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# Artificial intelligence-based public healthcare systems: G2G knowledge-based exchange to enhance the decision-making process

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ABSTRACT

With the rapid evolution of data over the last few years, many new technologies have arisen with artificial intelligent (AI) technologies at the top. Artificial intelligence (AI), with its infinite power, holds the potential to transform patient healthcare. Given the gaps revealed by the 2020 COVID-19 pandemic in healthcare systems, this research investigates the effects of using an artificial intelligence-driven public healthcare framework to enhance the decision-making process using an extended model of Shaft and Vessey (2006) cognitive fit model in healthcare organizations in Saudi Arabia. The model was validated based on empirical data collected using an online questionnaire distributed to healthcare organizations in Saudi Arabia. The main sample participants were healthcare CEOs, senior managers/managers, doctors, nurses, and other relevant healthcare practitioners under the MoH involved in the decision-making process relating to COVID-19. The measurement model was validated using SEM analyses. Empirical results largely supported the conceptual model proposed as all research hypotheses are significantly approved. This study makes several theoretical contributions. For example, it expands the theoretical horizon of Shaft and Vessey's (2006) CFT by considering new mechanisms, such as the inclusion of G2G Knowledge-based Exchange in addition to the moderation effect of Experience-based decision-making (EDBM) for enhancing the decision-making process related to the COVID-19 pandemic. More discussion regarding research limitations and future research directions are provided as well at the end of this study.

## 1. Introduction

With the rapid evolution of data in recent years, several new technologies have emerged, with artificial intelligence (AI) being the most prominent (Balakrishnan & Dwivedi, 2021a; de Sousa, de Melo, Bermejo, Farias, & Gomes, 2019; Janssen, Brous, Estevez, Barbosa, & Janowski, 2020). AI has been extensively discussed in the healthcare literature (Bunker, 2020; Dilsizian & Siegel, 2014; Patel et al., 2009). The new coronavirus (COVID-19) pandemic is the most serious international crisis in a generation, and it has occurred at a time when the widespread use of AI in the real world is being demonstrated (Dwivedi et al., 2020; Puaschunder, 2020). With its extensive power, AI has the potential to transform patient healthcare (Chung et al., 2020). Powered by the growing availability of healthcare data and rapid analytical techniques, AI has introduced a paradigm shift in healthcare (Yu, Beam, & Kohane, 2018). In addition, AI techniques are a potentially effective method for crisis management and decision-making (Dwivedi et al., 2021). Guided by relevant clinical concerns, AI techniques can unlock clinically key data hidden in massive datasets, with the result that clinical decision-making can be assisted (Dilsizian & Siegel, 2014).

AI systems help healthcare practitioners offer appropriate patient care by providing up-to-date health information from publications and clinical practices (Lee, Nagy, Weaver, & Newman-Toker, 2013; Sun & Medaglia, 2019). AI system can help in reducing diagnostic and

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therapeutic errors that are inevitable in human clinical practice (Dilsizian & Siegel, 2014; Sodhro, Luo, Sangaiah, & Baik, 2019). It can also retrieve useful information from a large patient population to make factual inferences for health risk alerts and health outcome predictions (Neill, 2013; Sipior, 2020).

The 2020 COVID-19 pandemic has had a global impact and revealed gaps in the structure of healthcare systems across the world (Coombs, 2020). In fact, The nature of this epidemic is that it needs the cooperation of all governmental and civil authorities specialized in the health and medical area as well as requires a large degree of information exchange and sharing so as to facilitate making accurate decisions on the right time and right place. This, in turn, created persistent need to think more about using emerging systems (i.e. AI and machine learning) to handle such crisis (Raza, 2020). Different countries have responded to the crisis in different ways, sharing experiences and responses and using cutting-edge innovative AI-based technologies to flatten the crisis curve and develop the most effective means of dealing with the pandemic (Puaschunder, 2020). Thus, a good number of researchers have argued the potential comprised in using AI applications to contribute to the way that health organizations can provide their services to a large number of patients in more efficient and reliable manner than human (i.e. Davenport & Kalakota, 2019; Lalmuanawma, Hussain, & Chhakchhuak, 2020). This does not mean dispensing with the role of human interaction but rather empowering and enabling healthcare practitioners to have accurate diagnosis and make correct decisions (i.e. Lalmuanawma et al., 2020). Practically, there are many uses of AI-based healthcare technologies, from tracking and monitoring cases and preventing the spread of infection to helping doctors and specialists share knowledge in order to better solve problems and make accurate decisions (Vaishya, Javaid, Khan, & Haleem, 2020).

However, there is still a concern regarding the applicability and effectiveness of such emerging systems in dealing with COVID-19 crisis especially over the developing countries like Saudi Arabia. This is especially in the light of the fact that the investment from the government in AI-based technologies over the medical and health area is not easy process and asking for more resources and efforts. Therefore, there is a need to have a full understanding regarding the aspects pertaining to using an AI-based public healthcare system and how these emerging systems could contribute to both problem solving performance and decision making process.

Given the nature of the new Corona epidemic that appeared at the beginning of 2020 also the novelty of artificial intelligence application, there is a dearth of studies that have examined the applicability of AI-based healthcare technologies to deal with COVID-19. Based on that, this research aims to investigate the effects of using an AI-based public healthcare system to enhance the decision-making process. This study focuses on public healthcare organizations in Saudi Arabia and uses an extended version of Shaft and Vessey's (2006) cognitive fit model in the presence of government-to-government (G2G) knowledge-based exchange in addition to the moderation role of experience-based decision-making (EBDM) as a confirmation step. Thus, in order to acknowledge the previous knowledge gaps, this research will examine the following research question:

RQ: How can health institutions improve the quality of decision-making process through the use of AI-based public healthcare systems?

This study will advance the current understanding of the successful use and implementation of AI in the government health sector, especially in light of the impact of the COVID-19 epidemic (Jiang et al., 2017). From practical perspective, this study will also attempt to provide a solid framework of governing guidelines that will help Saudi healthcare authorities in their endeavours to successfully implement and effectively use AI applications for problem-solving and decision-making.

In light of the above, the study is structured as follows. In the next section, we reviewed the related literature and addressed different studies that discuss the definition of the concept of "artificial intelligence, the importance of AI in Healthcare and the role of AI in Healthcare has been addressed. In addition, series of technologies related to AI techniques which have immediate relevance to the health sector and the usage of these AI-based technologies in Healthcare have been discussed. Moreover, the literature review explored the AI situation in Saudi Healthcare and investigated the Usage of AI-based Healthcare Technologies after COVID-19 in Saudi Arabia. In the third section, the research outlined the theoretical background and a critical literature review is presented regarding the conceptual model and hypotheses development. A brief overview of the methodology and Research designs is presented in Section 4. Additionally, Section 5 presents the results of the descriptive statistics preview of data characteristics, an illustration of data dispersion, inferential statistics and summary of the tests of the conjectured hypotheses. Followed by Section 6 about the research discussion; where we present the theoretical contortions, the practical implication and the limitations as well as the future research directions. Finally, in Section 7, the conclusion is drawn against the research problem, the objectives achieved leading to the summary and concluding remarks.

## 2. Literature review

In a rapidly changing world, unexpected global crises can dramatically and rapidly change traditional behavioural norms (Puaschunder, 2020). AI is the principle and development of computer systems capable of performing tasks that typical involve human intelligence (Laï, Brian, & Mamzer, 2020). AI consists of mechanisms that behave in ways known to be intelligent if performed as a human activity. These mechanisms can be used to solve difficulties that affect numerous applications associated with intelligent behaviour (Schwab, 2017). This is linked to an individual's capacity of observation and learning as well as to their ability to make concrete decisions on subjects related to intelligent reasoning (Benko & Lányi, 2009). Therefore, AI and related applications have been representing interesting issues for researchers in various sectors (Fahle et al., 2020; Lalmuanawma et al., 2020). Among the sectors that have been the focus of attention of AI researchers are E-government and digital healthcare sector (i.e. Chen, Guo, Gao, & Liang, 2020; Dilsizian & Siegel, 2014; Jiang et al., 2017; Kaushik & Raman, 2015; Matheus, Janssen, & Janowski, 2020). In the current literature review, more clarifications and discussion will be provided regarding the AI concept, importance and implications. Further, it will be provided a part of discussion regarding the role of AI to deal with COVID-19 especially these attempts by Saudi Arabia healthcare organizations.

### 2.1. Definition of AI

The definition of the concept of "intelligence", and even more so of "artificial intelligence", is the subject of much debate and has created considerable confusion. According to the definition of Marvin Minsky, one of the founding fathers of AI, "AI simply means that a machine is able to do a task which is considered to be an intelligent one by human beings" (Laï et al., 2020, p. 1). Turing (1950) argued that, in order for a machine to be called intelligent, it would have to demonstrate behaviour that is indistinguishable from that of a human being. Indeed, AI is a practice that can be categorized in two ways: (1) as an effort to replicate the human mind's capabilities; and (2) as the development of resources for carrying out tasks that currently involve human action. AI has been split into several sub-disciplines that relate to unique aspects (such as problem-solving and learning).

There is no single research model, and some branches of AI have developed an interdisciplinary exchange among scholars, psychologists, computer scientists, and those interested in the different issues of AI (Schneider, 1996). McCorduck, Minsky, Selfridge, and Simon (1977) noted that AI can also be understood as a concept; during the 1956

Dartmouth Conference, John McCarthy and Marvin Minsky invented AI not only as a discipline but also as a concept. The general and abstract concept that the human mind makes of a real or abstract object of thought allows it to integrate the different interpretations of that object.

Moreover, the definitions have also changed over time due to the rapid developments in the field. AI commonly refers to the computational technologies that mimic or simulate processes supported by human intelligence, such as reasoning, deep learning, adaptation, interaction, and sensory understanding (Kok, Boers, Kosters, Van der Putten, & Poel, 2009). The current digital revolution is characterized by a fusion of technologies developing at unprecedented rates (Schwab, 2017). This convergence is best demonstrated by Turing's (1950) description of AI as the science and engineering of intelligent machines (Yampolskiy, 2013).

