International Journal of Production Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tprs20

Applying artificial intelligence in healthcare: lessons from the COVID-19 pandemic

Sreejith Balasubramanian, Vinaya Shukla, Nazrul Islam, Arvind Upadhyay & Linh Duong

To cite this article: Sreejith Balasubramanian, Vinaya Shukla, Nazrul Islam, Arvind Upadhyay & Linh Duong (03 Oct 2023): Applying artificial intelligence in healthcare: lessons from the COVID-19 pandemic, International Journal of Production Research, DOI: 10.1080/00207543.2023.2263102

To link to this article: https://doi.org/10.1080/00207543.2023.2263102

Published online: 03 Oct 2023.

INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH
https://doi.org/10.1080/00207543.2023.2263102

Applying artificial intelligence in healthcare: lessons from the COVID-19 pandemic

Sreejith Balasubramanian [a], Vinaya Shukla [b], Nazrul Islam [c], Arvind Upadhyay [d] and Linh Duong [e]

[a]Chair of Research & Head, Centre for Supply Chain Excellence, Middlesex University Dubai, Dubai, UAE; [b]Department of Business and Management, Middlesex University London, London, UK; [c]University of East London, London, UK; [d]Guildhall School of Business and Law, London Metropolitan University, London, UK; [e]Bristol Business School, University of the West of England, Bristol, UK

ABSTRACT
The COVID-19 pandemic exposed vulnerabilities in global healthcare systems and highlighted the need for innovative, technology-driven solutions like Artificial Intelligence (AI). However, previous research on the topic has been limited and fragmented, leading to an incomplete understanding of the 'what', 'where' and 'how' of its application, as well as its associated benefits and challenges. This study proposes a comprehensive AI framework for healthcare and assesses its effectiveness within the UAE's healthcare sector. It provides valuable insights into AI applications for healthcare stakeholders that range from the molecular to the population level. The study covers the different computational techniques employed, from machine learning to computer vision, and the various types of data inputs fed into these techniques, including clinical, epidemiological, locational, behavioural and genomic data. Additionally, the research highlights AI's capacity to enhance healthcare's operational, quality-related and social outcomes, and recognises regulatory policies, technological infrastructure, stakeholder cooperation and innovation readiness as key facilitators of AI adoption. Lastly, we stress the importance of addressing challenges such as data privacy, security, generalisability and algorithmic bias. Our findings are relevant beyond the pandemic in facilitating the development of AI-related policy interventions and support mechanisms for building resilient healthcare sector that can withstand future challenges.

ARTICLE HISTORY
Received 9 January 2023
Accepted 17 September 2023

KEYWORDS
Artificial intelligence; Industry 4.0; healthcare; COVID-19; UAE

1. Introduction

The healthcare sector is well known for its intrinsic complexities and inefficiencies (Balasubramanian et al. 2021). These issues were made more evident during the COVID-19 pandemic, during which an overburdened workforce proved unable to meet patients' needs (Dicuonzo et al. 2023). Fresh ideas and innovative strategies, particularly from the perspective of leveraging advanced technologies, are therefore needed so that the sector's efficiency, effectiveness and resilience can be significantly boosted. While there are several promising technologies, Artificial Intelligence (AI) has emerged as one of the key possibilities, with a high degree of adoption across several sectors (George et al. 2019; Rodríguez-Espíndola et al. 2020; Sharma et al. 2022), including healthcare, during the COVID-19 pandemic (Baz et al. 2022).

AI is a field of science and technology that enables computers and software to perform certain tasks by mimicking or duplicating human thought processes and cognitive abilities (Ali et al. 2023). AI can execute and eventually replace a wide range of human tasks. Additionally, it can learn from experience and adjust to new inputs and environments. Consequently, it has great potential for the healthcare sector, enabling it to overcome its challenges and inefficiencies (Ali et al. 2023). For example, AI could facilitate faster and more effective drug/vaccine development (Wang et al. 2021), quicker and more accurate disease detection/diagnosis (Verde et al. 2021), and more accurate prediction of a pandemic's trajectory (Surianarayanan and Chelliah 2021; Khalilpourazari and Doulabi 2021). Additionally, it could free healthcare professionals from routine manual tasks and help in planning and organisation, such as by optimally allocating hospital resources (Shah et al. 2021; Dicuonzo et al. 2023). Not surprisingly, the anticipated value of AI in healthcare is projected to rise to USD 194 billion by 2030 (from around USD 8 billion in 2020) (Allied Market Research 2021).

While there is considerable interest and appreciation of AI's potential in healthcare, current understanding of

CONTACT Sreejith Balasubramanian S.balasubramanian@mdx.ac.ae Chair of Research & Head, Centre for Supply Chain Excellence, Middlesex University Dubai, P.O. Box 500697, Dubai, UAE

the subject remains limited and fragmented. One reason for this may be the disjointed nature of previous research. For instance, Verde et al.'s (2021) AI focus is only on disease detection, while Adamidi et al.'s (2021) specific emphasis is on AI-based diagnosis and prognosis of diseases, especially COVID-19. A similar, narrow AI focus is seen in other studies, such as for drug development (Ho 2020), vaccine design (Russo et al. 2020), contact tracing (Tang, Westover, and Jiang 2021) and lung cancer prognosis (Johnson, Albizri, and Simsek 2022). Therefore, a comprehensive understanding of the various AI applications that could benefit different healthcare stakeholders, including governments, hospitals, pharmaceutical companies and patients, is lacking. This also means that there is limited clarity on the range of different computational methods that could be employed and the different data types that could be used as inputs to these AI applications.

Another area where there is limited understanding is the 'antecedents,' which are the factors that enable and hinder a development (in this case, the adoption of AI in healthcare). This again can be attributed to the narrow scope of previous studies on the subject. For instance, Müller et al. (2021) explored the enablers and challenges of AI, but focused solely on dental diagnostics. Acquiring a wide-ranging and comprehensive knowledge of the topic can help practitioners and policymakers to develop strategies for strengthening the enablers and/or weakening the hindrances to increase AI adoption in the sector. Furthermore, the lack of understanding of the performance impact of, and improvements facilitated by, AI applications for different healthcare stakeholders could also constrain its widespread acceptance/application. Finally, most previous AI studies in healthcare are based on literature reviews, simulations and conceptual analyses rather than empirical data, which has also impeded the development of a realistic understanding of the subject. All of these research and knowledge gaps motivated this work, the objectives of which are as follows:

(1) To develop a comprehensive, multi-dimensional AI application framework for healthcare that encompasses both the technical elements (AI applications, computational techniques and data requirements) and the managerial ones (enablers, challenges and performance benefits).
(2) To validate the framework empirically by testing it in a real-world setting.

We used a systematic review of AI studies in healthcare to develop the framework. Since no such framework exists at present, the one proposed is both novel and significant. We then applied and evaluated the framework within the context of the world-leading UAE healthcare sector. While realising these objectives, the study aimed to answer the following research questions (RQ) from the perspective of the UAE healthcare sector:

> RQ1: What are the AI applications relevant to individual healthcare sector stakeholders?
>
> RQ2: What are the computational techniques/models used to build these AI applications, and what data is used to develop/train them?
>
> RQ3: What are the key enablers facilitating AI applications in healthcare?
>
> RQ4: What are the different performance benefits derived from AI applications in healthcare?
>
> RQ5: What are the key challenges faced by healthcare sector stakeholders when building AI applications?

This study is timely, as the COVID-19 pandemic revealed vulnerabilities in global healthcare systems, underscoring the need for technology to address these shortcomings. Concurrently, the field of AI has undergone rapid advances recently, carrying significant potential to transform the healthcare sector. Additionally, an unparalleled volume of health-related data is now accessible, ranging from electronic health records to wearable devices capturing real-time health statistics. This data can be analysed and leveraged through AI to derive insights that can improve health outcomes. In summary, the pandemic provided both the urgency and the data to study AI's impact on healthcare comprehensively.

However, the study's contributions go beyond the COVID-19 pandemic, as the suggested AI framework can enhance healthcare system efficiency and effectiveness in general, and improve preparedness for future pandemics. Scrutinising and vetting the framework in a practical setting gives it legitimacy and practical utility. We expect that healthcare practitioners and policymakers will find the framework and related findings useful for devising suitable policy interventions and support mechanisms to accelerate the adoption of AI in the sector and build more resilient healthcare systems that can withstand future challenges, whether pandemics like COVID-19 or other unforeseen crises.

This study makes several research contributions. It introduces a novel AI application framework and empirically validates its applicability through the UAE healthcare sector case study. While other conceptual frameworks exist in the literature, none has been validated empirically in this way. Additionally, the AI framework proposed here is more comprehensive, providing a holistic understanding of AI's role in healthcare and covering a wide range of techniques, applications and data types. By addressing the 'what,' 'where,' and 'how'

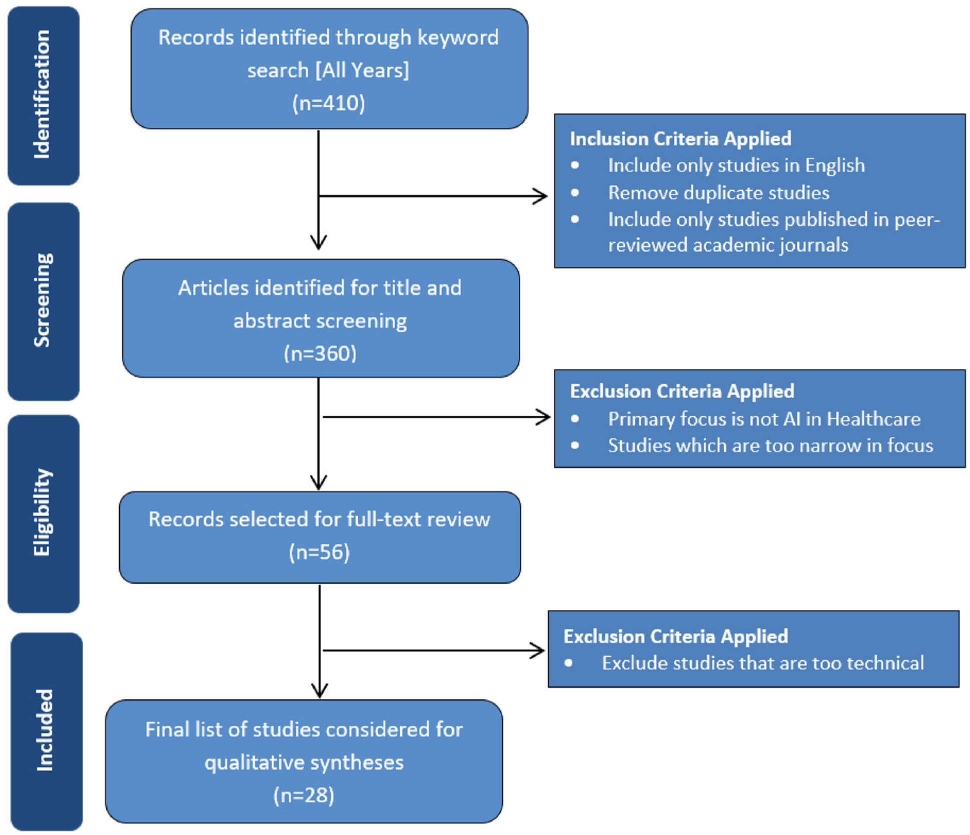

Figure 1. Systematic Review of AI Studies in the Healthcare Sector.

of AI application in healthcare, this study bridges critical knowledge gaps and positions itself as a reference point for future research and policy discussions. Furthermore, given the universal nature of healthcare challenges, the framework can be adjusted and its findings applied to other global regions. In essence, this study is the first to undertake such a comprehensive and in-depth analysis of AI in healthcare, making its insights both significant and beneficial for advancing the field.

