., 2022; Hsu and Ching, 2023; Lee et al., 2002; Sallam, 2023; Seppänen and Virrantaus, 2015; Surameery and Shakor, 2023).

The structural model results strongly support the significant role of GCAIAAIQ in enhancing DME. Accessibility and access security have consistently been the most critical aspects when using generative conversational AI agents, as reported by Bozkurt and Sharma (2023), Lomas (2023), and Ray (2023). Indeed, generative AI service providers have shown a strong commitment to improving technical aspects such as user-friendly navigation and enhanced security, aiming to deliver a distinct and positive user experience (Baidoo-Anu and Owusu Ansah, 2023; Bozkurt and Sharma, 2023). This has been observed in newer versions of ChatGPT (ChatGPT4) which considered users' online security fears and attempted to fix the chatbot's incorrect behaviour regarding sensitive and unauthorised information on the Internet (Statista, 2023c). These results are consistent with what has been validated and supported regarding the significant role of GCAIAAIQ (see Ge and Helfert, 2013; Houhamdi and Athamena, 2019; Kim et al., 2017; Lee et al., 2002; Seppänen and Virrantaus, 2015).

The last information quality dimension, GCAIARIQ has also been shown to have a positive and significant impact on DME. These results suggest that users can make highly efficient decisions if the content created by generative conversational AI agents is interpreted and represented consistently (Seppänen and Virrantaus, 2015). Developers of generative conversational AI agents have been increasingly invested in improving the technical features of information structure and interpretability. This, in turn, positively reflects users' experiences and makes such systems more informative and useful for the decision-making process. Theoretically, the significant impact of the GCAIARIQ has been tested and validated by several studies that proposed information quality models, such as Chae et al. (2002), Ghasemaghaei and Hassanein (2019), and Seppänen and Virrantaus (2015).

As expected, external factors, ethical concerns, and novelty seeking were approved for DME prediction. The significant result for ethical concerns demonstrates that users are attentive to ethical issues related to the implications of generative conversational AI agents in decision-making. The credibility of generative conversational AI agents as reliable sources of information remains highly debated among academics