### *2.2. AI in healthcare*

AI research in healthcare is accelerating rapidly, with potential applications being demonstrated across various medical and decision-making domains. However, only a few examples of such approaches have successfully been applied in clinical practice (Jiang et al., 2017; Kumar, Dwivedi, & Anand, 2021). Traditional methods of building intelligent systems, such as rule-based systems, were unable to produce the desired results until people discovered that computers can measure more than just numbers. With its apparently limitless power, AI holds the promise to revolutionize patient healthcare. It creates a paradigm shift in healthcare due to increasing healthcare data availability and the rapid progress of analytical techniques (Yu et al., 2018). AI is already commonly used to access information, and it is starting to be introduced in healthcare for various purposes, such as facilitating clinical ordering systems and identifying high-risk patients for screening tests (Reddy, Fox, & Purohit, 2019). In their systematic review study, Lalmuanawma et al. (2020) recently have scanned and analysed the main body of literature that have tested the related issues of using AI and learning and learning machine to address the consequences of COVID-19 epidemic. Their results assured the crucial role of these emerging systems in epidemiological survey and investigation, prediction, and track positive cases.

The revolutionary promise of AI in healthcare has been widely documented, with possible applications across a broad range of medicines and healthcare (Ericsson, 2004). This promise has been embraced as healthcare systems strive to deliver on the "quadruple goal": to enhance the care experience, to improve public health, to reduce per capita healthcare costs, and to improve healthcare providers' working lives (Phillips, Androski, & Winks, 2018). Significant concerns about the implementation of AI systems in healthcare include those inherent to the science of machine learning, technical difficulties, barriers to adoption, and the required socio-cultural or pathway changes (Kelly, Karthikesalingam, Suleyman, Corrado, & King, 2019; Shareef et al., 2021). The efficient and secure translation of AI research into clinically validated and properly regulated systems that can benefit everyone is challenging. AI systems can minimize undue variance in clinical practice, increase quality, and avoid preventable medical errors (Ruffolo, Curia, & Gallucci, 2005). AI will enable patients to play a more critical role in managing their wellbeing, primary care doctors to treat a wider variety of complex diseases, and specialists to provide greater diagnostic accuracy and infection control (Shen et al., 2019).

In recent years, significant progress has been made in the field of AI with advances in deep neural networks, natural language processing, computer vision, and robotics (Reddy et al., 2019). The future functions of AI techniques in the delivery of healthcare and medical research are becoming increasingly clear (Agah, 2013). Studies have highlighted the efficacy and potential of AI-enabled health applications (Ramesh, Kambhampati, Monson, & Drew, 2004). These applications are now actively being applied in healthcare, and many health service activities currently being delivered by clinicians and administrators are predicted to be taken over by AI in the coming years (Hurst, 2000). As a result, there is an active discussion about whether AI health professionals will eventually replace human physicians (Murdoch & Detsky, 2013). Another systemic review study by Vaishya et al. (2020) has also reported a number of common AI applications which have been actively used by specialist and practitioners over the healthcare area to deal with COVID-19 epidemic. Such of these applications reported by Vaishya et al. (2020) are early diagnosis of positive cases; intelligent observation platform and mechanism to predict the spread of COVID-19; following up contacts of infected cases and communicating with them; using the huge data sources available on social media platforms and analysing them in order to predict the nature of the virus (Dwivedi et al., 2020), how it will spread, the risks associated with it, and the expected deaths.

Artificial intelligence is one of the most important tools that experts and researchers use to access a large amount of research and scientific articles that they need in order to develop vaccines and drugs that contribute to treating this disease. The use of artificial intelligence applications also helped to greatly reduce the burden of health personnel and increase the efficiency of treatment for them; finally, the ability of artificial intelligence to collect, analyse and provide updated information helps greatly to contain this disease and reduce the rate of infection spread (Vaishya et al., 2020). However, Naudé (2020) argued that that the applications of artificial intelligence were not sufficiently effective in limiting the impact and spread of the COVID-19 epidemic due to the lack of the large volume of information required or even the inability to easily access the bases of that information.

Although we do not believe that machines will replace human physicians in the foreseeable future, AI can nevertheless help physicians make better clinical decisions and possibly even replace human judgment in healthcare-specific functional areas. The increased availability of health data and the rapid growth of broad data analytical methods have made possible the current successful applications of AI in healthcare. Driven by relevant clinical issues, effective AI techniques can unlock clinically relevant knowledge from a vast volume of data, thereby assisting clinical decision-making (Dilsizian & Siegel, 2014). Analysis of the large amount of data obtained from electronic health records can yield clinically relevant knowledge, facilitate diagnostic tests, provide real-time risk ratings, and enhance decision-making strategies (Horn, 2000).

### *2.3. AI-based healthcare technologies*

The growing use of AI in health and medicine has received extensive research attention. In addition, advances in computational power paired with massive amounts of data generated in healthcare systems make many clinical problems ripe for AI applications. A global network of authors' keywords and content analysis of related scientific literature highlight several significant techniques, including robotics, machine learning, artificial neural networks, AI, and natural language processing, as well as their most frequent applications in clinical prediction and treatment (Pawar, O'Shea, Rea, & O'Reilly, 2020). AI and related inventions are increasingly prevalent in business and society and are starting to be applied in healthcare. These technologies can transform many aspects of patient care and administrative processes for providers, patients, and customers of pharmaceutical and healthcare organizations (Davenport & Kalakota, 2019).

AI is not a single technology; instead, it is a series of technologies. Most AI techniques have immediate relevance to the health sector, but there are wide differences between the particular processes and tasks that they help (Puaschunder, 2020). A significant strength of AI in healthcare applications is an ultra-rapid analysis of large datasets (Big Data) (Bag, Pretorius, Gupta, & Dwivedi, 2021). AI uses rule-based systems to capture high-level articulable patterns and relationships, neural network-based deep learning systems to capture low-level, non-articulable patterns and relationships, and the two-hybrid system (Zang, Zhang, Di, & Zhu, 2015). More recently, Rasheed et al. (2020) have attempted to discover the most common AI tools and applications considered by health organizations to handle the related issues of COVID-19. This paper aimed to explore and understand how and which different technological tools and techniques have been used within the context of COVID-19. According to three common applications have been extensively applied and used in this regard which are machine learning, computer-aided diagnosis, and deep learning.

In particular, through the use of deep learning image analysis tools, AI technology can be developed to support radiologists in the triage, quantification, and trend analysis of data (Ackermann et al., 2020). According to Shi et al. (2020), AI for imaging may be used to improve workflow at the hospital level by automating practitioners' interpretations and forecasting the future need for ICU and ventilator capacity. At the societal level, AI may be used to forecast hospital capacity needs and to aid in assessing the need for lockdowns and reopenings (Shi et al., 2020). A fascinating aspect that has emerged around the utilization of AI-based approaches in managing the COVID-19 pandemic has been the speed of prototyping solutions and their integration in end-to-end applications that can be easily deployed in healthcare settings and even in makeshift caring facilities (Greenspan, Van Ginneken, & Summers, 2016). The pandemic has revealed deep neural networks' ability to develop end-to-end products based on a model representation that can be executed across a wide range of devices (Rodrigo, Aledo, & Gámez, 2019). Another important aspect has been the need for large-scale deployments due to the high incidence of COVID-19 infections (Pan & Zhang, 2020). Greenspan, Estépar, Niessen, Siegel, and Nielsen (2020) indicated that these deployments have been empowered by using cloud-based computing architectures and multi-platform web-based technologies. Multiple private and open-source systems have been rapidly designed, tested, and deployed in the last few months (Greenspan et al., 2020).

### 2.4. The usage of AI-based healthcare technologies

During the current COVID-19 pandemic, several governments have enforced numerous social distancing strategies such as travel bans, border protection, shutting public areas, and advising people to keep 1.5–2 m apart while going outdoors (Meinert, Milne-Ives, Surodina, & Lam, 2020). However, such drastic and significant interventions are difficult to implement; for example, not all public areas can be shut, and individuals always leave the house for meals, healthcare, or jobs. In such situations, technologies can help to promote social distancing initiatives. For example, artificial intelligence (AI), thermal imaging, machine learning, ultrasound, and electromagnetic waves have recently been implemented to solve several emerging issues about social distancing, including contact tracking, locked up individuals, identification and tracking, and symptoms predictions (Hameed et al., 2020).

Governments need to provide accurate, useful, and up-to-date information to people, particularly during times of crisis. According to the United Nations Division for Public Institutions and Digital Government (2020), governments started providing information on their national portals, mobile apps, or social media platforms during the COVID-19 pandemic. A review of the national portals of the 193 members of the UN showed that by 25 March 2020, 57% (110 countries) of them had put in place some kind of information on COVID-19, while around 43% (83 countries) had not provided any information; however, by 8 April 2020, around 86% (167 countries) had included information and guidance in their portals about COVID-19.

### 2.5. The global AI in healthcare market size

The value of AI in the healthcare sector is forecast to expand from US $4.9 billion in 2020 to US$45.2 billion by 2026, and it is projected to rise at a compound annual growth rate of 44.9% over the coming years (Markets & Markets, 2020). The main factors driving sector growth are the growing volume of health data and the increasing complexity of datasets, the increasing need to reduce high healthcare costs, improved computing power and declining hardware costs, an increasing number of cross-industry partnerships and collaborations, and the adoption of AI technology by numerous pharmaceutical and biotechnology companies to accelerate vaccine or drug development processes for COVID-19.

### 2.6. AI in Saudi healthcare

Social distancing is critical in avoiding the spread of infectious diseases including certain COVID-19. We may minimize the likelihood of getting the infection and transmitting it across the population by limiting close physical interactions between people. Evolving artificial intelligence (AI)-driven technologies have the potential to allow, promote, and even implement social distancing. These tools provide several innovative solutions and strategies for dealing with social distancing issues, such as symptom identification, detection and tracking of quarantined individuals, interaction tracing, and the creation of various realistic social distancing contexts (Nguyen et al., 2020).

Healthcare applications with integrated AI are currently being developed around the world and raise several professional, societal, and ethical issues (Pauwels & Vidyarthi, 2017). The Kingdom of Saudi Arabia is not considered a pioneer in the "AI for health" landscape. Nevertheless, Saudi Arabia is on the verge of entering into the international competition with the implementation of new strategies within its Vision 2030 to improve healthcare activities and citizens' health (ElGibreen, 2020).

Medical data can be used to make effective decisions on the spread of disease. At present, machine learning and predictive analytics techniques have proved to be important in the analysis of data. Predictive analytics techniques can provide practical solutions for healthcare-related problems, and machine learning models can automatically predict critical information to learn about COVID-19 and its patterns of infection. In Saudi Arabia, the technology to tackle COVID-19 and predict its spread in various cities has largely taken a dataset perspective and employed methodologies such as naïve Bayes and support-vector machine approaches. Saudi Arabia uses prediction models to understand recovery and mortality cases of COVID-19 infection in Saudi regions (Muniasamy, Bhatnagar, & Karunakaran, 2020).