The rest of the paper is structured as follows. In the next section, we review studies on AI in healthcare during the COVID-19 pandemic and use the insights gained to develop the framework. Section 3 details the case study methodology used in applying and evaluating the framework. The findings from the case study are covered in Section 4. We conclude in Section 5, where the discussion/implications of the results, limitations of the study, and suggestions for future research are covered.

2. Systematic literature review and AI framework development

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were used for our review (see Figure 1).

The database used for the review was 'Web of Science' because of its high-quality content and broad coverage. The keywords used to identify the initial list included 'Artificial Intelligence' AND 'Healthcare' AND 'COVID' (extraction date: 1st June 2022). The initial search revealed 410 studies. After eliminating duplicates and limiting studies to those from peer-reviewed academic journals that are in English, the list was reduced to 360 studies. Next, we screened titles and abstracts to create a shortlist of 58 studies whose primary focus was on AI and healthcare.

In the next stage, a we conducted a full-text content review of the 58 shortlisted articles to exclude studies that were too narrowly focused, such as those on AI and cardiac surgery (Khalsa et al. 2021), AI and COVID screening based on chest X-rays (Santosh, Ghosh, and GhoshRoy 2022), contact tracing using Bluetooth and AI (Tang, Westover, and Jiang 2021), and mental health index using machine learning (Nanath et al. 2022). The remaining 28 studies were then adopted for detailed syntheses, along with a further five studies identified from the reference list of shortlisted articles or published after the extraction date. Table 1 presents a synthesis of the shortlisted articles. Please note that, for the sake of brevity, findings from similar studies are combined in

Table 1. Summary of Artificial Intelligence (AI) related work on healthcare involving COVID-19.

Studies	Methodology	Relevant Stakeholders	AI Applications	AI Computational Technique(s)	Data Type(s)	Benefits	Challenges
Wang et al. (2021); El-Sherif et al. (2022); Alhasan and Hasaneen (2021); Jabarulla and Lee (2021); Khan et al. (2021); Sarker et al. (2021); Malik et al. (2021); Aruleba et al. (2022); Carriere et al. (2021); Swayamsiddha et al. (2021); Vaishya et al. (2020); Mohamadou, Halidou, and Kapen (2020); Naseem et al. (2020); Nguyen et al. (2021); Shah et al. (2021); Piccialli et al. (2021); Adamidi, Mitsis, and Nikita (2021); Pankhania (2021); Kaur et al. (2021); Albalawi and Mustafa (2022); Arora et al. (2021); Rasheed et al. (2021); Abdulkareem and Petersen (2021)	Literature Review and Conceptual	Hospitals & Patients	Detection and diagnosis using medical imaging modalities	Deep Learning (DL), Machine Learning (ML)	Radiographic images (Chest CT, X-rays, MRI, Ultrasound)	Assistance to Radiologists in clinical decisions, higher speed, and accuracy, round the clock diagnosis possible	Limited data sharing to train the AI model, Lack of generalizability in different settings, difficult in low-income countries
Aruleba et al. (2022); Adamidi, Mitsis, and Nikita (2021); Arora et al. (2021); Rasheed et al. (2021); Abdulkareem and Petersen (2021)	Literature Review and Conceptual	Hospitals & Patients	Detection and diagnosis using hematology (blood samples)	ML	Clinical data (blood indices), demographic data	Higher accuracy for Covid-19 diagnosis; Blood samples are easier to obtain	Lack of collaboration between AI experts and healthcare professionals; lack of data governance frameworks
Sarker et al. (2021); Swayamsiddha et al. (2021); Naseem et al. (2020); Shah et al. (2021); Piccialli et al. (2021); Albalawi and Mustafa (2022); Arora et al. (2021); Rasheed et al. (2021); Abdulkareem and Petersen (2021)	Literature Review	Hospitals & Patients	Remote/Virtual diagnosis, monitoring and care using acoustics, other patient data available remotely	ML, DL	Smartphone sensor data (e.g. images, fingerprints, and audio incl. coughing and breathing sounds, voice); Clinical data (e.g. temperature and symptoms)	Remote detection and monitoring; Non-invasive, faster, and cost-effective; Reduced burden on staff	Noise (where sound used) may hinder accuracy
Verde et al. (2021)	Simulation using secondary dataset (global)	Hospitals & Patients	Detection and diagnosis using acoustics (Speech and voice-based detection)	ML	Acoustic data (voice, coughing & breathing sounds)	Easy, non-invasive, and low-cost early detection and assessment, including asymptomatic subjects;	
Shirazi, Kia, and Ghasemi (2021); Jahangiri et al. (2023)	Simulation-based optimization using secondary data	Hospitals & Patients	Prediction of blood demand and optimal allocation during Covid-19; reduction in patient waiting time during emergency	ML	Facility capacity; inventory, time and costs, blood lifespan, and number of collection centers; number of patients	Less waiting time for blood donation; reduction in blood deterioration; reduction in supply chain costs; less waiting time for patients in emergency department	Quality of data (no official database); assumptions made could change due to the dynamic nature of the pandemic

Hosseini et al. (2022)	Multi-criteria decision making	Hospitals & Patients	Performance evaluation of emergency centers	ML	Number of personnel; employee behavior; training sessions; capabilities of facilities; availability of equipment and supplies	Improvement in performance of emergency centers	Lack of quality data; generalizability of findings (non-cooperation of some emergency centers)
Wang et al. (2021); El-Sherif et al. (2022); Alhasan and Hasaneen (2021); Khan et al. (2021); Sarker et al. (2021); Malik et al. (2021); Aruleba et al. (2022); Swayamsiddha et al. (2021); Vaishya et al. (2020); Ngabo et al. (2021); Naseem et al. (2020); Nguyen et al. (2021); Shah et al. (2021); Adamidi, Mitsis, and Nikita (2021); Arora et al. (2021); Rasheed et al. (2021); Abdulkareem and Petersen (2021)	Literature Review and Conceptual	Hospitals & Patients	Prognosis-based prediction of Covid-19 patients – severity, disease progression, recovery and mortality risk	DL, ML	Clinical and laboratory data (temperature, blood indices, oxygen levels, comorbidities, cough, other symptoms), radiographic images (Chest CT and X-ray), demographic data (e.g. age, sex, province), travel history	Greater validity/accuracy of prediction (from multimodal data); Early assessment – enables priority care for patients at risk, better capacity planning for ICU beds, oxygen, and ventilators	Requires huge amount of data to train and test models, security, and privacy concerns; Fairness and inclusiveness (algorithmic bias)
Mahboub et al. (2021)	Modeling using a secondary dataset (UAE)	Hospitals & Patients	Prognosis-based prediction of COVID-19 patient (Mortality risk prediction, length of hospitalisation)	ML	Clinical and demographic data	Improves management strategies to save lives, improves allocation of resources	Requires cross-validation of models in different settings
Carriere et al. (2021); Nguyen et al. (2021)	Conceptual	Hospitals & Patients	Disease severity risk prediction, Treatment effectiveness	Natural Language Processing (NLP)	Text data (Patient profile and medical history), clinical records	Establishes relationship between treatments (in healthcare records) and eventual patient outcomes, enables prioritised treatment for at risk patients	
Carriere et al. (2021)	Conceptual	Hospitals	Speech processing technologies	NLP	Voice data	Reduces the amount of time a clinician spends on documentation	Not all languages supported
Alhasan and Hasaneen (2021); Sarker et al. (2021); Carriere et al. (2021); Swayamsiddha et al. (2021); Naseem et al. (2020); Shah et al. (2021); Baz et al. (2022); Albalawi and Mustafa (2022)	Literature Review	Hospitals & Patients	Medical Chatbots (Conversational AI) for patient/public queries	NLP	Text-based (user generated)	Initial screening – minimises unnecessary hospital visits, reduces misinformation, schedules doctor appointments, guides emergency cases to nearby clinics, and provides medication-related information	False responses

(*continued*)

Studies	Methodology	Relevant Stakeholders	AI Applications	AI Computational Technique(s)	Data Type(s)	Benefits	Challenges
Kamran et al. (2023)	Simulation-based optimization using secondary data	Hospitals & Patients, Pharmaceuticals	AI-enabled new COVID-19 vaccine supply chain to manage production, distribution, location, allocation, and inventory control decisions	ML	Vaccine demand at different locations; supply chain costs; capacity of facilities; inventory levels; inventory age; production rate	Minimize supply chain costs, maximise student desirability for vaccination, and maximise justice in vaccine distribution	No official data or database for some measures
Ghasemi et al. (2021)	Literature Review + Mathematical Modelling using secondary data	Hospitals & Patients; Pharmaceuticals, Government	Route Optimization	ML	Patient demand; transportation costs; facility and vehicle capacities; allocated budget	Minimise fixed and operational costs associated with location, routing, and allocation of medical centers to the distribution depots	Lack of access to accurate data
Wang et al. (2021); El-Sherif et al. (2022); Jabarulla and Lee (2021); Khan et al. (2021); Malik et al. (2021); Aruleba et al. (2022); Carriere et al. (2021); Swayamsiddha et al. (2021); Vaishya et al. (2020); Ngabo et al. (2021); Naseem et al. (2020); Nguyen et al. (2021); Shah et al. (2021); Piccialli et al. (2021); Kaur et al. (2021); Baz et al. (2022); Albalawi and Mustafa (2022); Arora et al. (2021); Rasheed et al. (2021); Abdulkareem and Petersen (2021)	Literature Review and Conceptual	Government & Public	Public health monitoring/surveillance and tracking of Covid-19 infection trends; Outbreak detection and pandemic trajectory assessment incl. of clusters and hotspots	DL, ML, NLP	Time series epidemiological data (e.g. confirmed cases, deaths, recoveries), location data (Bluetooth, GPS), google trends, credit card transactions, smartphone data (activity and usage patterns), Facebook and twitter data, audio conversations with hospitals, wearable sensor data (e.g. heart rate, temperature, sleep duration) Text data (clinical notes and discharge summaries)	Better preparedness and control; timely enforcement of preventive measures – lockdown, sanitation procedures, real-time updates for public, optimal allocation of healthcare resources	Lack of standard datasets, Generalizability of the model to other settings, privacy, and security of data incl. cyber attacks