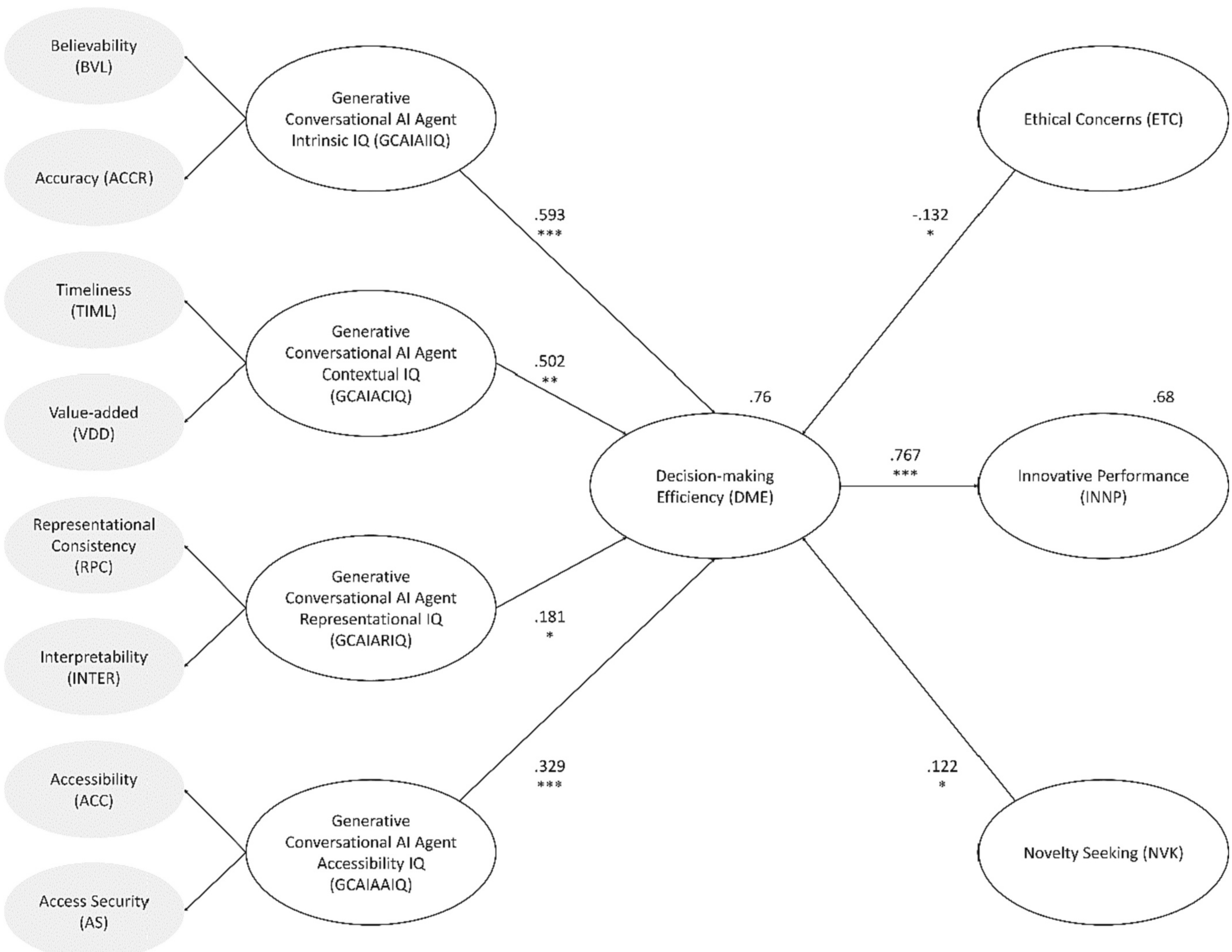

Fig. 2. Validation of conceptual model.
(***: *p*-value ≤001; **: p-value ≤01; *: p-value ≤005).

and practitioners (Hsu and Ching, 2023; Koroma et al., 2022). This controversy stems from ongoing discussions regarding the ethical and legal considerations associated with the proper and secure utilisation of generative conversational AI agents (Sallam, 2023; Treiblmaier and Sillaber, 2021). Consequently, relevant questions arise regarding the potential impact of ethical and accountability issues on the successful implementation of this technology (Hsu and Ching, 2023; Rahimi and Abadi, 2023; Treiblmaier and Sillaber, 2021). Indeed, ethical aspects of using generative conversational AI agent has been a key issue reported by different studies to be considered and tested (i.e. Hsu and Ching, 2023; Koroma et al., 2022; Sallam, 2023; Treiblmaier and Sillaber, 2021).

Novelty seeking was the least significant factor according to the path coefficient analyses. This implies that users with a strong inclination towards novelty seeking are more inclined to actively use generative conversational AI agents. Consequently, they are more likely to achieve improved performance in the decision-making process. Generative conversational AI agents debuted in November 2022, marking a significant milestone in this field. Since their introduction, they have been widely recognised for their novelty and innovativeness. Researchers and experts in this field have acknowledged the unique capabilities and potential of generative conversational AI agents in revolutionising various industries. The emergence of these technologies has captured the attention of academics, industry professionals, and technology engineers. Its introduction sparked a flurry of research, discussions, and explorations of its applications, implications, and impact on society. The novelty of generative conversational AI agents lies in their ability to generate human-like conversations, facilitating engaging interactions between AI systems and users. The novelty of generative conversational AI agents has recently been reported by various researchers including Dwivedi et al. (2023b), Elmustapha et al. (2018), and Javaid et al. (2023). In addition, novelty seeking has been confirmed by different information systems and innovation diffusion studies as a key driver that accelerates the adoption and usage of such innovative systems and applications (Borhan et al., 2019; Correia et al., 2008; Dabholkar and Bagozzi, 2002; Jang and Feng, 2007).