With the official release of Vision 2030 in Saudi Arabia, the Ministry of Health (MoH) has been developing new strategies to transform the entire health sector (ElGibreen, 2020). Recent investments in the Saudi technology sector have proved successful with the use of technology interventions to combat COVID-19. Various services have been provided to the public through mobile applications (e.g., 'Mawid' booking appointments), and drone technology has been used to track and monitor infected individuals. Thus, Saudi Arabia's containment strategy focuses on mitigation and suppression approaches alongside technology interventions to prevent the virus's spread (Alanezi et al., 2020). These approaches are intended to minimize personal interaction between patients and doctors in a real-time healthcare environment by using the latest applications of neural networks, AI, Big Data, and predictive data analytics within healthcare operations (Galetsi, Katsaliaki, & Kumar, 2020; Jadi, 2020). Technical healthcare services, which have been rapidly growing in Saudi Arabia over several years, offer a wide range of solutions to various medical problems. These services extensively use information and communication technologies to obtain information and apply it when necessary (Blaya, Fraser, & Holt, 2010). Finally, to ensure effectiveness and patient safety, it is of the utmost importance for all Saudi healthcare authorities to build a dynamic framework to carry out the development of the regulatory guidelines for all AI implementations of healthcare products and services (Baig, Almuhaizea, Alshehri, Bazarbashi, & Al-Shagathrh, 2020).

### 2.7. The usage of AI-based healthcare technologies after COVID-19 in Saudi Arabia

The Saudi MoH has been using AI to facilitate medical care during the COVID-19 emergency. It has launched several electronic services to help people and promote health awareness. The services include 'Tetamman', which is an app designed to provide protection and healthcare for citizens and residents in domestic isolation or quarantine. In addition, the MoH has released a WhatsApp chatbot, featuring an interactive chat that enables users to choose one of the following services: information on COVID-19, Primary Healthcare Centre locations, 'Mawid' (appointment) service, initiatives for health volunteering and blood donation, and contact with a COVID-19 representative. Both systems use AI, business intelligence, and a new electronic inspection system. Moreover, the MoH developed the 'Tabaud' app to track the spread of COVID-19. The app allows users to know if they have had contact with people confirmed to be infected with COVID-19. In addition, it sends proactive notifications to users if any confirmed cases during the previous 14 days are detected through the app, while maintaining data confidentiality. Furthermore, the MoH released 'Tawakkalna', an app that shows users' health status through coloured codes. The app also allows individuals to break the infection chain by reporting infected cases or gatherings that violate the adopted precautionary measures. Furthermore, the MoH introduced the e-health 'Seha' app for doctors and patients, which is designed to provide an online medical consultation with the elite of the MoH's accredited doctors across all specialties. It enables patients to receive these consultations via chat, voice, or video calls, and users can evaluate their experience at the end of the medical consultation (Ministry of Health, 2020).

Habeeb and Lo'ai (2018) presented details about the analysis of mobile cloud-based networked healthcare systems and proposed a topology for converging the mobile healthcare cloud infrastructure in Saudi Arabia. The authors focused on the city of Makkah. The healthcare systems' network contains three hospitals: Al Noor Specialist Hospital, King Abdullah Medical City Specialist Hospital, and Maternity and Children Hospital. The three hospitals and the Makkah City Data Centre are connected to hospitals in other Saudi cities via the InterCity links (using a separate router called the Makkah City Healthcare Systems Router), which enables access to data from the Makkah City Data Centre.

## 3. Theoretical background, conceptual model and hypotheses

### 3.1. Theoretical background

This section discusses the use of the extended cognitive fit theory (CFT) of Shaft and Vessey (2006) as a theoretical basis for this research. We consider previous studies that have adopted this theory in the area of AI, especially in healthcare, and outline the factors added to extend the theoretical base in the proposed model.

When it comes to understanding decision efficiency while using data representations to tackle decision making tasks, cognitive fit theory (CFT) has emerged as an important theoretical lens. Given the supposed consensus about the theoretical criticalities of cognitive effort in CFT-based studies, researchers have made minimal efforts to assess cognitive effort and its effects on an empirical basis. Bacic and Henry (2018), assessed cognitive effort specifically to explain how cognitive fit affects and how decision performance affects. They found that cognitive fit only affects cognitive effort in more complicated tasks and cognitive effort, but does not affect decision time. These results helped in understanding the existing IS concept and promote more research into the cognitive foundations of CFT. In addition, Kopp, Riekert, and Utz (2018) have investigated the influence on users' accuracy and speed in the resolution of business tasks based on various types of tasks of data labels in row and bar charts. Their findings showed that users interpret diagrams with repetitive labels as much more useful and address relevant queries more accurately and faster and that they have the cognitive fit theory as an explanation. They provide useful insights into the cognitive processing of diagrams and enable graphic designers to take redundant components as possible for performance improvements in such circumstances. In contrast, Padilla, Creem-Regehr, Hegarty, and Stefanucci (2018) have examined empirical decision-making studies based on a broad range of research objectives with static two-dimensional visualizations and find substantial direct and indirect support for dual process decision-making accounts with visualizations. They highlighted the usefulness of a decision-making dual process account through visualizations, which may be general concepts of visualization. In addition, Baker, Jones, and Burkman (2009) clarified how visual data representations make data exploration possible for individual sensory processes. They draw on human cognition and cognition theories, including the theory of cognitive health, in order to clarify the factors that make sensory representations for the audience simpler. Three main contributions were made: first, they include an overall characterization of the visual images used for data exploration. Second, Cognitive Fit Theory is expanded into the task domain of data exploration. Thirdly, they propose a number of theoretical proposals on how visual representation of data should serve the purpose of sensing.

CFT suggests that the efficiency and effectiveness of a solution to a problem depends on a fit between the problem representation and problem-solving (Vessey, 1991). Cognitive fit occurs when the decision processes required by the task match the decision processes supported by the problem representation. When cognitive fit occurs, a consistent and accurate mental representation of the problem results (Vessey & Galletta, 1991). In turn, this leads to more effective and efficient task performance. When the problem representation does not match the task, cognitive fit will not occur because similar decision processes cannot be used for both the problem representation and the task (Jonassen, 2000). As a result, the problem solver must exert additional cognitive effort either to transform the problem representation to better match the task or to transform their decision processes to better match the problem representation. The increased cognitive effort due to a lack of cognitive fit will increase task time and/or decrease accuracy (Vessey, 1991, 1994; Vessey & Galletta, 1991).

Shaft and Vessey (2006) extended the cognitive fit model by distinguishing between the external problem representation – that is, the information presentation format – and the internal representation of the problem domain – that is, the individual's prior task knowledge. According to Shaft and Vessey (2006), both the external and internal representations and their interactions influence the mental representation of a task solution. Thus, cognitive fit depends on the characteristics of the task's internal problem representation, characteristics, and presentation format. Research findings generally support the theory of cognitive fit (Kershaw & Tuttle, 1998; Speier, 2006; Umanath & Vessey, 1994).

### 3.2. Conceptual model

As seen in Fig. 1, the current study conceptual model comprises 7 latent constructs [Internal AI-based COVID-19 Problem Domain Representations (Int.AI.PDR); External AI-based COVID-19 Problem Representations: G2G Knowledge-based Exchange (G2G.KE); AI-enabled COVID-19 Problem-Solving Performance (AI.PSP); Mental Representation for AI-based COVID-19 Task Solution: AI-based COVID-19 Diagnosis (AI·D); AI-enabled COVID-19 Decision-Making Process (AI.DMP); Experience-based Decision-Making (EBDM); AI-based COVID-19 Problem-Solving Task (U.AI.HT): Usage of AI-based Healthcare Technologies (U.AI.HT)]. Fig. 1 shows that AI·D is expected to be predicted by the role of Int.AI.PDR, G2G.KE, and U.AI.HT. AI.PSP was also proposed by be influenced by the role of AI·D, which in turn, influences AI.DMP. As seen in Fig. 1, EBDM was proposed to moderate the relationship between AI.DMP and G2G.KE. More discussion and justifications regarding these factors and the proposed research hypotheses will be found in the forthcoming subsections.

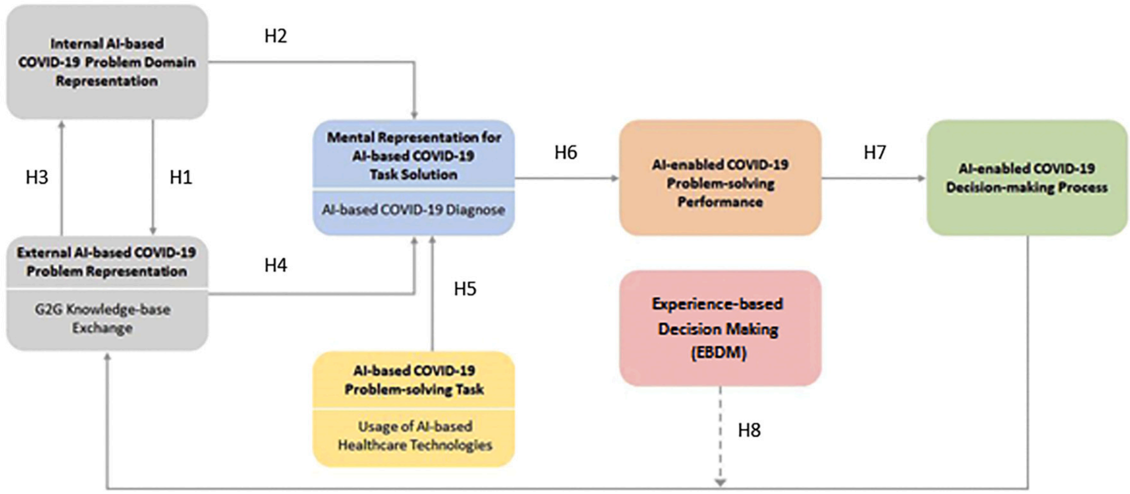


**Fig. 1.** Proposed conceptual model (adapted from Shaft & Vessey, 2006).

We found that the fit theory alone cannot cope with the research problem after analysing the literature, since it only focuses on the cognitive dimension which has been found to have an effect on the use of IS. This theory, however, disregards the technical characteristics of the decision-making task as a major factor deciding usage; in this case, the task technology fit (TTF) theory by Goodhue and Thompson (1995) may better explain this relationship by combining TTF with CFT, which would cover the organizational task and personal cognition. The literature indicates that, in addition to our key theory (CFT), the Task Technology Fit (TTF) theory is one of the most relevant theories used to explain this model extension. TTF theory argues that when technologies are used to match a task, they have a positive effect on performance outcomes. As a consequence, the TTF principle applies to the compatibility between a task and the technologies. Since its emergence, (TTF) has been used in a number of ways to better understand the relationship between tasks, technologies, usage, user responses, and productivity. Furthermore, we expanded the CFT model to incorporate experience-based decision making based on Leon Festinger (1962) Cognitive Dissonance Theory (CDT). Individuals, as per cognitive dissonance theory, have a propensity to seek continuity among their cognitions. As a result, after making the decision, we must ensure that it met the objectives. Where there is a mismatch between the target and the outcome (dissonance), actions must be taken to remove the dissonance. As a result, based on the CDT, we propose implementing an experience-based decision-making system to incorporate more consonant experience that outweighs dissonant outcomes and leads to consistent decisions with desired goals.