Alhasan and Hasaneen (2021); Jabarulla and Lee (2021); Sarker et al. (2021); Aruleba et al. (2022); Vaishya et al. (2020); Swayamsiddha et al. (2021); Naseem et al. (2020); Shah et al. (2021); Baz et al. (2022); Abdulkareem and Petersen (2021)	Literature Review and Conceptual	Government & Public	Monitoring/ surveillance of COVID-19 patients and close contacts for contact tracing, quarantine	-	Location data (GPS, Bluetooth) using AI-enabled smartphone applications and wearables, social media activity, credit card transactions, car number plate details, clinical data	Faster, more efficient; lower occupational hazard vis-à-vis conventional human-tracing; Patients can home quarantine instead of institutional quarantine	Privacy and security concerns, risk of breaches, Lack of robust regulatory landscape, lack of awareness of regulatory issues
Jabarulla and Lee (2021); Sarker et al. (2021); Aruleba et al. (2022); Ngabo et al. (2021); Shah et al. (2021); Piccialli et al. (2021); Albalawi and Mustafa (2022)	Literature Review and Conceptual	Government & Public	Contactless and autonomous public health surveillance – facial recognition and thermal imaging for monitoring mask-wearing, social distancing, and fever	Computer vision, ML	Video-feed from cameras, images	Safer, autonomous, faster, and efficient; relatively inexpensive to monitor large and populated regions	Privacy and security concerns
Shah et al. (2021)	Literature Review	Government & Public	Vaccination Drive (Identification of vaccines with best efficacy among approved vaccine list)	-	Multimodal data (age, gender, comorbidities etc.)	Maximum efficacy and least adverse effects on the patient	
Kaur et al. (2021)	Literature Review	Public	Self-assessment of symptoms	NLP	Text and Voice data (on public queries)	Public get answers to their questions related to infection and further direction	
Wang et al. (2021), Alhasan and Hasaneen (2021); Khan et al. (2021); Sarker et al. (2021); Malik et al. (2021); Aruleba et al. (2022); Swayamsiddha et al. (2021); Vaishya et al. (2020); Naseem et al. (2020); Nguyen et al. (2021); Shah et al. (2021); Piccialli et al. (2021); Kaur et al. (2021); Baz et al. (2022); Albalawi and Mustafa (2022); Arora et al. (2021); Rasheed et al. (2021)	Literature Review and Conceptual	Pharmaceuticals	Identification/ prediction of virus protein structure; molecule scoring process; predict drug-target interactions (DTIs); screening potential drug candidates; Essentially Drug/vaccine repurposing, development.	DL, ML, NLP	Genomic, chemical and molecular data, drug database	Millions of compounds can be screened against a druggable target in a speedy manner; Faster and cost-effective drug and vaccine discovery and development	Ever-changing nature of the virus (mutations)

(*continued*)

Table 1. Continued.

Studies	Methodology	Relevant Stakeholders	AI Applications	AI Computational Technique(s)	Data Type(s)	Benefits	Challenges
Sarker et al. (2021); Albalawi and Mustafa (2022)	Systematic Literature Review	Researchers & Pharmaceuticals	Extraction of medical information from scientific research papers for treatment	NLP	Text data (Research papers and documents)	Extract medical information from the unstructured text	-
Surianarayanan and Chelliah (2021)	Literature review + Modelling using a hypothetical training dataset	Government & Public	Public health surveillance and early outbreak detection using heterogeneous data	-	Epidemiological time series data, textual clinical reports, social media data, data from wearable devices, airline tickets sale, demographic data, and environmental data (temperature, humidity)	Assist in implementing preventive countermeasures such as lockdown, keeping isolation centers ready, etc.	
		Hospitals & Patients	Detection and diagnosis using medical imaging modalities	DL	Chest CT scans	Fast and reliable	Requires large, accurately labeled/curated datasets to produce sufficient accuracy
			Detection and risk assessment/classification based on symptoms	ML	Clinical symptoms (Contact, fever, cough, sneeze, shortness of breath, sore throat, comorbidity)	Easy to detect the symptoms	
			Prognosis-based prediction of COVID-19 patient (Mortality risk prediction, length of hospitalisation)	ML	Clinical data (e.g. oxygen saturation), demographic data (e.g. sex, age)	Identification of high-risk patients up to 10 days in advance, resource estimation (patients who need ventilators and in need of ICUs)	Need to be tested over diverse data sets to enhance generalizability
		Pharmaceuticals	Drug repurposing, new drug and vaccine development	ML, DL, NLP	Genomic and molecular data, drug and disease databases with published and unpublished data	Significant reduction in time and cost	

the table. Also, if a study covered multiple stakeholders and/or multiple AI applications (for a stakeholder), it is repeated for each.

The review (see Table 1) revealed several gaps. First, there is no comprehensive investigation covering all the key AI applications for different stakeholders in the healthcare sector. Existing literature mostly focuses on the use of AI in specific applications, such as disease detection, drug development or resource allocation. Similarly, the information about computational techniques and data needs is scattered across different studies, making it difficult for stakeholders to understand how to implement AI. A comprehensive examination of different AI applications, computational methods and data types across different areas of healthcare, and an integrated perspective on how AI could benefit the entire healthcare sector, including the role of various stakeholders such as governments, hospitals, pharmaceutical companies and patients, is missing. These gaps led to research questions RQ1 and RQ2. Answers to these questions will enable stakeholders to choose the most appropriate AI solutions for their specific needs.

Most studies in the literature have focused on the technical aspects of AI application in healthcare, with limited or no attention given to managerial aspects like enablers and implementation-related challenges. Research that addresses these antecedents could help practitioners and policymakers develop more effective strategies to encourage AI adoption. Furthermore, there seem to be few studies exploring the performance impact of AI applications for different healthcare stakeholders. Investigating the tangible and intangible benefits of AI in different healthcare contexts would be beneficial for understanding its overall impact and could aid its wider acceptance and application.

Addressing these managerial aspects is important, as they can help healthcare providers, policymakers, and other stakeholders make well-informed decisions about AI adoption and implementation strategies. These knowledge gaps led to research questions RQ3, RQ4 and RQ5.

There is no comprehensive AI framework for the healthcare sector. Those frameworks that exist are too narrowly focused: one, for example, is patient-centric and wholly blockchain- and AI-based (Jabarulla and Lee 2021). A holistic framework for AI in healthcare that incorporates both technological and management levers is required.

Finally, there are very few empirical studies. Most of the studies are conceptual (relying on selective secondary data), literature review-based or simulation-based, and are also limited in scope. In-depth country-level investigations, such as those based on case studies, appear to be missing. Therefore, it is unclear how AI is adopted in healthcare at the stakeholder or country level.

The literature contains many valuable studies that provide the theoretical basis for the framework on AI in healthcare. However, the lack of empirical support for the framework may limit its credibility, applicability, and generalizability. For instance, without practical assessment and validation, it may be difficult to ascertain the framework's relevance and effectiveness in addressing real-world problems. Additionally, inconsistencies within the framework may remain unaddressed. As a result, practitioners and policymakers may be hesitant to adopt or utilise such frameworks.

The present study aims to address these gaps by proposing a comprehensive AI framework for healthcare that includes all key stakeholders, AI application areas, and relevant technical and managerial aspects/levers (Research Objective 1). To ensure the proposed framework is comprehensive, we also reviewed several established and emerging AI and technology frameworks in healthcare and other sectors, including the Technology, Organization, and Environment (TOE) framework (e.g. Pillai et al. 2021), the patient-centric framework (e.g. Jabarulla and Lee 2021), AI frameworks for public management (e.g. Wirtz and Müller 2019; Wirtz, Weyerer, and Sturm 2020), AI frameworks on techniques and benefits from the supply chain domain (e.g. Naz et al. 2022), AI and blockchain readiness and adoption frameworks (e.g. Issa, Jabbouri, and Palmer 2022; Balasubramanian et al. 2021), and frameworks enabling Industry 4.0 (e.g. Balasubramanian et al. 2022). These generic frameworks provide a good theoretical basis and knowledge (including knowledge of pitfalls) for developing an AI framework for healthcare. Previous studies have also advocated for the amalgamation of existing frameworks to ensure both that multiple theoretical perspectives are simultaneously considered and that the boundaries of the field are more rigorously defined (Balasubramanian et al. 2021). However, it is important to emphasise that the key components of our framework are not directly derived from previous examples; rather, they have been carefully framed and contextualised based on our understanding of the healthcare sector and AI technologies. This framework's other significant contribution, in contrast to the others in the literature, is that it has been practically validated in the UAE healthcare sector (Research Objective 2).

2.1. Components of the framework

The components of the framework were carefully derived from the literature. The first task in any such endeavour is