6.1. Theoretical implications

As discussed in the Introduction and Literature Review, few studies have empirically tested generative conversational AI agents from a business perspective. This is because of the recent introduction of these technologies. Therefore, this study makes a considerable contribution as it is among the first empirical studies to expand the current understanding of the effective use of generative conversational AI agents for managerial practices (i.e. decision-making and innovation).

Furthermore, this study concentrated on the quality of the content created by these smart systems. Generative conversational AI content quality has recently been considered a highly controversial topic, and there is a significant gap between supporters and opponents regarding the use of these systems as credible sources of information, especially in decision-making processes. Therefore, this study provides a clear framework for monitoring the use of generative conversational AI agents. This could be attributed to the fact that this is the first study to propose an information quality model (Wang and Strong, 1996) that presents a comprehensive theoretical framework to provide a clear picture regarding the most important criteria of information quality.

This proposed information quality model makes a significant theoretical contribution. This model can assess the credibility and accuracy of the information generated by smart systems, ensuring its safe and effective use in the decision-making process. Furthermore, four main dimensions–GCAIAIIQ, GCAIACIQ, GCAIARIQ, and GCAIAAIQ–were proposed in the information quality model and considered in this study. Each of these dimensions also consist of sub-aspects that allow for a more accurate perception of the criteria governing the quality of the information created by generative conversational AI agents. For example, accuracy and believability were captured in GCAIAIIQ, timeliness and value-added were addressed in GCAIACIQ, interpretability and presentational consistency were captured in GCAIARIQ, and accessibility and access security were reflected in GCAIAAIQ. Consequently, decision makers are equipped with a clearer and more accurate understanding, enabling them to assess the value and quality of the available information and its suitability for the decision-making process.

Another contribution of this study is the consideration of two external factors—ethical concerns and novelty seeking—alongside information quality dimensions. This expands the scope of generative conversational AI agents by addressing societal and ethical issues. The information quality model concentrates solely on the content provided by generative conversational AI agents, whereas ethical concerns are primarily related to the user's perspective and the mechanisms involved in using such systems without biases and information distortion. Novelty seeking considers the user's perspective by considering the influence of personal traits. Therefore, this study was able to expand the theoretical horizon of the information quality model by considering ethical concerns and novelty seeking, as well as new settings.

6.2. Practical implications

The results of this study also provide insights for practitioners and decision makers regarding the main conditions and standards that guarantee the safe and effective use of generative conversational AI agents. Thus, the significant role of GCAIAIIQ in enhancing DME focuses on the aspects related to believability and accuracy. Further efforts are required to sustain these aspects. Enhancing information believability requires decision makers to critically review and assess the content of generative conversational AI agents by initially considering information plausibility and seeking authenticating evidence from trustworthy sources to validate the generated content. For example, fact-checking, which is conducted by comparing a generative conversational AI agent's content with reliable and official sources of information, is highly recommended. This helps avoid any distortion or imprecision in the content provided.

The significant role of GCAIACIQ also assures the importance of both the value-added and timeliness of the content of generative conversational AI agents. This requires decision makers to initially define the key standards that determine the feasibility and usability of a generative conversational AI agent's content. Such standards should measure the relevance, inclusiveness, and novelty of the generated content. The decision maker should also check that the information provided is up-to-date and relevant to current issues that the organisation seeks to address.

These results provide valuable insights into the significant influence of GCAIARIQ. Consequently, greater attention should be directed towards the aspects of representational consistency and interpretability in generative conversational AI systems. Improving representational consistency requires greater emphasis on the structure and style of presenting information in a consistent and readable manner. This also requires providing users with different formats to present the given information, and allows them to freely select a suitable presentation format for their tasks. The degree of clarity and ease of interpretation of information are also considered mandatory requirements for facilitating its use in the decision-making process. This requires training on how to use key phrases and words accurately to obtain accurate, relevant, and interpretable answers.

The final information quality dimension, GCAIAAIQ, should also be considered. Specifically, security and accessibility features should be improved by ensuring that all information provided to a generative conversational AI agent or provided by such systems is fully protected from unauthorised access. Decision makers should focus on which organisational information should be uploaded to a generative conversational AI agent and it should be securely stored and retrieved. This requires an ethical reference framework that regulates the correct and ethical use of such applications while ensuring their integrity and high transparency.