The framework presented above in Fig. 1 has its roots in Shaft and Vessey's (2006) extended cognitive fit model, which has been modified and extended to incorporate stored knowledge in enhancing the decision-making process regarding the COVID-19 pandemic. CFT offers an excellent and reliable theoretical lens for examining this model. Previous research on CFT emphasized the importance for user mental representation and total problem-solving performance of a congruence between problem task and problem representation (Vessey, 1991). While preliminary findings concentrated on tables versus diagrams, subsequent work has extended CFT to other specific representations, such as maps (Dennis & Carte, 1998), and has considered the impact of users' prior domain knowledge and the effect of subtasks (Shaft & Vessey, 2006). These results have important implications for analysing the effect of AI characteristics on problem-solving in general, especially in the context of healthcare, and for providing a range of knowledge in real time (Ismagiloiva, Dwivedi, & Rana, 2020). On the other hand, AI characteristics can also offer theoretical extensions. The implications of problem-solving in such multi-representation, multi-subtask, and real-time conditions remain uncertain, so our model makes a potentially important contribution to the theory. CFT, with suitable adaptations, can inform the design and construction of novel user interface artefacts (Vance, Lowry, & Eggett, 2015) for presenting AI.

### 3.3. Hypotheses development

#### 3.3.1. Internal AI-based COVID-19 problem domain representations

Vessey (1991) introduced CFT to explain presentation format research results and provide a theoretical basis for understanding information presentation effects. The early research focused on problem representation (i.e., presentation format), usually by comparing graphical and tabular presentations, to identify the most effective format for judgment and decision-making tasks using internal AI-based problem domain representations (Kelton, Pennington, & Tuttle, 2010). In this research, internal AI-based COVID-19 problem domain representations are the problem-solvers' own knowledge structures, which include those that can be retrieved from memory (e.g., a set of symbols to accomplish a particular task), the rules that govern them, and the processes for acting on them. On the other hand, external AI-based COVID-19 problem representations or knowledge-based systems are the most common AI systems in routine clinical use. They have knowledge about a specific task and can respond to patients' queries with data collected from various individual patients (Zaina, Negrini, & Atanasio, 2009). Therefore, we hypothesize:

**H1.** : Internal AI-based COVID-19 problem domain representations have a positive influence on G2G knowledge-based exchange.

The knowledge-based approach uses human logic to represent the solution for any given scenario. Since its central and core parts consist of interrelated statements that are not entirely identical but have a similar representation of the natural language, this mechanism has a significant advantage (Zhu et al., 2014). Knowledge representation using natural language is easy to understand and develop (Schlutter & Vogelsang, 2018). The AI-based COVID-19 task solution can be used in an automated decision system in which a general solution to a problem is fed using human logic (Harris & Davenport, 2005). Task solutions in knowledge-based mechanisms are mostly represented using logical operators or binary elements (Kiritsis, 1995). The benefit of this technique is the simplicity in designing and implementing the logic in an automated system (Zhu et al., 2014). Thus, we hypothesize:

**H2.** : Internal AI-based COVID-19 problem domain representations have a positive influence on AI-based COVID-19 diagnose.

#### 3.3.2. G2G knowledge-based exchange

External AI-based problem representations are the environment's knowledge and structures (Zhang, 1997). In this research, the proposed conceptual model uses the knowledge-based exchange system and AI-based G2G processes system to collect the updated knowledge of countries' experiences with COVID-19. According to Iyer, Singh, Salam, and D'Aubeterre (2006), the semantic G2G integration can support the transparent flow of semantically enriched information and knowledge. This research context includes content and know-how, and it enables collaborative G2G processes within and across government agencies regarding the COVID-19 pandemic, which influences AI-based COVID-19 problem domain representations (Putri, Sensuse, Mishbah, & Prima, 2020). The connections among the internal and external representations and the problem-solving task contribute to the progress of the mental representation for the task solution (Shaft & Vessey, 2006). This research stage concerns how AI can assist the practitioners in reaching a high level of knowledge quality for COVID-19 diagnosis using the G2G knowledge-based exchange and the internal AI-based COVID-19 problem domain representations. Nevertheless, humans will still have an important role. Although AI can improve diagnosis, leading to more effective treatments and better patient care, treatment and healthcare will still depend on human judgment. Different patients have different diagnosis needs and humans can respond better than machines (Agrawal, Gans, & Goldfarb, 2017). Therefore, we hypothesize:

**H3**. : G2G knowledge-based exchange has a positive influence on internal AI-based COVID-19 problem domain representations.

Interest in platforms linking the health sector, policymakers, and researchers in low- and middle-income countries has been growing. Sriram, Bennett, Raman, and Sheikh (2018) found that stakeholders could learn from the Indian experience and foresee some of the facilitators and obstacles that potentially emerge in the creation of such frameworks. Governments must provide a G2G knowledge-based exchange system and implement new techniques and practices for the centralized management of these systems, which would promote trust in the actors who use them and, by extension, in the actors' mental models that aid in problem-solving and decision-making processes (Sarantis, Charalabidis, & Askounis, 2010). Problem representation is how the solver mentally processes or reflects the information found in the problem using the AI-based task solution. This representation is related directly to the solver's current knowledge of the problem's content from the external AI-based problem representations (Lauterman & Ackerman, 2019). Relevant literature can be divided into two major topics: first, assessment of the relationship between government intervention and the spread of pandemics from the point of view of prevention and control of epidemics; and second, reflection on the government's knowledge exchange experience in managing epidemics from the point of view of public crisis governance (Duan, Jiang, Deng, Zhang, & Wang, 2020). The global "infodemic" resulting from the 2020 COVID-19 pandemic highlights the challenge of addressing the discipline of the information system and the urgency of finding workable solutions (Bunker, 2020). Thus, we hypothesize:

**H4**. : G2G knowledge-based exchange has a positive influence on AI-based COVID-19 diagnose.

#### 3.3.3. Usage of AI-based healthcare technologies

This stage considers the latest technologies that use AI in healthcare. AI can enhance the medical response to the COVID-19 pandemic in many different ways: supporting physicians by automating aspects of diagnosis, prioritizing healthcare resources, and improving vaccine and drug development (Shahid et al., 2020). In addition, AI has potential applications beyond instant responses, such as combatting online misinformation about COVID-19. Chatbots are the best example of an AI-based healthcare application (Nadarzynski, Miles, Cowie, & Ridge, 2019). Put simply, bots can do many things. For instance, if a patient wants to book an appointment with a doctor, the chatbot can find the next available time slot with a specific doctor, book the appointment, and (if appropriate) carry out a payment procedure (Burki, 2019). In addition, the healthcare organization can upgrade their bots to provide remote e-consultations with specialists through the audio and video features of a chatbot (Mold, Hendy, Lai, & de Lusignan, 2019). AI is superior in some respects to human intelligence, such as in visuospatial processing speed and pattern recognition, but it lags behind in terms of reasoning, new skill learning, and creativity (Wahl, Cossy-Gantner, Germann, & Schwalbe, 2018). Prediction of disease and improving an individual's healthcare can be made more efficient by integrating computing systems with AI methodologies (Simsek, Obinikpo, & Kantarci, 2020).

AI-based healthcare technologies can imitate human intelligence by classifying and predicting patient diseases using specific predictive and analytical approaches (Raza, 2020). The high-quality reporting of machine learning studies is critical. Only full and transparent reporting of information on all aspects of a diagnosis or prognosis model can lead to the adequate assessment of the prediction potential of these models and the avoidance of risk bias (Choy et al., 2018). AI-based healthcare technologies are expected to change the landscape of diagnosis and decision-making for physicians and patients and to affect all healthcare field stakeholders (Laï et al., 2020). Mental representations for the AI-based COVID-19 task solution allow us to represent things that have either never occurred or are impossible to occur, yet which can be imagined by our mental imagery (Shaft & Vessey, 2006). The research model will visualize the information in question and mentally represent the pictures to solve it using AI-based COVID-19 problem-solving task technologies. Therefore, we hypothesize:

**H5**. : Usage of AI-based healthcare technologies has a positive influence on AI-based COVID-19 diagnose.

#### 3.3.4. AI-based COVID-19 diagnosis

In the diagnosis stage, an AI-based COVID-19 task solution analyses a substantial proportion of data from diagnosis imaging, genetic testing, and electro diagnosis. For example, Gillies, Kinahan, and Hricak (2016) urged radiologists to adopt AI-based COVID-19 task solution when analysing diagnostic images that contain vast information. Shin et al. (2010) developed an AI-based COVID-19 diagnosis support system for locating neural injuries. In addition, physical examination notes and clinical laboratory results are primary data sources. They contain large portions of unstructured narrative texts, such as clinical notes; consequently, AI applications focus on converting the unstructured text to machine-understandable electronic medical records. For example, Karakülah et al. (2014) used AI technologies to extract phenotypic features from case reports to enhance the accuracy of diagnoses of congenital anomalies.