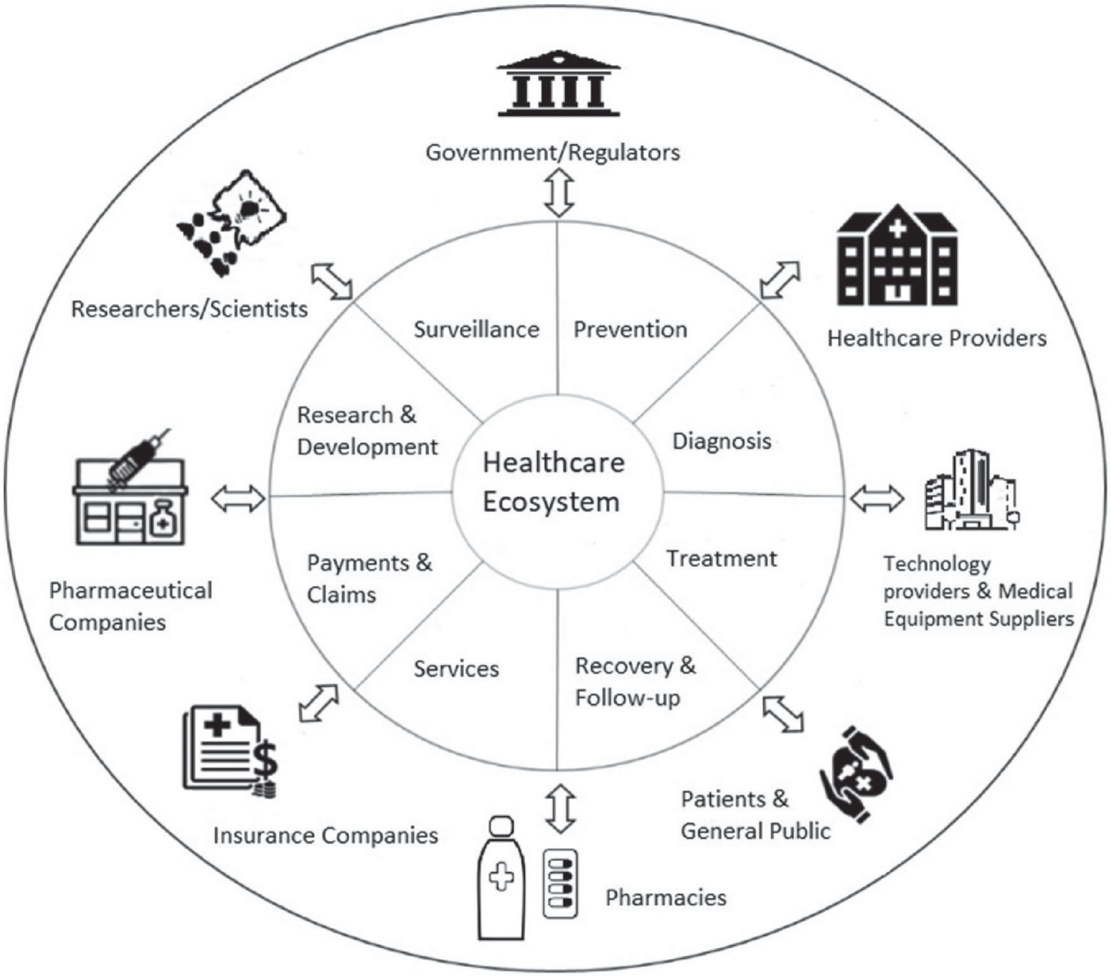

Figure 2. Key healthcare sector stakeholders and their roles (Source: Authors).

to identify the key stakeholders that provide the technology solution, as well as those benefitting from it (Balasubramanian et al. 2021). These stakeholders for healthcare are given in Figure 2, below.

The technology aspects of the framework (which we call 'technology levers') are organised into three layers (Jabarulla and Lee 2021): the Applications layer (i.e. the different AI applications for the healthcare stakeholders), the Computational layer (i.e. the different AI techniques/models), and the Data layer (i.e. the different kinds of data used to train/develop the AI techniques/models). The management aspects/levers consist of the different enablers, the risks/challenges (Müller et al. 2021; Balasubramanian et al. 2022), and the performance benefits arising from AI adoption (Naz et al. 2022). These are detailed below.

2.1.1. Technology levers

The organisation of the three layers can be bottom-up (Data -> Computational Technique -> Applications) or top-down (Applications -> Computational Technique -> Data), with both approaches being appropriate depending on data availability, expertise and the flexibility of the application.

Data Layer. AI is data-driven, making decisions based on the data on which it was trained. More and better-quality data make the resulting AI model more accurate and robust (Forbes 2018; Surianarayanan and Chelliah 2021), which is particularly critical for healthcare, where inaccuracies can be life-threatening. Table 1 displays the wide range of data used for building AI models in healthcare, which extends from genomic to multimedia to epidemiological data. Data availability-related challenges can be addressed by collaborating with other hospitals and obtaining data from there. Data collection can be done in person (e.g. for blood samples) or remotely (e.g. for heart rate or temperature). The mode of collection may be invasive (CT scans, blood samples) or non-invasive (cough sounds). All of these have implications for the nature of the AI applications that can be developed.

Computational Layer. The computational layer consists of AI techniques/models (developed using input data from the data layer) based on four generic approaches: Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP) and Computer Vision (Shah et al. 2021; Deloitte 2020; Arora et al. 2021). ML techniques learn from data, classify things, identify patterns and correlations, make decisions and predictions, and improve with experience. They can be supervised, unsupervised, semi-supervised, or reinforcement learning-based depending on the problem context (SAP 2022; SAS 2022). ML techniques are preferred for structured data such as time series epistemological data, where they are considered to be more accurate.

DL is based on a conceptual model of the brain called 'neural network' (Deloitte 2020), where there is an input layer for receiving data samples, a number of hidden layers that reflect the depth of the deep learning training, and an output layer for generating the training outcomes (Nguyen et al. 2021; Jabarulla and Lee 2021). DL methods are preferred for assessments involving unstructured data such as medical images (Nguyen et al. 2021).

NLP techniques focus on obtaining information representations for text and speech data, which in the case of healthcare means analysing, summarising, clustering and classifying disease-related data and data in scientific texts (Carriere et al. 2021; Albalawi and Mustafa 2022).

Finally, computer vision techniques enable the extraction of meaningful information from visual elements such as characters (as in the case of digitisation of documents) or images such as faces, objects, scenes and activities (Deloitte 2020). They were widely exploited during the COVID-19 pandemic to control the spread of the virus.

While all four generic techniques have been used to develop AI models, and from both diagnostic and prognostic perspectives (Adamidi, Mitsis, and Nikita 2021), the key application determinant is overall performance in terms of accuracy, sensitivity and specificity (Aruleba et al. 2022).

Application Layer. It is useful to categorise AI applications according to individual stakeholders, although some of them are considered together because of their close association with each other, such as healthcare providers and patients, and government and the (general) public. Pharmaceutical companies are classified separately.

Healthcare Providers and Patients. Healthcare providers include hospitals, clinics, laboratories and pharmacies, with the relevant AI applications in their cases being disease detection, diagnosis, and patient prognosis and classification (see Table 1). For COVID-19 detection and diagnosis, AI techniques based on medical imaging (CT scan, MRI, ultrasound and X-ray), blood samples and acoustics were tried (Abdulkareem and Petersen 2021). While the approaches based on CT scans yielded the best results, those based on X-rays were most commonly used. In the case of techniques based on blood samples (Mohamadou, Halidou, and Kapen 2020), their sensitivity and specificity were found to be greater than that of the RT–PCR test (Arora et al. 2021). For techniques based on acoustic data, the patient's voice, coughing and breathing sounds were used. These can be recorded remotely via smartphone/computer, which makes them more convenient and cost-effective to use. The acoustic data-based techniques have also been found to be effective for asymptomatic patients (Sarker et al. 2021). COVID-19 detection/diagnosis based on AI using clinical data such as temperature, heart rate, oxygen levels and clinical symptoms such as cough, fever, sneezing, shortness of breath, sore throat and comorbidity has also been reported (Surianarayanan and Chelliah 2021).

AI models have also been employed for prognostic assessment and the classification of COVID-19 patients based on disease severity, mortality, length of hospitalisation and recovery duration (Wang et al. 2021). These models are also used to classify patients into the overall risk categories of high, moderate and low risk (Shah et al. 2021), taking into account gender and age factors as well (Malik et al. 2021). Through improved prediction accuracy, the models enable better planning for ICU admissions, as well as for assessing the requirements for oxygen, ventilators, beds and healthcare staff (Vaishya et al. 2020). They also contribute to better planning for treatment regimens for high-risk patients, reducing disease severity and mortality (Alhasan and Hasaneen 2021).

AI-based medical chatbots were also tried successfully during the COVID-19 pandemic. They provided online consultation/support on issues such as symptoms, drugs, mental stress (virtual therapy), infection avoidance/reporting, self-screening/quarantining, and nearest hospital location, thereby helping to avoid physical crowding at hospitals and associated disease transmission (Wang et al. 2021; Baz et al. 2022).

Government and Public. Governments oversaw the implementation of measures such as lockdowns, quarantining, social distancing, face masking, contact tracing, thermal screening (for fever detection) and the roll-out of vaccination programmes to reduce the spread of the virus and ensure citizens' safety. AI played a crucial role in all of these activities (Surianarayanan and Chelliah 2021). Public health surveillance based on computer vision systems with thermal imaging capabilities proved effective in screening febrile cases. Other related applications focused on face mask detection, social distancing assessment, motion detection and number plate recognition, which improved compliance with lockdowns and other COVID-19 regulations. Similarly, AI-enabled smart wearables and smartphone applications (Alhasan and Hasaneen 2021) could check whether quarantine/isolation/social distancing norms were being followed. Also successfully applied were AI-based surveillance systems that used social media data (Twitter and Facebook) and associated sentiment analysis, credit card purchases, global positioning system (GPS) data, flight booking data, internet search activity, and Wi-Fi and mobile data (which identified abnormal usage such as earlier morning calls, sudden cessation of calls, calls suddenly appearing from a different city, etc.) (Nguyen et al. 2021; Shah et al. 2021). NLP-based methods provided additional surveillance opportunities by using information present in clinical notes and discharge summaries (Carriere et al. 2021).

Finally, AI-based forecasting approaches could learn from massive datasets on factors such as the number of COVID-19 cases, deaths, demographics and related environmental conditions in order to predict the future course of the disease, including peaks, reappearance, preventive measure effect and overall impact (Vaishya et al. 2020). This could be done for different geographical locations, which enabled governments to devise appropriate and timely remedial actions (Nguyen et al. 2021; Naseem et al. 2020).

Pharmaceutical Companies. New drug/vaccine development takes a long time and is also very expensive for pharmaceutical companies. AI can accelerate this process and make it more cost-efficient. For example, for COVID-19, AI models that could screen targets on the virus's surface and identify potential compounds (adjuvants for drugs and vaccines) were successfully explored (Surianarayanan and Chelliah 2021). An example of this is AlphaFold, a deep learning system developed by Google DeepMind, which was able to provide valuable information on the COVID-19 virus's protein structure quickly, thereby accelerating vaccine development (Naseem et al. 2020). AI can also help run simulations to predict the effectiveness of potential drugs/vaccines.

AI also helps in drug repurposing so that existing drugs can be used to treat new diseases. This was seen for COVID-19, where a DL-based drug-target interaction model called Molecule Transformer-Drug Target Interaction (MT-DTI) was used to identify commercially available drugs that could act on the viral proteins of the COVID-19 virus (Shah et al. 2021). AI models could also identify COVID-19 vaccines that had greater effectiveness and fewer/lesser side effects (Shah et al. 2021). They could also determine existing COVID-19 virus mutations as well as predict future ones (Albalawi and Mustafa 2022).

2.1.2. Management levers

This section discusses the various enablers, benefits and challenges associated with AI adoption in healthcare.

Enablers of AI. *Regulatory and Legal Environment.* While AI applications are beneficial, the related legal and regulatory frameworks need to be robust so that the people associated with the applications' development can be held accountable (Nguyen et al. 2021). This is particularly critical for healthcare, where people's health and lives are at stake. Appropriate government policies, directives, regulations and laws therefore need to be in place (Google 2022a; 2022b). They must also be easily comprehensible and accessible to AI developers and should keep pace with the development of new AI applications (Balasubramanian et al. 2021; Abdulkareem and Petersen 2021). This can also help in attracting more AI developers to the sector.