6.3. Limitations and future research directions

Although this study is of considerable value to both researchers and practitioners, there are several limitations which should be addressed in future studies. This study has exclusively considered decision-making efficiency as the key outcome of using generative conversational AI agents. However, this study uncovered other important factors (i.e. user engagement, user flow experience, user attitudes, and trust), which future studies should focus on to provide an accurate picture of the user's interaction and perception towards these aspects. This study proposes a model based on the information quality model, ethical concerns, and novelty seeking. However, new perspectives and theories (i.e. the social cognitive model, technology readiness, knowledge-based views, and information boundary theory) should also be considered in future research. This study has addressed the issues related to the use of generative conversational AI agents from a decision-making perspective in the business sector. Thus, concerns exist regarding the generalisability of this study's results to other contexts and from the perspective of different types of users. Therefore, it would be useful to examine the implications of these systems from other user perspectives (i.e. students, employees, technicians, and entrepreneurs) in different settings (i.e. universities, healthcare, tourism, and hospitality). Furthermore, future studies should examine the reflection and implications of generative artificial intelligence on emerging horizons, such as the metaverse, in terms of consumers, employees, firm interfaces, and value creation. This recommendation is strongly supported by Dwivedi et al. (2022), Pandey (2023), and Ratican et al. (2023).

7. Conclusion

As discussed at the beginning of this study, generative conversational AI agents (i.e. ChatGPT and Google Bard) present a major breakthrough in the world of technology and information and have received considerable interest across various sectors and professional domains. Notably, the business sector attaches great importance to the use of generative conversational AI agents. However, the implications of these technologies as credible sources of information remains a controversial issue, lacking consensus among academics and practitioners. Therefore, this study focused on the adoption of generative conversational AI agents within the business sector and from the perspective of decision makers. The information quality model was adopted as the theoretical foundation for the conceptual model in this study. Four constructs from the information quality model–GCAIAIIQ, GCAIACIQ, GCAIARIQ, and GCAIAAIQ–have been proposed as the key determinants of DME. Furthermore, this study conducted 20 exploratory interviews with employees involved in decision-making processes and with experience with generative conversational AI agents. Accordingly, two external factors (novelty seeking and ethical concerns) were derived from these interviews and proposed as key predictors of DME. An online questionnaire was used to collect quantitative data from a purposive sample of 228 (response rate of 57 %) business organisations in Saudi Arabia. SEM analyses largely supported the impact of information quality dimensions and external factors (novelty seeking and ethical concerns) on DME, which, in turn, influence innovation performance. This study makes a considerable contribution to both academics and practitioners, as it expands the current understanding of the effective use of generative conversational AI agents within decision-making contexts.

CRediT authorship contribution statement

Conception and design of study; Acquisition of data; Analysis and/or interpretation of data; Drafting the manuscript; Revising the manuscript critically for important intellectual content; Approval of the version of the manuscript to be published: **Abdullah M. Baabdullah**.

Data availability

The data that has been used is confidential.