In cognitive psychology, the term "problem-solving" refers to the mental process used to discover, analyse, and solve problems. Before problem-solving can occur, it is important first to understand the exact nature of the problem itself (Wang, 2020). The brain's mental process helps us to remember, make decisions, organize, set goals, and be innovative, and the cognitive approach next focuses on the mental process of knowing how to direct attention, interpret, remember, perceive, and solve problems (Araujo, Mendez, & Gonzalez, 2019). Thus, we hypothesize:

**H6**. : AI-based COVID-19 diagnosis has a positive influence on AI-enabled COVID-19 problem-solving performance.

#### 3.3.5. AI-enabled COVID-19 problem-solving performance

Although there are many instances in which AI can perform healthcare tasks as well as or better than humans, implementation factors will prevent the large-scale automation of healthcare professional jobs for a considerable time to come (Bansal et al., 2019). Performance metrics should aim to capture real clinical and healthcare applicability and be understandable to intended users. Only through prospective studies will we understand AI systems' utility, as performance is likely to worsen when encountering real-world data (Kelly et al., 2019). Proper evaluation of real-world health performance and generalization requires sufficient external confirmation, including testing the AI system and the use of adequate datasets obtained from institutions (Kelly et al., 2019). This will ensure that all significant differences in patient demographics and disease status in real-world clinical practice are appropriately reflected in the frameworks where they will be used (Debray et al., 2015). Currently, this practice, although of critical concern, is rare in the literature.

In this research, we address how all the items in the model contribute to raising the level of knowledge for solving problems related to COVID-19. AI-enabled COVID-19 problem-solving can be defined as a collection of interrelated technologies used to solve problems autonomously (Kim & Hannafin, 2011). In addition, it performs tasks to achieve defined objectives, sometimes without explicit guidance from a human being (Debray et al., 2015). The AI-enabled COVID-19 decision-making process aims to construct a two-way exchange of symbols and actions that produce a holistic performance that exceeds the sum of the parts (Duan, Edwards, & Dwivedi, 2019). If this level of performance is to be achieved, the decision-making process must not only improve decision quality but also facilitate the decision-maker's interpretation of the quality of decisions made using the AI technology (Kasper & Andoh-Baidoo, 2015). The AI-enabled COVID-19 decision-making process can be a significant asset in the public health response to a pandemic or other health threat (Garcia, Cerrotti, & Palminteri, 2021). The AI-enabled COVID-19 decision-making process provides essential lessons about processes and outcomes for decision-making related to COVID-19. Thus, we hypothesize:

**H7.** : AI-enabled COVID-19 problem-solving performance has a positive influence on the AI-enabled COVID-19 decision-making process.

### *3.3.6. Experience-based decision-making*

Most AI systems are far from achieving accurate generalizability, let alone clinical applicability, for most forms of medical data. A vulnerable model can have blind spots that can lead to bad decisions (Kelly et al., 2019). Methods for detecting out-of-distribution inputs and providing a reliable measure of model confidence will be critical to avoid making clinical decisions on incorrect model outputs (DeVries & Taylor, 2018). This stage involves the highest levels of knowledge mining so that decisions are based on different experience-based decision-making scenarios related to COVID-19. There is a distinction between the two elements of choice: problem-solving and decision-making. This distinction helps identify appropriate roles for patients and providers, thereby leading to genuinely shared decision-making (Dubromel, Duvinage-Vonesch, Geffroy, & Dussart, 2020). If the decisions are inconsistent with the diagnosis of COVID-19, the steps are to be repeated from the beginning of the conceptual model. In addition, AI can use the cumulative lessons learned from COVID-19 to alert governments through the external AI-based COVID-19 problem representations to likely future pandemics (Davenport & Kalakota, 2019). Similarly, AI can further help analyse information and knowledge collected throughout the various phases of the COVID-19 pandemic around the world and enhance the AI-enabled COVID-19 problem-solving process (Kumar, Raut, & Narkhede, 2020). Some AI systems will be designed to evolve over time, representing a challenge to conventional assessment processes (Weiss-Cohen, Konstantinidis, & Harvey, 2021). Development of ongoing performance monitoring guidelines to consistently calibrate models using experience-based decision-making would help the recognition of performance deficits over time (Muro, Larburu, Bouaud, & Seroussi, 2017). Therefore, we hypothesize:

**H8.** : Experience-based decision-making moderates the impact of an AI-enabled COVID-19 decision-making process on G2G knowledge-based exchange.

## 4. Methodology

Given the COVID-19 epidemic and the resulting lockdown in areas with high numbers of infections, an online questionnaire was considered more suitable and safe to collect the empirical data for the current study. Using a persuasive sample technique, we approached healthcare CEOs, senior managers/managers, doctors, nurses, and other relevant healthcare practitioners under the MoH in Saudi Arabia who were involved in the decision-making process related to COVID-19. In details, this study mainly targeted those health professionals who are responsible for managing and providing health care services for COVID-19 patients (i.e. Anaesthesia, abdominal, and respiratory) or those involved in managing all issues related to COVID-19 in general. However, number of those participants who work in the Ministry of health in Saudi Arabia presents different backgrounds such as physician, pharmacist, medical analysis, public health, community health. Initially, we sent the digital version of the questionnaire to participants' official emails over the period between August to November 2020. However, as the response rate was very low using this method (less than 35%), we then considered using a number of social media platforms, such as WhatsApp, Facebook, Twitter, and LinkedIn, on which virtual professional communities of those who involved in the COVID-19 decision-making process made it easier to distribute the questionnaire more widely. Due to these efforts, we reached 362 respondents, which was sufficient for conducting structural equation modelling (SEM) analysis. According to Faul, Erdfelder, Buchner, and Lang (2009), the current sample size is close to the sample size suggested by G*Power test (341).

The scale measurements were carefully selected from the prior literature as shown in detail in appendix. Five-point Likert scales, ranging from "Strongly agree" to "Strongly disagree", were used to measure the participants' perceptions of and attitudes to the model's constructs, apart from usage of AI-based healthcare technologies which was tested using a scale of usage frequency comprising "Always", "Usually", "Often", "Sometimes", and "Rarely". A pilot study with 25 participants from the public healthcare sector was undertaken to check the validity and reliability criteria prior to conducting the main survey on a large scale. In this pilot, the Cronbach's alpha values were tested for all seven constructs, and they were found to be not less than the suggested value of 0.70 (Nunnally, 1978).

## 5. Results

### *5.1. Respondents demographic characteristics*

As reported in the research methodology part, the current study participants have been selected from 20 Primary COVID-19 Hospitals and 5 COVID-19 Backup Hospitals allocating in all regions of Saudi Arabia. A part of sample was also targeted from those who worked in Clinics 'Tetamman' designated by the Saudi Ministry of Health to serve everyone who feels symptoms of the Coronavirus. Those participants should also be engaged in the decision-making process related to COVID-19. Mainly, the current sample was distributed as follow: CEOs (10%), senior managers/managers (20%), doctors (27%), nurses (28%), and other relevant healthcare practitioners (14%) (See Table 1). About 64% of those participants were male instead of 36% are female. In terms of educational level, the vast majority of the current sample (79%) have bachelor degree and above. As for the working experience, most of the participants (73%) have reported that they have working experience in the medical sector for 5 years and more. In terms of experience in using AI-based health applications, only 17% of the current sample mentioned that they have known and used such AI applications before COVID-19 crisis and for 3 years and more, about 19% reported that they have engaged in using AI heath applications for 1 to 2 years before COVID-19 crisis, while 64% of participants demonstrated that they have started using AI health applications over the COVID-19 crisis.

**Table 1**
Respondents' demographic characteristics.

| Demographic profile | Number of respondents (*N* = 362) | Percentage (%) |
|---|---|---|
| Gender | | |
| Male | 232 | 64 |
| Female | 130 | 36 |
| Total | 362 | 100 |
| Age | | |
| 22–24 | 46 | 12 |
| 25–30 | 78 | 21 |
| 31–40 | 109 | 30 |
| 41–50 | 87 | 24 |
| 51–60 | 31 | 58 |
| 60+ | 11 | 3 |
| Total | 362 | 100 |
| Title of the participants | | |
| CEO | 37 | 10 |
| Senior manager/managers | 76 | 20 |
| Doctors | 98 | 27 |
| Nurses | 100 | 28 |
| Other relevant healthcare practitioners | 51 | 14 |
| Total | 362 | 100 |
| Education Level | | |
| Diploma | 20 | 5 |
| Bachelor | 286 | 79 |
| Master | 44 | 12 |
| PhD | 12 | 3 |
| Total | 362 | 100 |
| Working experience | | |
| Less than 1 year | 18 | 5 |
| 1 to 3 years | 34 | 9 |
| 3 to 5 years | 46 | 12 |
| More than 5 years | 264 | 73 |
| Total | 362 | 100 |
| Experience in using AI-based health applications before COVID-19 crisis | | |
| During the pandemic of COVID-19 | 232 | 64 |
| 1 to 2 years | 69 | 19 |
| 3 years and more | 61 | 17 |
| Total | 362 | 100 |

### 5.2. Descriptive statistics of the measurement items

Most of the scale items used in the survey were positively rated by the respondents (see Table 2). For example, items used to measure internal AI-based COVID-19 had an average mean value of 3.3232 with a standard deviation of 1.17597. Likewise, external AI-based COVID-19 scale items had an average mean for all scale items of 3.8239 with a standard deviation of 1.12633. With an average mean value of 3.884 and a standard deviation of 0.9829, scale items for AI-enabled COVID-19 problem-solving performance were generally rated by respondents positively. Similarly, scale items to measure mental representation for AI-based COVID-19 task solution were also rated positively with an average mean of 3.9282 and a standard deviation of 0.9577. Four items used for AI-enabled COVID-19 decision-making process were mostly appraised positively by sample participants, as the average mean value was 3.33045 with a standard deviation of 1.43858. Furthermore, experience-based items were positively rated with a mean value of 3.4484 and standard deviation of 1.1024. Finally, five common AI healthcare technologies were considered in the study, all of which were highly rated with an average mean of 3.41768 and standard deviation of 1.054098.

### 5.3. Common method bias

The current study data was collected using a self-reported questionnaire in which constructs scale items were to be responded by the same participant. Therefore, there was a concern regarding the common method bias (Bhattacherjee, 2012; Podsakoff et al., 2003). So as to address this, 27 scale items used in the current questionnaire were targeted to Harman's single factor test and loaded into exploratory factor analysis (Harman, 1976; Podsakoff et al., 2003). About 33.996% of variance was reported to the first factor which is not higher than the threshold level of 50% as suggested by Podsakoff et al. (2003). It has also been applied common latent factor method and confirmatory factor analysis marker variable method (Podsakoff et al., 2012). The yielded value of the marker variable was not higher than the common latent factor method. Thus, more evidences supporting that the current study data is fee common method bias issues.