Technology Infrastructure. AI algorithms and associated data are growing in complexity and therefore require increasing computational power and technology infrastructure, such as hardware, software, networks, applications, and other information and communications technology (ICT) resources (Jabarulla and Lee 2021). For example, the availability of CT scanning facilities in clinics and hospitals is essential for implementing AI-based imaging techniques, just as high-resolution thermal imaging cameras are important for AI-driven public health surveillance. The preference should be for infrastructure and equipment that can be integrated with the existing set-up rather than adopting those that are totally novel (Shah et al. 2021). In order to fully leverage the benefits of AI, patients and healthcare providers should have access to electronic devices such as smartphones and tablets with 4G/5G connectivity, as well as high-speed internet (Balasubramanian et al. 2021).

Stakeholder Collaboration. In a sector as complex as healthcare, no single player possesses all the solutions. Collaborations between stakeholders, such as between clinicians, epidemiologists, computer scientists, software developers, AI experts, and others, are therefore needed for developing (and subsequently applying) AI solutions (Abdulkareem and Petersen 2021). Such collaborations can be between the public and private sectors (van Der Schaar et al. 2021), as well as between different healthcare institutions (Nguyen et al. 2021). Global collaboration and data sharing are also needed to evaluate newly developed AI techniques. For example, developing a common dataset using samples from different institutions can overcome any data scarcity encountered when training AI techniques. Similarly, collaborations with telecommunications and cloud solution providers can strengthen the technology infrastructure needed for AI technique development and application (Balasubramanian et al. 2021). Additionally, partnerships between healthcare institutions, multinational technology companies (e.g. Google), universities, startups, et cetera, could foster the development of novel AI healthcare applications. For example, Fitbit© is collaborating with Apple© and the Stanford Healthcare Innovation Lab to develop AI algorithms capable of detecting COVID-19 even before symptoms become apparent (Snider 2020). These collaborations all facilitate complementary knowledge and skill acquisition, ecosystem integration, and the development of new business models from an AI perspective (EIT 2021).

Innovation Propensity. Cultivating a robust innovation culture is essential for AI's successful adoption, and this is something required for all stakeholders. For instance, customer orientation is an important factor for innovation. Customer-oriented organisations such as hospitals should therefore seek innovations that contribute to customer satisfaction (or patient satisfaction in healthcare) (Pillai et al. 2021). A country's vision and its government can also play critical roles in promoting innovation within the healthcare sector (Balasubramanian et al. 2021).

Benefits of AI in Healthcare. In healthcare, as in other sectors, performance benefits resulting from a technology are critical to its adoption (Pillai et al. 2021; Balasubramanian et al. 2021). This means that the greater the potential benefits of AI for healthcare stakeholders, the more resources such as time, money and personnel, they will spend on it. These benefits are presented below.

Operational Benefits. Operational benefits primarily involve higher speed and lower cost through the AI-enabled automation of processes. For example, in the case of CT scan assessment, while a radiologist takes an average of 10 min and 9 s, the deep learning algorithm completes the task in just 4.5 s (Khan et al. 2021; Naseem et al. 2020). The automated nature of assessment in the latter case, which also applies to MRI and X-ray scans, also improves cost efficiency by reducing both the radiologist's time commitment and the need for support staff (Wang et al. 2021; Khan et al. 2021). Similarly, AI-enabled remote diagnoses and medical chatbots provide quicker responses. They also reduce patient hospital visits and the associated resource requirements, offer scalability to meet increased demand, and can work long hours without fatigue – all of which contribute to improved cost efficiency.

AI's predictive modelling algorithms can also provide accurate assessments of resource requirements such as hospital beds, ICUs, ventilators and healthcare professionals in a timely fashion (Adamidi, Mitsis, and Nikita 2021), which again leads to quick response (for the patients) and cost efficiency (for the hospital). Similarly, the AI model-enabled accurate prognosis of patients enables fast and appropriate treatment to be provided to those at high risk while conserving scarce resources.

On the Research and Development (R&D) front, AI significantly reduces the time required for drug/vaccine discovery. For example, it can facilitate the rapid shortlisting of the most promising molecules from among thousands, which can then be evaluated for the development of therapeutic drugs/vaccines (Malik et al. 2021). This also reduces the R&D resource requirements, such as equipment, reagents, chemicals and researchers.

Quality Benefits. Healthcare staff are under high levels of stress during pandemics, such as the COVID-19 outbreak, as a result of which manual/traditional protocols for diagnosing and treating patients could become prone to error (Alhasan and Hasaneen 2021). AI-based approaches, on the other hand, are unaffected by either stress/anxiety or the nature of the workload and can continue to provide consistent detection and diagnosis; they can also be less prone to biases if they learn from sufficiently representative datasets. Studies have shown AI-assisted radiologists to be more successful in diagnosing COVID-19 than those without such assistance (Pankhania 2021). Finally, AI-based pandemic forecasting models have been reported to be more accurate than conventional linear regression-based ones (Abdulkareem and Petersen 2021).

Social Benefits. AI can enhance public health surveillance, including spatial epidemiology, and improve epidemiological forecasting capabilities, thereby improving the population's health (Abdulkareem and Petersen 2021). Real-time AI-based monitoring capabilities are helpful in assessing the spread of outbreaks, including by identifying hotspots and clusters (Alhasan and Hasaneen 2021). AI ensures that preventive measures such as contact tracing and social distancing can be implemented effectively and efficiently. It also enables personalised patient care and ensures priority treatment for those who need it the most, based on their medical history and clinical data (Jabarulla and Lee 2021). Moreover, AI facilitates the identification of vulnerable sections of the population based on demographic data such as age, gender, and ethnicity (Vaishya et al. 2020). Additionally, AI-enabled virtual applications and medical chatbots provide accurate and timely responses to patient and public queries, thereby preventing misinformation and associated panic or chaos (Sarker et al. 2021).

Challenges of AI in Healthcare. Several challenges have been identified in the literature. The key ones include:

Privacy and Security Concerns. Sensitive and personal healthcare data must be handled with the utmost privacy and trust because of its potential for abuse and discrimination, and in accordance with the legislation enacted for precisely that reason. According to the global IPSOS/World Economic Forum study of 2019, 41% of people did not trust their healthcare providers with their private data (IPSOS 2019). Therefore, assuring healthcare stakeholders that their information will be kept private, safe and anonymous is critical for the successful adoption of AI.

The Generalisability of AI Models. One of the main challenges facing AI computational techniques/models is their lack of generalisability across settings (Arora et al. 2021). This is often due to the dataset used to train the model being local or specific and therefore unsuitable for use in a different setting. Most of the studies in Table 1 are based on single locations; the applicability of the model they discuss may therefore be limited to the same geographical region. Another issue with ML and DL models pertains to model overfitting, as the training and testing data may come from the same dataset due to limited data availability (Wang et al. 2021).

Data and Algorithmic Bias. Another concern with AI models is algorithmic bias, which involves issues of fairness and inclusiveness (Arora et al. 2021). For instance, for disease severity risk prediction, biases in modelling may result in genuine high-risk patients being excluded from priority care. In the case of NLP-based models, language processing may not be feasible for certain languages, leading to inclusivity concerns. Additionally, AI models often suffer from data selection bias, such as training data being from a single hospital only. They must be therefore tested on diverse datasets covering wider demographics (Surianarayanan and Chelliah 2021). Similarly, AI diagnostic models based on a single data type could display biases, which would result in the models needing to be used in conjunction with traditional laboratory tests. This necessitates a multimodal AI framework that uses different types of data (Wang et al. 2021).

Lack of Data Standards. One of the main challenges associated with the use of AI models is the absence of standard datasets (Khan et al. 2021). Using wrong or unreliable data sources can result in inaccurate results (Nguyen et al. 2021). Although several static datasets may be available, the dynamic nature of a context like COVID-19 can quickly render them obsolete. Moreover, there is a shortage of epistemological time-series datasets of the type employed in epidemiological models (Albalawi and Mustafa 2022).

Our proposed AI framework containing all of the above elements is shown in Figure 3. By developing this comprehensive AI framework, we accomplished the first research objective of this study. However, it is important to emphasise that, like any research framework, the one we propose relies on foundational assumptions that shape its approach, methodology and analysis. We list these assumptions because knowing them is vital for understanding the research's scope, applicability and potential limitations:

- AI has the potential to transform healthcare by addressing inefficiencies and complexities in the sector, particularly those highlighted by the COVID-19 pandemic.
- AI can substantially improve operational, quality-related and societal outcomes in healthcare.
- A comprehensive approach or framework (as opposed to a fragmented one) that encompasses a variety of AI applications, computational methods, data types, and both technical and management factors is essential for the widespread adoption of AI in healthcare.
- A framework that has been empirically validated in a real-world setting (such as the UAE) provides more robust and actionable insights than those that are based on literature reviews, simulations and conceptual analyses.
- The framework is relevant to other healthcare contexts around the world and can provide useful insights there.

3. Case study methodology

Having developed the AI healthcare framework, the next stage was to test its applicability and usefulness using the case study method (Yin 2009). We decided on a single case study of the UAE's healthcare sector that embedded multiple units of analysis (Yin 2009). This was necessary as many different strands of the framework – technology levers, management levers and their sub-components – needed to be explored.