Appendix A. Measurement items

Construct		Items		Sources
Generative Conversational AI Agent Intrinsic IQ (GCAIAIIQ)	Believability (BVL)	BVL1	The information generated by generative conversational AI agent is credible.	Lee et al. (2002); Shamala et al. (2017)
		BVL2	The information generated by generative conversational AI agent is believable.	
		BVL3	The information generated by generative conversational AI agent is trustworthy.	
		BVL4	The information generated by generative conversational AI agent is referred as true.	
		BVL5	The information generated by generative conversational AI agent is accepted as correct.	
	Accuracy (ACCR)	ACCR1	The information generated by generative conversational AI agent is accurate.	
		ACCR2	The information generated by generative conversational AI agent is correct.	
		ACCR3	The information generated by generative conversational AI agent is reliable.	
		ACCR4	The information generated by generative conversational AI agent is meaningful	
		ACCR5	The information generated by generative conversational AI agent is certified error-free.	
Generative Conversational AI Agent Contextual IQ (GCAIACIQ)	Timeliness (TIML)	TIML1	The information generated by generative conversational AI agent is sufficiently timely.	
		TIML2	The information generated by generative conversational AI agent is sufficiently current for our work.	
		TIML3	The information generated by generative conversational AI agent is sufficiently up to date for our work.	
		TIML4	The information generated by generative conversational AI agent can be used on timely for risk response decisions.	
		TIML5	The information generated by generative conversational AI agent is current at the time creation and revision dates.	
		TIML6	The information generated by generative conversational AI agent is initiated and assessed with respect to a specific time frame.	
	Value-added (VDD)	VDD1	The information generated by generative conversational AI agent offer us an advantage of letting to know more than we already do.	Rasool et al. (2020)
		VDD2	Generative conversational AI agent provides beneficial information which helps the task at hand and also adds a pool of knowledge to us.	
		VDD3	The information generated by generative conversational AI agent adds value to our knowledge.	
Generative Conversational AI Agent Representational IQ (GCAIARIQ)	Representational Consistency (RPC)	RPC1	The information generated by generative conversational AI agent is presented consistently.	Lee et al. (2002); Shamala et al. (2017)
		RPC2	The information generated by generative conversational AI agent is represented in a consistent format.	
		RPC3	The information generated by generative conversational AI agent is consistently presented in the same format.	
		RPC4	The information generated by generative conversational AI agent provides a consistent response to risk in accordance with the organisational risk frame.	
	Interpretability (INTER)	INTER1	It is easy to interpret what generative conversational AI agent's information means.	Lee et al. (2002)
		INTER2	Generative conversational AI agent's information is easily interpretable.	
		INTER3	The measurement units for generative conversational AI agent's information are clear.	
Generative Conversational AI Agent Accessibility IQ (GCAIAAIQ)	Access Security (AS)	AS1	This information generated by generative conversational AI agent is protected against unauthorised access.	
		AS2	This information generated by generative conversational AI agent is protected with adequate security.	

(continued on next page)

(*continued*)

Construct		Items		Sources
		AS3	This information generated by generative conversational AI agent can only be accessed by people who should see it.	
	Accessibility (ACC)	ACC1	This information generated by generative conversational AI agent is easily retrievable.	
		ACC2	This information generated by generative conversational AI agent is easily obtainable.	
		ACC3	This information generated by generative conversational AI agent is quickly accessible when needed.	
Decision-making efficiency (DME)		DME1	In our firm, decision outcomes are often accurate.	Jarupathirun (2007)
		DME2	In our firm, decision outcomes are often precise.	
		DME3	In our firm, decision outcomes are often flawless.	
		DME4	In our firm, decision outcomes are often reliable.	
		DME5	In our firm, decision outcomes are often correct.	
		DME6	In our firm, the time to arrive at decisions is fast.	
Innovative performance (INNP)		INNP1	Our firm is quick in coming up with novel ideas as compared to key competitors.	Mardani et al. (2018)
		INNP2	Our firm is quick in new product launching as compared to key competitors.	
		INNP3	Our firm is quick in new product development as compared to key competitors.	
		INNP4	Our firm is quick in problem solving as compared to key competitors.	
Ethical concerns (ETC)		ETC1	I always comply with ethical principles when using generative conversional AI agent.	Koroma et al. (2022); Wang et al. (2023)
		ETC2	I am always alert to privacy and information security issues when using generative conversional AI agent.	
		ETC3	I am always alert to the abuse of generative conversional AI agent.	
		ETC4	Ethics impact knowledge requirements regarding the adoption of generative conversational AI agent.	
Novelty seeking (NVK)		NVK1	In our firm, we are always seeking new ideas and experiences using generative conversational AI agent.	Dabholkar and Bagozzi (2002)
		NVK2	In our firm, we like to find unfamiliar experiences using generative conversational AI agent.	
		NVK3	In our firm, we like to continuously change activities using generative conversational AI agent.	
		NVK4	In our firm, we like to experience novelty and change in our daily routine using generative conversational AI agent.	

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