**Table 2**
Descriptive statistics of the measurement items.

| Latent construct | Scale item | Mean | Std. deviation | Factor loading |
|---|---|---|---|---|
| Internal AI-based COVID-19 Problem Domain Representations | Int.AI. PDR1 | 3.591 | 1.227 | 0.775 |
| | Int.AI. PDR2 | 3.629 | 1.094 | 0.874 |
| | Int.AI. PDR3 | 3.593 | 1.152 | 0.921 |
| | Int.AI. PDR4 | 2.477 | 1.230 | 0.456 Removed |
| | Average | 3.323 | 1.175 | |
| External AI-based COVID-19 Problem Representations: (G2G Knowledge-based Exchange) | G2G. KE1 | 3.751 | 1.164 | 0.813 |
| | G2G. KE2 | 3.908 | 1.049 | 0.813 |
| | G2G. KE3 | 3.734 | 1.055 | 0.937 |
| | G2G. KE4 | 3.900 | 1.234 | 0.341 Removed |
| | Average | 3.823 | 1.126 | |
| AI-enabled COVID-19 Problem-Solving Performance | AI.PSP1 | 3.870 | 1.019 | 0.820 |
| | AI.PSP2 | 3.837 | 0.966 | 0.920 |
| | AI.PSP3 | 3.944 | 0.963 | 0.858 |
| | Average | 3.884 | 0.98 | |
| Mental Representation for AI-based COVID-19 Task Solution: (AI-based COVID-19 Diagnosis) | AI·D1 | 4.157 | 0.929 | 0.732 |
| | AI·D2 | 3.826 | 0.973 | 0.793 |
| | AI·D3 | 3.911 | 0.951 | 0.779 |
| | AI·D4 | 3.817 | 0.976 | 0.827 |
| | Average | 3.928 | 0.957 | |
| AI-enabled COVID-19 Decision-Making Process | AI. DMP1 | 3.378 | 1.357 | 0.932 |
| | AI. DMP2 | 3.259 | 1.370 | 0.942 |
| | AI. DMP3 | 3.444 | 1.359 | 0.431 Removed |
| | AI. DMP4 | 3.238 | 1.667 | 0.877 |
| | Average | 3.330 | 1.438 | |
| Experience-based Decision-Making | EBDM1 | 3.491 | 1.109 | 0.875 |
| | EBDM2 | 3.494 | 1.086 | 0.903 |
| | EBDM3 | 3.359 | 1.110 | 0.889 |
| | Average | 3.448 | 1.102 | |
| AI-based COVID-19 Problem-Solving Task: (Usage of AI-based Healthcare Technologies) | U.AI. HT1 | 3.657 | 1.033 | 0.724 |
| | U.AI. HT2 | 3.284 | 1.057 | 0.787 |
| | U.AI. HT3 | 3.105 | 1.162 | 0.758 |
| | U.AI. HT4 | 3.491 | 1.058 | 0.785 |
| | U.AI. HT5 | 3.549 | 0.958 | 0.695 |
| | Average | 3.417 | 1.054 | |

### 5.4. Structural equation modelling (SEM) analysis

#### 5.4.1. Confirmatory factor analyses (CFA)

Seven latent constructs with 27 scale items (observed variables) were initially subject to CFA., Several highly suggested indices (i.e., CMIN/

DF ≤ 3.000; GFI ≥ 0.90; AGFI ≥0.90; IFI ≥ 0.90; TLI ≥ 0.90; CFI ≥ 0.95, and RMSEA ≤0.08) were considered to evaluate the measurement goodness of fit (Hair Jr., Black, Babin, & Anderson, 2010; Bagozzi and Yi, 1988; Hooper et al., 2008; MacCallum et al., 1996; McDonald and Ho, 2002). The first version of the measurement model was not able to adequately fit the observed data because most indices were not within their recommended level (CMINN/DF = 3.979; GFI = 0.818; AGFI = 0.764; IFI = 0.898; TLI = 0.878; and CFI = 0.897). Therefore, the measurement model was revised by dropping the most problematic items, especially these with a factor loading below 0.50. Inspection of the standardized regression weights in the AMOS output file showed that Int.AI.PDR4, G2G.KE4, and AI.DMP4 had factor loading values below 0.50; accordingly, these items were dropped from the measurement model. The measurement model was tested again, and all the indices were within their threshold levels (CMINN/DF = 2.524; GFI = 0.924; AGFI = 0.852; IFI = 0.951; TLI = 0.941; CFI = 0.981; RMSEA = 0.049).

All retained items were then subject to further analyses to ensure adequate levels of the constructs' reliability and validity. Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE) were tested. As shown in Table 3, Cronbach's alpha values were all higher than 0.70, as recommended by Nunnally (1978). The highest Cronbach's alpha value (0.94) was for scale items of AI.DMP, while the lowest value (0.864) was for both AI·D and U.AI.HT. Likewise, AI.DMP has the highest CR value (0.940), followed by EBDM (0.919); the lowest CR value (0.864) was for AI·D, but this was still above the cut-off value (0.70) (Anderson & Gerbing, 1988). With values fluctuating from 0.563 (U.AI.HT) to 0.842 (AI.DMP), AVE values for all constructs within their suggested level (above 0.50; (Fornell & Larcker, 1981; Hair Jr. et al., 2010). Furthermore, all retained scale items capture a standardized regression weight value (factor loading) not less than 0.50, as seen in Table 2 (Anderson & Gerbing, 1988; Hair Jr. et al., 2010). Table 4 also shows that all latent constructs matched the criteria of discriminant validity, as the intercorrelation values between all constructs were found to be less than the square root of the AVE with the targeted construct (Kline, 2005).

*5.4.2. Structural model analyses*

The results for the structural model largely supported the proposed research hypotheses (See Fig. 2.). Like the measurement model, the structural model adequately fit the observed data as all fit indices were within their threshold levels (CMINN/DF = 2.614; GFI = 0.920; AGFI = 0.849; IFI = 0.945; TLI = 0.939; CFI = 0.975; RMSEA = 0.052). According to AMOS analyses, all the research hypotheses are supported as all paths have CR values higher than 1.96 and significant *p*-values of less than 0.05. For example, AI·D was found to be significantly predicted by U.AI.HT ($\gamma = 0.473$, $p < 0.000$), as were Int.AI.PDR ($\gamma = 0.108$, $p < 0.036$) and G2G.KE ($\gamma = 0.115$, $p < 0.019$). A strong relationship was also noticed between Mnet.R and AI.PSP ($\gamma = 0.672$, $p < 0.000$). AI.PSP was able to significantly predict AI.DMP ($\gamma = 0.6165$, $p < 0.000$). As proposed, a strong relationship was found between AI.DMP and G2G.KE ($\gamma = 0.288$, $p < 0.000$). Int.AI.PDR and G2G.KE were found to influence each other; respectively, ($\gamma = 0.738$, $p < 0.000$) and ($\gamma = 0.669$, $p < 0.000$). As shown in Table 5, Int.AI.PDR has a larger significant impact on G2G.KE, with a coefficient value of 0.738 and a *p*-value of 0.000.

Lastly, in line with Chin, Marcolin, and Newsted's (2003) suggestion, the moderation effect of experience-based decision-making on the relationship between AI.DMP and G2G.KE was tested with the SmartPLS software program. This is due to the features of SmartPLS software program that makes ease testing the moderation factors measured using interval scales (i.e. Likert scale) as for experience-based decision making in the current study. Further, the two-stage approach was employed in the current study as the moderating factor (EBDM) is more to be formative (Henseler & Chin, 2010). Furthermore, the two-stage method takes advantage of the SmartPLS path modelling feature in clearly assessing the scores of the latent variable (Chin, 1993-2003; Henseler & Chin, 2010; Henseler & Fassott, 2010). As Table 6 shows, the results largely supported the moderating impact of experience-based decision-making.

**Table 3**
Constructs' reliability and validity.

| Latent construct | α | CR | AVE |
|---|---|---|---|
| AI·D | 0.864 | 0.864 | 0.614 |
| U.AI.HT | 0.864 | 0.866 | 0.563 |
| EBDM | 0.919 | 0.919 | 0.790 |
| AI.PSP | 0.897 | 0.901 | 0.752 |
| G2G.KE | 0.886 | 0.891 | 0.733 |
| AI.DMP | 0.940 | 0.941 | 0.842 |
| Int.AI.PDR | 0.889 | 0.894 | 0.738 |

AI·D: External AI-based COVID-19 Problem Representations: (G2G Knowledge-based Exchange).
U.AI.HT: AI-based COVID-19 Problem-Solving Task: (Usage of AI-based Healthcare Technologies).
EBDM: Experience-based Decision-Making.
AI.PSP: AI-enabled COVID-19 Problem-Solving Performance.
G2G.KE: External AI-based COVID-19 Problem Representations: (G2G Knowledge-based Exchange).
AI.DMP: Mental Representation for AI-based COVID-19 Task Solution.
Int.AI.PDR: Internal AI-based COVID-19 Problem Domain Representations.

**Table 4**
Discriminant validity.

| | AI·D | U.AI.HT | EBDM | AI.PSP | G2G.KE | AI.DMP | Int.AI.PDR |
|---|---|---|---|---|---|---|---|
| AI·D | **0.783** | | | | | | |
| U.AI.HT | 0.672 | **0.751** | | | | | |
| EBDM | 0.459 | 0.453 | **0.889** | | | | |
| AI.PSP | 0.545 | 0.416 | 0.291 | **0.867** | | | |
| G2G.KE | 0.436 | 0.294 | 0.255 | 0.655 | **0.856** | | |
| AI.DMP | 0.251 | 0.156 | −0.026 | 0.448 | 0.393 | **0.917** | |
| Int.AI.PDR | 0.413 | 0.295 | 0.201 | 0.595 | 0.715 | 0.480 | **0.859** |

Note: Diagonal values are squared roots of AVE; off-diagonal values are the estimates of inter-correlation between the latent constructs.