We chose the UAE's healthcare sector due to its global reputation and exceptional performance during the COVID-19 pandemic. The UAE ranks as the 20th best healthcare country globally according to the World Index of Healthcare Innovation (Roy 2021), with 125

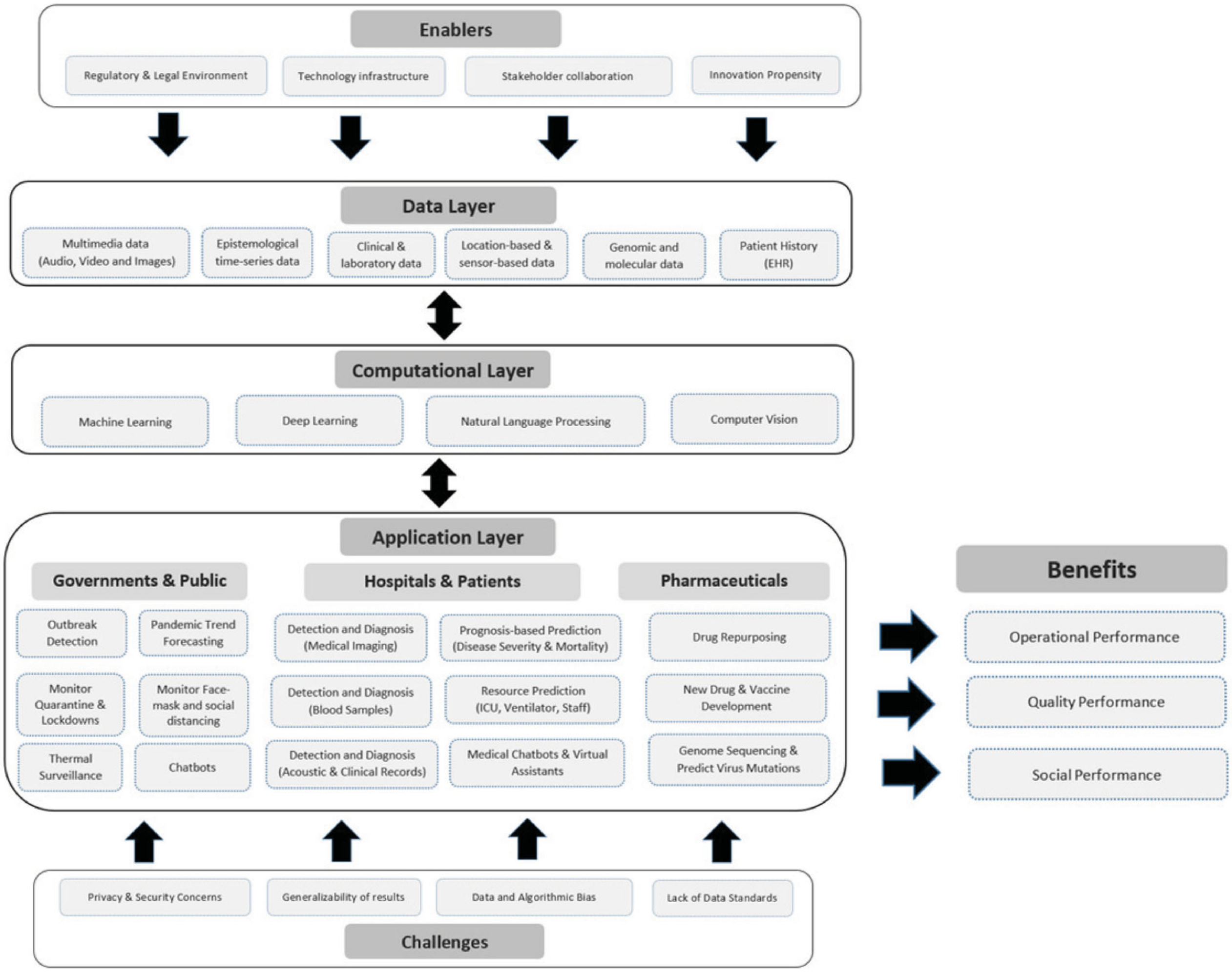

Figure 3. Proposed AI Framework for the Healthcare Sector.

large public and private hospitals possessing advanced facilities (Balasubramanian et al. 2021). It was one of the first countries to vaccinate its entire eligible population, with per-capita vaccination rates among the highest in the world (Weqaya 2021a). Additionally, it had the highest per-capita testing rate and the lowest death rate from COVID-19 (FCSC 2022). Advanced technologies, including AI, were a significant factor in these achievements (Weqaya 2021b).

Given the novelty of the topic and the need for practical solutions, we employed a pragmatic approach using both primary and secondary data (Balasubramanian et al. 2021; 2022). The secondary data relevant to AI application in the UAE's healthcare sector case was sourced from reliable sources such as industry and consultancy reports, government reports and policy documents, news articles, websites, successful use cases, and published interview data and transcripts. The primary data served to fill the gaps in the secondary data and involved semi-structured interviews with 12 participants (see Table 2). These participants were carefully selected using a purposive sampling technique to cover the various stakeholders in the healthcare sector with knowledge of AI applications. The interviews were conducted via Zoom and lasted 30–45 min.

Table 2. List of primary respondents.

S. No	Interviewee	Experience (in Years)	Stakeholder
1	Healthcare Researcher (Government entity)	11	Researcher
2	Physician	20+	Practitioner
3	IT Infrastructure Manager	8	Hospital
4	IT Director	15	Clinics
5	IT Security and Compliance Lead	30+	Hospital
6	Physician	3	Practitioner
7	Chief Technology Architect	25+	IT solution provider
8	IT Consultant (Advisory and Legal)	9	Consulting Firm
9	Senior IT Infrastructure Engineer	15	IT solution provider
10	Physician	12	Practitioner
11	Service Delivery Manager (Infrastructure & Data Center)	14	Hospital
12	Administration Manager	10	Hospital

We then used a top-down, deductive method for thematic analysis, enabling the systematic categorisation and coding of data obtained from primary (interview transcripts) and secondary sources. Our decision to use this technique was guided by the pre-established themes and sub-themes present in the proposed AI framework for the healthcare sector (Figure 3), and it accommodated new perspectives and modifications during data analysis. Previous studies have recommended the use of top-down approaches when researchers aim to establish the relevance and validity of a theoretical framework (Balasubramanian et al. 2021; 2022).

Accordingly, the first stage involved high-level categorisation of primary and secondary data into Technology (T) and Management (M) levers. The second stage entailed thematic classification and coding. For the technology lever, data were further classified into three primary themes: Application (A), Computational (C) and Data (D) layers. These themes were subsequently divided into sub-themes as defined in the framework. For instance, AI applications related to pandemic trend forecasting were grouped under the sub-theme A1. Specific applications within sub-theme A1, such as epistemological time series forecasting, then received unique codes (e.g. A1.1). Similar sub-theme categorisation and coding were applied to the computational and data layers. For example, X-ray images were coded as D1.1 under the sub-theme multimedia data (D1) and the main theme data layer (D). These sub-themes and codes were further classified for each stakeholder group: governments & public (G&P), hospitals & patients (H&P), and pharmaceuticals (P).

A similar approach was taken for the management levers. The data were classified into three broad themes: Enablers (EN), Challenges (CH) and Performance Benefits (PB), which were further divided into sub-themes and then assigned codes. For instance, within enablers, specific aspects like regulatory policies (EN1.1) and regulatory toolkit (EN1.2) were given unique codes and grouped under the sub-theme regulatory and legal environment (EN1), which falls under the central theme of enablers (EN).

4. Case study findings

The findings are organised in line with the core components of the framework, as presented in Table 3, which address research questions RQ1 to RQ5. To provide a comprehensive perspective, technology and management levers are mapped to each stakeholder.

4.1. Technology levers

4.1.1. Application layer (Answer to RQ1)

Government. The UAE government implemented numerous AI applications (see Table 3) and most interviewees appreciated their role in monitoring and preventing COVID-19. In particular, they emphasised the contributions of Rokid T1 (AI-powered Smart Glass), Dubai Police's flagship AI project 'Oyoon' (which involves the use of advanced AI-powered cameras for facial recognition and behavioural analysis),and smart helmets (equipped with thermal cameras and sensors). AI-powered thermal infrared cameras were also installed indoors in leading malls, hospitals and clinics. According to one interviewee, '*These cameras can not only read the patients' and visitors' temperatures but also determine whether they are wearing face masks and maintaining social distancing, and provide related alerts*'. The Abu Dhabi government also deployed intelligent scanners at border crossings, malls and other public locations. These scanners could detect COVID-19 infections within seconds by measuring people's electromagnetic wave emissions (which are altered by the presence of the viral RNA) and were found to be 93.5% and 83% accurate in identifying infected and non-infected individuals, respectively (The National News 2021a; Abu Dhabi Government Media Office 2021). These findings are consistent with previous research on AI applications for social monitoring. For example, Surianarayanan and Chelliah (2021) discussed the use of intelligent infrared cameras with facial recognition systems to measure body temperature and assess compliance with mask-wearing and social distancing guidelines. These technologies can enable healthcare authorities to detect COVID-19 symptoms and determine non-compliance with pandemic-related regulations (Jabarulla and Lee 2021; Shah et al. 2021). In Hyderabad, India, CCTV cameras installed throughout the city were equipped with deep learning and computer vision technologies to identify individuals not wearing face masks. These cameras then triggered alerts in the control centre for necessary actions (Surianarayanan and Chelliah 2021).

The UAE government also employed several AI applications for COVID-19 quarantine, with the ALHOSN UAE app being one of the most notable ones. This app features a unique personal QR code and a colour-coding system that indicates the user's health status, enabling it to trace individuals (through Bluetooth technology) who have come into close proximity with confirmed COVID-19 cases. This approach is similar to solutions that have been developed by other countries for location-based COVID-19 notifications and communication. For

Table 3. Mapping of AI Framework to UAE healthcare sector.

		Technology Lever			Management Lever			
Stakeholders	Initiative	Application	Computational Technique(s)	Data Type(s)	Enablers	Benefits	Challenges	Reference
Dubai police (Government)	Smart Glass (Rokid T1)	Public health surveillance – temperature screening of commuters at public transport stops	Computer Vision (Infrared thermal cameras with facial and object recognition)	Image and Video	Technology infrastructure, innovation propensity	Operational: Detection capacity of 100 people per minute from 2 m distance with information on suspected cases then automatically communicated Quality: 100% detection rate with accuracy of 99.8%.	Privacy and security concerns	Dubai Police (2020)
Dubai police (Government)	Oyoon' ('eye' in English)	Public health surveillance – temperature screening, social distancing, face-mask detection	Computer Vision (Thermal cameras with facial recognition and behavioral analysis)	Image and Video	Technology infrastructure, innovation propensity	Operational and Social: Large scale non-intrusive surveillance, automatically detect and alert authorities of breach in protocols	Privacy and security concerns	Dubai Police (2020)
UAE Ministry of Interior (Government)	The smart helmet	Public health surveillance – temperature screening, social distancing, face-mask detection	Computer Vision (Thermal cameras with facial and object recognition)	Image and Video	Technology infrastructure, innovation propensity	Operational and Social: Control the spread of virus	Privacy and security concerns	MOI (2021); UAE (2022)
Local and Federal Government	ALHOSN UAE	Public health surveillance – contact tracing, quarantine, hot spot detection using real-time COVID-19 status of public health	AI-enabled Smart Application	Location-based (Bluetooth, GPS)	Legal and regulatory environment, technology infrastructure, innovation propensity	Operational and Social: Official one stop for all (citizens, residents, tourists, and visitors), provides vaccination status, and can be used as travel pass for movement within the country	Require smartphones and internet connectivity, difficult for non-technical users	NCEMA (2022)
Abu Dhabi Government	Intelligent electronic wristbands	Isolation and home quarantine	AI-enabled Smart Wearable technology	Location-based (Geo-tagged)	Technology infrastructure, innovation propensity	Social: Detects breach of quarantine and isolation rules, tamper-proof	Privacy, security, and ethical concerns	UAE (2022)

(*continued*)

Table 3. Continued.