## 6. Discussion

The empirical results of the current study were in line with what was proposed in the conceptual model as all research hypotheses were supported (see Table 5 and Table 6). In detail, the results of both CFA and the structural model largely supported all the criteria pertaining to model fitness, constructs' reliability and validity, and predictive power. For example, 52% of variance recorded in Int.AI.PDR by G2G.KE. In addition, Int.AI.PDR, G2G.KE, and U.AI.HT accounted for 50% of variance in AI·D. The role of AI.DMP and Int.AI.PDR accounted for 50% of variance in G2G.KE. AI·D accounted 53% of variance in AI.PSP. 47% of variance was explained in AI.DMP. This, in turn, supports the

**Table 5**
Hypotheses testing.

| | | | Estimate | SE | CR | P | Label |
|---|---|---|---|---|---|---|---|
| AI·D | <-- | U.AI.HT | 0.473 | 0.050 | 9.529 | *** | par_20 |
| AI.DMP | <-- | AI.PSP | 0.616 | 0.083 | 7.394 | *** | par_15 |
| G2G.KE | <-- | AI.DMP | 0.288 | 0.043 | 6.707 | *** | par_16 |
| Int.AI.PDR | <-- | G2G.KE | 0.669 | 0.052 | 12.836 | *** | par_17 |
| G2G.KE | <-- | Int.AI.PDR | 0.738 | 0.062 | 11.863 | *** | par_22 |
| AI·D | <-- | Int.AI.PDR | 0.108 | 0.052 | 2.096 | 0.036 | par_18 |
| AI·D | <-- | G2G.KE | 0.115 | 0.049 | 2.341 | 0.019 | par_19 |
| AI.PSP | <-- | AI·D | 0.672 | 0.076 | 8.878 | *** | par_22 |

**Table 6**
Moderation test.

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | *T* Statistics (\|O/STDEV\|) | *P*-values |
|---|---|---|---|---|---|
| EBDM Moderating Effect | 0.21 | 0.201 | 0.067 | 3.124 | 0.002 |

applicability of CFT as a theoretical basis of the current study model, which is in line with studies such as Umanath and Vessey (1994), Kershaw and Tuttle (1998), and Speier (2006).

The path coefficient analyses revealed that all proposed paths in the conceptual model were significant. The highest coefficient value was between G2G.KE and Int.AI.PDR. As discussed in relation to the conceptual model, Int.AI.PDR is more like a structure of the problem-solvers' knowledge that could help in performing particular functions and address patients' questions and queries based on information captured from G2G.KE, such as that collected from numerous individual patients. This, in turn, provides significant help to those patients. Such results align with those reported by Zaina et al. (2009).

With the same impact and momentum, G2G.KE was found to positively accelerate Int.AI.PDR. The related results indicate that the transparent processing and exchange of information and knowledge about the COVID-19 pandemic between government agencies could also have a back effect on internal AI-based COVID-19 problem domain representations. Furthermore, such a causal and interrelated association between Int.AI.PDR and G2G.KE has a considerable positive impact on mental representation for task solution (AI·D). This is in line with what validations of CFT (Shaft & Vessey, 2006). Various studies have reached the same conclusion, thus supporting the current study's results (Agrawal et al., 2017; Iyer et al., 2006; Putri et al., 2020; Zhang, 1997).

Both Int.AI.PDR and G2G.KE have a significant impact on mental representation for task solution (AI·D). As suggested by the research hypotheses, human logic could play an important role in feeding an automated decision system, which particularly applies to the specific AI-based COVID-19 task solution. This could be due to the logic operators or binary elements that are usually used to present the AI-based COVID-19 task solution and which are designed for knowledge-based mechanisms. Another explanation for the impact of Int.AI.PDR on AI·D is the simplicity in designing and implementing the logic in an automated system (Zhu et al., 2014); moreover, knowledge representation using natural language is easy to understand and develop (Schlutter & Vogelsang, 2018). Regarding the impact of G2G.KE on AI·D, problem representation presents how the solver cognitively engaged in processing information relating to the target problem when using the AI-based COVID-19 task solution. Such representation is connected directly to the solver's current knowledge of the problem's content from the external AI-based COVID-19 problem representations (Lauterman & Ackerman, 2019).

The results also demonstrated a strong relationship between the usage of AI applications and AI·D. AI applications have been widely reported by health informatics as smart mechanisms that leverage governments' ability to respond to the consequences of the COVID-19 pandemic. For example, AI applications have helped physicians by automating aspects of diagnosis, prioritizing healthcare resources, and improving vaccine and drug development (Shahid et al., 2020). Moreover, particular AI applications, such as chatbots, have helped to improve the efficiency and privacy of the process of receiving and addressing patients' inquiries (Nadarzynski et al., 2019; Vimalkumar, Sharma, Singh, & Dwivedi, 2021). AI enjoys a wide range of practical features that make such systems much smarter and more efficient in comparison with human intelligence, especially in relation to visuospatial processing speed, pattern recognition, and prediction of disease, thereby enabling better diagnoses (Kummitha, 2020; Simsek et al., 2020; Wahl et al., 2018). Therefore, AI can perform critical healthcare tasks as well as or better than humans, such as the diagnosis of diseases using the AI-based COVID-19 problem-solving task (Davenport & Kalakota, 2019).

A positive and significant relationship was also found between AI·D and AI.PSP. It has been commonly argued that the problem-solving concept is more likely to refer to the methodology that an individual adopts to figure out, test, and provide an appropriate solution. Therefore, prior to solving the targeted problem, it is important to initially comprehend the current nature of such problems (Wang, 2020). These results are similar to those reported by Araujo et al. (2019), Karakülah et al. (2014), and Shin et al. (2010).

The results also support the impact of AI.PSP on AI.DMP. In other words, attaining a high level of AI.PSP will contribute to the quality of decisions and help decision-makers logically interpret such decisions in a more conscious manner by using AI applications (Kasper & Andoh-Baidoo, 2015). Consequently, AI.DMP is more likely to play a positive role in providing immediate and accurate responses for risks associated with the COVID-19 pandemic (Garcia et al., 2021).

The results confirm the moderating impact of experience-based decision-making on the relationship between AI.DMP and G2G.KE. Indeed, capturing the required experience will help practitioners in the related

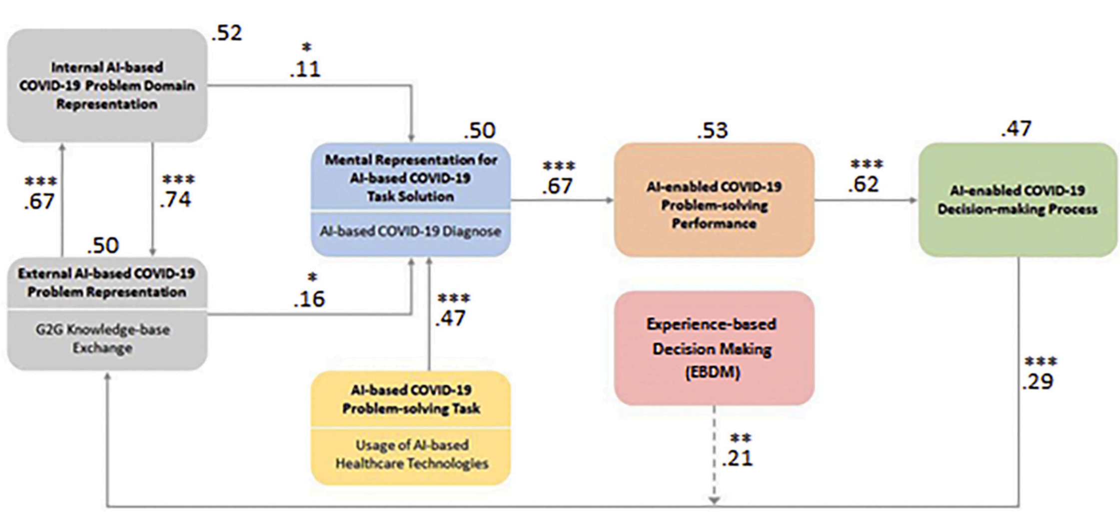


**Fig. 2.** Validated conceptual model.
[Dotted line: moderator, ns: $p > 0.05$, *: $p \leq 0.05$, **: $p \leq 0.01$, ***: $p \leq 0.001$].

area of health informatics to actively distinguish between problem-solving and decision-making. Therefore, patients and providers can more consciously recognize their roles and responsibilities, which in turn enhances the possibility of partnerships in decision-making and problem-solving (Dubromel et al., 2020). As assumed in the conceptual model, if there are any contradictions in the COVID-19 diagnostic process, procedures should be repeated from the beginning (see Fig. 1). Thus, a cumulative process of learning from previous lessons would be captured by AI applications. This would create more opportunities to notify governments about any contradictions in the diagnostic process via the facilities of the external AI-based COVID-19 problem representations, which would benefit responses to future pandemics (Davenport & Kalakota, 2019). The logical attribution of this could be due to the ability of AI applications to enhance the AI-enabled COVID-19 problem-solving performance process by validating and analysing all information, experiences, and knowledge in the different stages of the COVID-19 pandemic (Kumar et al., 2020). It is also based on the flexible nature of AI applications, such that they can be modified and improved over time (Weiss-Cohen et al., 2021). These results are in line with assumptions in several studies (Davenport & Kalakota, 2019; DeVries & Taylor, 2018; Dubromel et al., 2020; Kelly et al., 2019; Kumar et al., 2020; Muro et al., 2017).

### 6.1. Theoretical contributions

This study was conducted at a very critical time in which the world is searching for smart solutions that help reducing the severity of the Corona epidemic and supporting those who work in the health sector. The theoretical importance of this study is represented in the addition of theory in two important aspects. The first aspect relates to the use of artificial intelligence applications in the health sector while the second one pertains to studying issues of emerging COVID-19 epidemic, where there is an urgent need for more research and studies to enrich the theoretical and practical side. Therefore, this study is an attempt to advance the current understanding of the successful use and implementation of AI in the government health sector, especially in light of the impact of the COVID-19 epidemic (Jiang et al., 2017). Indeed, several theoretical contributions have been introduced in the current study. For example, it expands the theoretical horizon of Shaft and Vessey's (2006) CFT by considering new mechanisms, such as the inclusion of G2G.KE in addition to the moderating effect of EBDM on the relationship between AI.DMP and G2G.KE in public healthcare.

This study has added further understanding regarding the role that AI applications could play in enhancing the casual interactions between to Internal AI-based COVID-19 problem domain representations and external AI-based COVID-19 problem representations: (G2G knowledge-based exchange). Likewise, a contribution was provided in the current study by empirically approving the impact of AI-enabled COVID-19 Decision-Making Process on external AI-based COVID-19 problem representations: (G2G knowledge-based exchange). This, in turn, gives researchers over the related area of AI applications more clues that decision-making process would not only be a consequence of using technology like AI applications but rather could have crucial impact on such aspects like G2G knowledge-based exchange.

Furthermore, the current model proposed three main predictors (i.e. Internal AI-based COVID-19 problem domain representations, external AI-based COVID-19 problem representations, and AI-based COVID-19 Problem-Solving Task) of Mental Representation for AI-based COVID-19 Task Solution. Thus, this study was able to present a comprehensive picture regarding the levers of Mental Representation for AI-based COVID-19 Task Solution in terms of AI-based COVID-19 diagnose.

Another contribution of the current study is its extension of the applicability of CFT to a new context (i.e., healthcare) and to emerging systems (i.e., AI applications). Besides, the interactive features of AI potentially constitute other theoretical extensions, because problem-solving applications are still uncertain in terms of multi-representation, multi-subtasks, and real-time conditions; accordingly, the current study model provides a significant contribution to the theory. By adapting CFT, the current model can also inform the design and construction of novel user interface artefacts (Vance et al., 2015) for presenting AI.

### 6.2. Practical implications

One of the main reasons for conducting the current study is to provide a solid framework of governing guidelines that will help Saudi healthcare authorities in their endeavours to successfully implement and effectively use AI applications for problem-solving and decision-making. Therefore, the empirical results accurately depict the most important aspects that must be considered by practitioners and designers of AI in the Saudi healthcare sector in order to benefit all strategic partners and stakeholders.

The biggest challenge of such a highly evolved system is the adoption and usage rate, so more persuasive communication efforts should be initially devoted to showing stakeholders (i.e., users, policymakers, and patients) the potential benefits of AI for the healthcare system overall (Datafloq, 2019). Accordingly, different communication channels should be used to increase the current awareness about the values and opportunities of using AI healthcare applications and how they can contribute to the quality of services (Datafloq, 2019). It is also recommended to prepare and present a clear plan and an outline of the benefits of AI healthcare applications for various business practices and areas. For example, stakeholders should be clearly informed about how AI applications (e.g., neural networks, chatbots; AI-assisted medical diagnosis, and telemedicine) have mechanized managerial functions and simplified workflows, which in turn minimizes the time required to achieve such functions (Androutsopoulou, Karacapilidis, Loukis, & Charalabidis, 2019; Datafloq, 2019).

The results also indicate the importance of evaluating the readiness of health organizations to adopt AI systems. In other words, it is crucial to see the extent to which health institutions are ready to use and successfully implement AI systems. This would help practitioners and decision-makers to decide on the next steps and to evaluate which zones need to be focused on in order to address any gaps prior to the implementation process. This could be conducted by carefully inspecting the internal parts of the healthcare system and appraising managerial and health workflows, technical capabilities and infrastructure, organizational culture, and approved medical care methods (Datafloq, 2019).

Healthcare organizations should monitor AI systems' performance based on several recommended key performance indicators (KPIs) (e.g., staff-to-patient ratio, patient satisfaction, patient waiting time), which can be numerical or non-numerical (Datafloq, 2019). This could also help to identify the most significant aspects of human resources that should be improved (e.g., users' skills and experiences) (Balakrishnan & Dwivedi, 2021b). As reported by Datafloq (2019), users should be empowered by well-designed training programmes in data collection, data analytics, data mining, and data engineering. Healthcare institutions can seek the help of experts and consultants in AI systems to transfer their experience and knowledge to Saudi health organizations (Datafloq, 2019).

Using AI applications does not guarantee an effective solution to problems or ensure smart decisions, because they require a high quantity and quality of accurate, updated, and reliable data. It is the responsibility of healthcare institutions to collect, organize, and validate the required data and to make it available at the right time and place (Datafloq, 2019). More governance methods are also an urgent necessity in dealing with the health community and strategic partners to ensure a high level of transparency in data collection and processing (McGrail, 2019). For example, transparency should be guaranteed for all users, patient, and stakeholders so as to ensure an adequate level of confidence in the information exchanged and decisions made based on this information (McGrail, 2019). Well-designed guiding principles can reveal the extent to which information can be transparently exchanged between users, patients, and stakeholders.

More attention should be also paid regarding the extent of how much the data shared is easily accessed, standardized, and credible. This will surely improve the level of data accuracy and trustworthiness for all stakeholders. There is also a great need to focus on the ethical and legal aspects in order to achieve safe use of AI-based health applications, which preserves a large degree of privacy and security of health data. This, in turn, will improve the level of confidence perceived in artificial intelligence systems and increase the extent of their use by medical personnel.

### *6.3. Limitations and future research directions*

This study also has some limitations that need to be addressed. For example, the main focus of the current research was on the governmental healthcare sector, which prevents the applicability of the results to the private healthcare sector. In order to have a full picture of the efficiency of using AI, therefore, future research should investigate AI systems in relation to the problem-solving and decision-making process in the private healthcare sector. The current data was also collected from one country (i.e., Saudi Arabia), which might mean that the results are not generalizable to other countries and cultures. Thus, future studies should extend the validity of the current study model to other countries. Due to the circumstances of the COVID-19 epidemic, there was the difficulty of personal contact with the study sample participants, and therefore, a number of social media platforms were used to increase the response rate. This, in turn, reflected negatively on the degree of representation of the sample and creating an opportunity of sampling bias as well. A cross-cultural study between a developing country such as Saudi Arabia and a developed may give more depth in understanding the form of relations within the study model and how they might change from one country to another depending on cultural differences. Finally, aspects pertaining to the technical infrastructure, information quality, system quality, and users' self-efficacy have not been fully addressed in the current study. Hence, future studies should investigate these areas to explore how these mechanisms could contribute to AI-enabled problem-solving performance and an AI-enabled decision-making process.

## 7. Conclusion

The main objective of this study was to examine how AI-based public healthcare systems can enhance problem-solving performance and the decision-making process in the presence of G2G.KE and EBDM. The conceptual framework was proposed based on the extended cognitive fit model of Shaft and Vessey (2006). The model was validated based on empirical data collected using an online questionnaire distributed to healthcare organizations in Saudi Arabia. The main sample participants were healthcare CEOs, senior managers/managers, doctors, nurses, and other relevant healthcare practitioners under the MoH involved in the decision-making process relating to COVID-19. The measurement model was validated using SEM analyses, and all the criteria for the model's goodness of fit, as well as for construct reliability and validity, were met. According to the structural model results, all the research hypotheses were found to be significant. This study has several practical and theoretical implications for practitioners and academics interested in AI-based public healthcare systems.

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## Appendix A. Measurement items

| Factor | Measurement items | Source |
|---|---|---|
| Internal AI-based COVID-19 Problem Domain Representations | AI-based healthcare technologies help healthcare practitioners to have sufficient compactness in perceiving the COVID-19 problem domain efficiently.<br>AI-based healthcare technologies help healthcare practitioners to define the initial situation/trend of COVID-19 in addition to potential solutions.<br>AI-based healthcare technologies provide healthcare practitioners with various possible techniques to analyse diagnosis instances related to COVID-19.<br>AI-based healthcare technologies provide healthcare practitioners with necessary utilities compatible with solution algorithms related to COVID-19. | Shaft and Vessey (2006) |
| External AI-based COVID-19 Problem Representations (G2G Knowledge-based Exchange) | G2G knowledge-based exchange helps healthcare practitioners to efficiently represent the COVID-19 environmental domain.<br>G2G knowledge-based exchange provides AI-powered knowledge base with COVID-19-related knowledge required to enhance the diagnostic accuracy of healthcare expert systems.<br>AI-based healthcare technologies are playing a crucial role in feeding G2G knowledge base relating to COVID-19 for best knowledge exchange practices.<br>G2G knowledge-based exchange helps healthcare practitioners to share/transfer COVID-19-related knowledge with/to other governmental entities within and outside Saudi Arabia. | Shaft and Vessey (2006) |
| AI-based COVID-19 Problem-Solving Task (Usage of AI-based Healthcare Technologies) | Chatbot.<br>AI-assisted medical diagnosis.<br>Telehealth/Telemedicine.<br>Robot.<br>Health wearables. | Adly, Adly, and Adly (2020); McCall (2020); Hollander and Carr (2020) |
| | | Lee et al. (2020); Thompson (2004); Shaft and Vessey (2006) |

(*continued on next page*)

(*continued*)

| Factor | Measurement items | Source |
|---|---|---|
| Mental Representation for AI-based COVID-19 Task Solution (AI-based COVID-19 Diagnosis) | AI capabilities, such as machine learning, natural language processing, expert systems, vision, speech, planning, and robotics help healthcare practitioners to diagnose and treat cases related to COVID-19. | |
| AI-based healthcare technologies provide healthcare practitioners with potential solutions for complex cases related to COVID-19 diagnosis. | AI-based healthcare technologies, which have the capacity to mimic human characteristics, help healthcare practitioners to solve problems related to COVID-19 diagnosis. | |
| AI-based healthcare technologies help healthcare practitioners in visualizing COVID-19-related information/ knowledge for an accurate diagnosis. | | |
| AI-enabled COVID-19 Problem-Solving Performance | AI-based healthcare technologies have the capability to automate healthcare practices, and to analyse and visualize relevant problems relating to COVID-19 cases.<br>AI-based healthcare technologies help healthcare practitioners to perceive problems related to COVID-19, such as diagnosis, treatment, and quarantine recommendations.<br>AI-based healthcare technologies have the ability to enhance the problem-solving performance related to COVID-19 instances. | Dong, Du, and Gardner (2020); Shaft and Vessey (2006) |
| AI-enabled COVID-19 Decision-Making Process | AI-based healthcare technologies help healthcare practitioners to track the discharge criteria for COVID-19 patients to determine and differentiate treated patients from those who still need to be isolated.<br>AI-based healthcare technologies help healthcare practitioners to address, for example, COVID-19 signs, symptoms, previous locations of the patient, travel history, and updated areas of the outbreak.<br>AI-based healthcare technologies help healthcare practitioners to predict and recommend quarantine in areas where a threshold number of cases is reached.<br>AI-based healthcare technologies help healthcare practitioners to remotely monitor home-quarantined COVID-19 patients and their families via smartphones or smart bracelets. | Lysaght, Lim, Xafis, and Ngiam (2019); Reddy, Allan, Coghlan, and Cooper (2020); Davenport and Glover (2018) |
| Experience-based Decision-Making | AI-based healthcare technologies help healthcare practitioners to detect non-routine decision problems related to COVID-19.<br>AI-based healthcare technologies help healthcare practitioners to detect unfamiliar decision problems related to COVID-19.<br>AI-enabled COVID-19 decisions help to reinforce the knowledge base based on healthcare practitioners' experience. | Muro et al. (2017); Dimopoulos-Bick, Dawda, Maher, Verma, and Palmer (2018) |

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