		Technology Lever			Management Lever			
Stakeholders	Initiative	Application	Computational Technique(s)	Data Type(s)	Enablers	Benefits	Challenges	Reference
Dubai Government	COVID19 – DXB Smart App	Public health surveillance – home isolation and quarantine for close contacts and positive cases	AI-enabled Smart Application with NLP	Location-based (Bluetooth, GPS)	Technology infrastructure, innovation propensity	Operational and Social: Patient can contact the health authorities 24/7 through the app for complications and make audio/video calls to anyone though the app to stay connected	Requires smart-phones and internet connec-tivity, difficult for non-technical users	UAE (2022)
Dubai Roads and Transport Authority (Government)	AI-enabled Cameras in Taxis	Public health surveillance – Face mask and facial detection, and physical distancing of driver and commuters	Computer Vision and ML	Image and Video	Technology infrastructure, innovation propensity	Operational, Quality and Social: The AI technology can automatically process video files spanning 200,000 h a day and report violations with an accuracy rate of 99.1%	Privacy and security concerns	RTA (2020)
Dubai Health Authority (Government)	Screening for tuberculosis & other diseases	Disease Detection using medical imaging	ML	Chest X-ray	Regulatory and legal environment, innovation propensity	Operational: Reduces work load of Radiologists, supports clinical decision-making	Only available in few facilities. Scaling up seems to be an issue	Gupta (2019); Zawya (2020)
Abu Dhabi Government	Intelligent Scanners	Public health surveillance – COVID-19 screening and detection	Computer Vision	Electro-magnetic (EM) wave emissions	Regulatory and legal environment, innovation propensity	Operational, Quality and Social: Non-invasive COVID-19 screening and detection in seconds, high sensitivity and accuracy	Public concern on the potential side effects from EM radiation; privacy concerns	Abu Dhabi Govern-ment Media Office (2021); Reuters (2021)
Prognica (Heathcare startup)	Screening for breast cancer	Disease detection and diagnosis using medical imaging	ML and Computer Vision	MRI and Ultrasound Images	Regulatory and legal environment, innovation propensity	Operational and Quality: Enables early detection, high training accuracy of 96.1%, improves interpretive capabilities of radiologists by ∼ 12%	Lack of public awareness and trust on AI-enabled technologies	de Leon (2021)

Researchers/Scientists	Severity assessment of COVID-19 patients	Prognostic-based severity prediction	ML	Chest X-ray	Innovation propensity	Operational and Social: Used federated learning to train the model to address privacy concerns	Availability of large-scale data	The National News (2021b; 2021c)
Healthcare Solution provider (Cerner) and American Hospital Dubai	COVID-19 Patient Mortality and ICU Admission	Prognostic-based severity and mortality prediction	ML	Clinical data of 50 risk identifiers	Stakeholder collaboration	Operational, Quality and Social: Prioritised treatment to save lives, allocation of resources, trained in large data set, high accuracy	Algorithmic bias	Cerner (2021)
Smart Dubai (Government) and Mohammed Bin Rashid University of Medicine and Health Sciences	COVID-19 epidemiological AI model	Forecasting the pandemic trend	ML	Epistemological time-series data (reported cases, deaths, recovered)	Stakeholder collaboration	Social: Implement preventive measures	Adaptability of the model in different scenarios	Smart Cities World (2021); Weqaya (2021c)
Hospitals (e.g. Medicare, Al Zahra)	Virtual health assistant	Medical Chatbots	NLP	Text (Patient queries)	Innovation propensity	Operational and Quality: Automated response to patient queries, reduce workload of medical staff, improve patient experience	Only English and Arabic languages are supported	Zawya (2020); Al Zahra Hospital Dubai (2020)
Ministry of Health and Prevention (Government)	Virtual Doctor for COVID-19	Chatbot	NLP	Text (Patient queries)	Innovation propensity	Social: Automated advice for patients and generic public, detect users at risk based on queries and alert authorities	Only support straight forward queries	UAE (2020)
Abu Dhabi Health Services Company (government), G42 (Healthcare solution provider), and Sinopharm (pharmaceutical company)	COVID-19 vaccine (Hayat-Vax)	Vaccine development and administration		Genomic, molecular data	Innovation propensity, regulatory and legal environment, stakeholder collaboration	Social: Control the spread of virus, reduce mortality	Small sample size during pilot phase; not very effective for different virus variants	Suliman et al. (2021); G42 (2021a)

(*continued*)

Table 3. Continued.

		Technology Lever			Management Lever			
Stakeholders	Initiative	Application	Computational Technique(s)	Data Type(s)	Enablers	Benefits	Challenges	Reference
Abu Dhabi Department of Health (government) and G42 (Healthcare solution provider),	Emirati Genome Program	Genome sequencing		Genomic data	Innovation propensity, regulatory and legal environment, stakeholder collaboration	Social: Personalised and preventive healthcare	Low participation, lack of public awareness	Department of Health (2019); G42 (2021b)
Dubai Silicon Oasis Authority (government) and Derq (a Massachusetts Institute of Technology spinoff)	Public compliance with COVID-19 measures	Public health surveillance – social distancing, face mask detection, and over crowding	Computer Vision	Image and Video	Innovation propensity, stakeholder collaboration	Operational and Social: No additional infrastructure or smart cameras. Video feed from existing cameras are analyzed by AI algorithms	Privacy and security concerns	Government of Dubai Media Office (2020)
Dubai Health Authority (government) and Healthcare and Innovative New Technology (HiNT)	Stroke detection headband	Remote patient Monitoring	AI-enabled smart wearables	Brain waves	Innovation propensity, stakeholder collaboration	Operational: 24/7 remote monitoring, and automated alerts to ambulance and caregiver in minutes	Scalability (Not widely used)	Gupta (2019); The National news (2018)
BodyO (Healthcare solution provider)	Mobile AI-assisted health pods	Preventive healthcare	Computer vision & health scans	Image, Video and sensor data	Innovation propensity	Operational: Provides 26 vital readings in 6 min, teleconsultation with specialists during and after procedure	Privacy and security concerns	Gupta (2019); BodyO (2022)
Abu Dhabi Health Services Company (government) and Mohamed bin Zayed University of Artificial Intelligence	Heart attack prediction	Preventive healthcare using medical imaging	-	Ultrasound image	Innovation propensity, stakeholder collaboration	Quality: Saving lives by predicting heart attack months in advance, accuracy rate of 87%	Privacy and security concerns	MBZUAI (2022)
Dubai Health Authority and Artelus (Healthcare AI solution provider); Abu Dhabi Health Services Company (SEHA)	Diabetic retinopathy	Detection and Diagnosis using medical imaging	DL	Retinal Images	Innovation propensity, stakeholder collaboration	Quality: Early detection, high degree of accuracy		Gupta (2019); Zawya (2022)
Daman (Medical Insurance Company) and Microsoft (Technology Solution Provider)	Medical Chatbot	Self-assessment tool on COVID-19	NLP	Text (patient symptoms)	Innovation propensity	Quality: Early screening and detection	Privacy and security concerns	Microsoft (2020)

instance, the Indian government developed the 'Aarogya Setu' mobile app to identify close contacts, facilitate communication between healthcare institutions and the public, and disseminate important information about the pandemic (Kaur et al. 2021).

The Abu Dhabi Government used intelligent electronic wristbands to track patients and ensure that they remained strictly confined to their homes, i.e. in isolation (UAE 2022). The effectiveness of these wristbands was corroborated by one of the interviewees who contracted COVID-19. Other emirates, such as Dubai, mandated that patients who tested positive install a smart app (the COVID-19 DXB Smart App) on their phones. During quarantine, patients could use this app to contact health authorities and report any complications, make audio/video calls to family and paramedics, and upload documents like passports or COVID test results. Previous studies reported similar applications. For example, In Hong Kong, a wristband synced with a mobile app alerted authorities if individuals left their designated quarantine locations (Kaur et al. 2021).

Dubai's Roads and Transport Authority (RTA) also employed AI technologies, such as computer vision and machine learning algorithms, to monitor and report offences such as failure to observe physical distancing and improper wearing of face masks inside taxis by drivers and passengers. The AI cameras were programmed to scan human faces, verify if masks were worn correctly, and estimate the distance between passengers and drivers (RTA 2020).

The UAE was at the forefront of applying AI to medical images for disease detection even before COVID-19. The UAE's Ministry of Health and Prevention (MOHAP) has been using machine learning algorithms on chest x-ray scans to detect diseases such as tuberculosis since 2018 (Gupta 2019; Zawya 2020). These algorithms support radiologists' assessments. In the words of one interviewee (a healthcare administrator), '*AI technologies are well suited to uncovering patterns from radiographic images that doctors may be unable to find*'. All three doctors interviewed confirmed that AI-enabled advances in medical imaging, including CT, MRI and X-ray scans, were being used in their hospitals' radiology departments for COVID-19 detection. These findings are consistent with previous research that advocates the use of AI in medical image-based diagnosis and assessment across various imaging modalities. AI can help healthcare practitioners and doctors to detect patterns or subtle details in medical images that might otherwise be difficult to find, thereby enhancing their diagnostic capabilities (Carriere et al. 2021; Mohamadou, Halidou, and Kapen 2020).

In terms of accurately forecasting COVID-19 pandemic trends, Smart Dubai, a government organisation in Dubai, collaborated with the Mohammed Bin Rashid University of Medicine and Health Sciences to develop a relevant AI-based epidemiological model (Smart Cities World 2021; Weqaya 2021c). Numerous studies in the literature also support the use of epidemiological models to effectively identify the peaks of COVID-19 (Naseem et al. 2020; Albalawi and Mustafa 2022). Additionally, the UAE's MOHAP introduced an AI-enabled chatbot service called 'Virtual Doctor for COVID-19', which the public could use to assess whether they had COVID-19. By using responses to questions about travel history, specific symptoms and health habits, the chatbot made assessments and connected potentially infected individuals to a doctor. While the chatbot service was successful and significantly reduced the workload of the UAE healthcare system, one interviewee from a leading global technology solution provider emphasised that, '*although we are 90% there, we need to work on further humanising the chatbots so that patients do not feel the difference between talking to a chatbot and a real person*'. Overall, participants agreed that advanced AI chatbots could make life easier for all healthcare stakeholders, including doctors, nurses, administrative staff and patients. These findings are consistent with the literature, which highlights the widespread and intensive adoption of medical chatbots, particularly those based on natural language processing (NLP), for question-answer systems during the COVID-19 pandemic (Albalawi and Mustafa 2022).

The advances in AI and genomics research also proved to be immensely beneficial for the UAE, helping to trace the origin of COVID-19 infections and developing an understanding of how the virus mutates and spreads from person to person (UAE 2021). Half the interviewees highlighted the role of AI in genome sequencing, such as determining protein structures or identifying markers and predictors of the disease. To build on this success, the Abu Dhabi Department of Health, in partnership with G42 (an AI healthcare provider), successfully launched the Emirati Genome Programme (EGP), a national-level project that aims to profile the gene sequences of UAE Nationals (G42 2021b). The complete genomic profiling of 1,000 UAE nationals using cutting-edge AI techniques has already been completed, and this initiative is now being extended to the broader Emirati population (G42 2021b). Previous research has explored and advocated the use of AI in genomics, for such purposes as extracting insights from COVID-19 genome sequences (Albalawi and Mustafa 2022).

Healthcare Service Providers. The interviews also revealed how AI adoption has increased efficiencies and improved workflow management at hospitals and clinics. AI's automated reporting feature, such as for radiology reports, was identified as significantly reducing the time taken to finalise such reports and lowering administrative costs – reductions that could then be passed on to the patients. It also increased radiologists' productivity as they could spend more time reviewing and approving AI model-based diagnoses rather than performing the time-consuming diagnoses themselves. These results support the growing calls in the literature for the use of AI in contactless image acquisition and disease diagnosis with minimal or no patient interaction. This approach enables medical professionals to make quick decisions, improving their work efficiency and reducing their workload (Swayamsiddha et al. 2021; Mohamadou, Halidou, and Kapen 2020).

For prognosis, an AI-based COVID-19 Patient Mortality and ICU Admission Predictor was developed by the American Hospital, Dubai, in partnership with the global healthcare technology company Cerner (Cerner 2021). This predictor could assess clinical outcomes, including ICU admission probability and mortality, based on existing comorbidities such as hypertension, diabetes, chronic kidney disease, obesity, gender, creatinine levels, white blood cell count and albumin (Cerner 2021). This approach is consistent with previous research, which suggests that AI can identify patients at an elevated risk of mortality, allowing them to be prioritised for increased allocation of hospital resources (Shah et al. 2021; Adamidi, Mitsis, and Nikita 2021).

Two interviewees from hospitals that used AI-enabled chatbots emphasised their usefulness in addressing patient inquiries and boosting hospital productivity. Similarly, Damam hospital's Covid-19 self-assessment and bilingual (English and Arabic) information-providing health bot aimed to reduce patient visits to hospitals, reduce call centre workloads, enhance patient experiences and encourage proactive health management (Microsoft 2020). Such chatbots were in operation in the UAE even before the COVID-19 pandemic struck. For instance, Medicare Hospitals, a prominent hospital chain in the UAE, has been using a state-of-the-art AI-based 'virtual health assistant' chatbot. This chatbot learns about patients and offers personalised, accurate, real-time responses regarding appointment bookings, rescheduling and cancellations (Daoud 2019). The CEO emphasised the importance of these chatbots, stating, '*In life, getting to a doctor when you are sick is a stressful experience. When you add having to call a call centre to schedule an appointment to that experience, it's very frustrating*' (Daoud 2019). Similarly, Al Zahra hospital's chatbot, integrated with the hospital's backend systems, can interpret a patient's written requests and respond accordingly (Al Zahra Hospital Dubai 2020). These chatbots can suggest necessary steps when specialists are unavailable, serve more people than a staffed call centre and reduce pressure on medical hotlines (Wang et al. 2021).

Several interviewees emphasised the growing use of AI-enabled remote monitoring through smart devices. One respondent highlighted that certain AI applications can integrate patient data from as many as 100 devices and generate a summary report for doctors. This reduces the need for in-patient care at the hospital, thereby reducing the hospital's workload and saving money for the patients.

Pharmaceuticals and Technology Solution Providers. The use of AI in vaccine development and clinical trials is evident in the literature (Shah et al. 2021; Kaur et al. 2021). The case study findings from the UAE corroborate the use of AI in these areas. The Abu Dhabi Health Services Company (SEHA) collaborated with G42 Healthcare, a subsidiary of Group 42, an Abu Dhabi-based AI and cloud computing company, to facilitate phase III clinical trials for the COVID-19 vaccine developed by the Chinese pharmaceutical company Sinopharm (Clinical Trials Arena 2020). Subsequently, the UAE became the first country in the Arab world to develop and produce a COVID-19 vaccine, Hayat-Vax, as a joint venture between Sinopharm and G42 Healthcare (Suliman et al. 2021; G42 2021a).

In addition to COVID-19 detection, AI applications were also found to be effective for cancer detection. Prognica, a Dubai-based AI-oriented proprietary technology company, has a product that automatically detects abnormal masses in mammograms (using MRI and Ultrasound), and segments and classifies tumours if present. The AI algorithm is trained with a large-scale, high-quality mammogram training dataset consisting of more than 60,000 cases, including 22,000 of cancer (de Leon 2021). Previous studies have advocated the use of AI in breast cancer detection and diagnosis (Desai and Shah 2021; Vaka, Soni, and Reddy 2020).

4.1.2. Computational and data layer (Answer to RQ2)

The interviews and secondary reports (see Table 3) highlighted computer vision, NLP and ML as the most commonly used computational techniques, with DL seeing limited application. The lack of DL adoption suggests that various types of unstructured data (suited for DL) are not effectively utilised in the UAE healthcare sector. However, a robust technology infrastructure and the availability of high-quality surveillance camera feeds have enabled the effective use of computer vision in combating COVID-19. This is unsurprising, given that computer vision has been one of the main areas of AI research in the context of COVID-19 (Albalawi and Mustafa 2022). Furthermore, high internet and smartphone penetration have made many location- and sensor-based AI (smart) applications possible. However, despite evidence in the literature on using the sounds of sneezing and coughing to detect COVID-19 (Albalawi and Mustafa 2022), acoustic detection and diagnosis has seen limited uptake in the UAE. On the other hand, the rise in medical chatbots and virtual assistants clearly demonstrates the UAE's progress on NLP techniques.

UAE hospitals are leveraging NLP to optimise their workflow administration. As one interviewee (a senior healthcare administrator) stated:

> As we speak, our digitalization [*sic*] team is converting our old paper-based medical records to digital through our state-of-the-art scanning facility. Also, we have the NLP technology to read, interpret and extract important information from the scanned documents'. Similarly, another interviewee (a doctor) highlighted that 'Our NLP system can read from images of ID cards, passports and other identity documents, saving a lot of time in administration and records management. These systems have lower error percentages than manual entries

The literature advocates the digitisation of patient records to facilitate the application of NLP (Baz et al. 2022).

In terms of the data layer, initiatives to develop public healthcare databases can facilitate AI adoption in the sector. Recognising this, the UAE's federal government has initiated an open data portal, including for healthcare, to enhance participation and transparency in AI application development (Bayanat 2022). For instance, the UAE recently launched the award-winning 'Riayati' platform that transforms the current healthcare landscape by centralising medical records and providing a fully integrated, digitised clinical information system for the country's population. The system has over 8.4 million unified medical records, and integrates 286 healthcare facilities and more than 31,000 clinicians (Riayati 2022). At the emirate level, the Department of Health in Abu Dhabi launched Malaffi in 2018. It is the region's first Health Information Exchange platform that safely and securely connects public and private healthcare providers there. Malaffi has developed a central database of unified patient records connecting 100% of hospitals in Abu Dhabi. It stores over 559 million unique clinical records and provides access to more than 39,600 end-users (doctors, nurses and other staff) from over 1,500 facilities, including hospitals, clinics and pharmacies (Malaffi 2021). Given the availability of vast amounts of quality data, the UAE healthcare sector can benefit from a bottom-up approach to developing suitable AI applications and techniques. In general, the findings are consistent with calls in the literature to use a data-driven approach to optimise resources in healthcare (Lotfi et al. 2022a).

4.2. Management levers

4.2.1. Enablers of AI in the UAE healthcare sector (Answer to RQ3)

Regulatory and Legal Environment. Although AI implementation offers advantages, it also presents legal and regulatory hurdles when no entity is held responsible or accountable (Nguyen et al. 2021). Related challenges include data privacy, safeguarding, ethical issues and compliance with professional standards (Abdulkareem and Petersen 2021; Kaur et al. 2021). The interviewees agreed that the UAE possesses a relatively robust regulatory and legal environment for AI adoption, and the country serves as a leading advocate for responsible and ethical AI use. The state is among the few globally with a national AI strategy (UAE National Strategy for Artificial Intelligence 2031 2021), as part of which an AI policy for healthcare has been developed (WAM 2021). This policy specifies the roles and responsibilities of stakeholders involved in the development and use of AI in healthcare, and is also tasked with proposing policies to create an AI-friendly ecosystem (WAM 2021). It also details the ethical requirements of AI-driven tools and applications, as part of which an Ethical AI Toolkit has been published by the Dubai Data Establishment within the Smart Dubai Office (Digital Dubai 2022). It is based on the four guiding principles of ethics, security, humanity and inclusiveness.

Other emirates have been equally active. For example, Abu Dhabi introduced a policy in 2018 (Department of Health 2018) that aims to provide the safe and secure use of AI in healthcare; enhance its reach, performance and precision; and minimise its potential risks to patients. However, one interviewee expressed concern about the absence of a federal-level (unified) policy for AI in healthcare. Previous studies have similarly reported a lack of federal-level policy and regulation as a barrier to technology adoption in healthcare (Balasubramanian et al. 2021).

Technology Infrastructure. A supportive and robust IT infrastructure is critical for technology adoption in healthcare (Balasubramanian et al. 2021). The UAE is a leader when it comes to AI and related high-technology infrastructure. It holds the top global rank for 'households with internet access' and 'population covered by at least a 3G network' (Network Readiness Index 2021 2021). Given that the UAE is a country with one of the highest incomes per capita in the world, these households also have extensive access to smartphones and laptops (Balasubramanian et al. 2021). Not surprisingly, most interviewees attributed the increasing use of technology in healthcare to these factors, as well as the government's aggressive efforts to promote digital awareness and literacy among the population. One interviewee from a government entity described several programmes initiated by the Dubai government, such as the 'Dubai Blockchain Strategy,' which strengthens healthcare data infrastructure by migrating healthcare records to the blockchain. This, in turn, facilitates the development of AI techniques and applications. The UAE has also established an AI Supercomputer Lab, optimised for AI machine learning computations. It is available to all UAE-based researchers and startups to maximise exploitation. Additionally, a National Program for Artificial Intelligence Initiative has launched an AI Code Hub on GitHub to share UAE-developed open-source AI projects globally. The private sector in the UAE also contributes enormously to technology infrastructure. For instance, G42's AI and cloud computing infrastructure played a crucial role in providing fast computation and synthesised insights during the Sinopharm vaccine phase III trials (G42 2020). This highlights the importance of having a robust IT infrastructure, particularly in developing countries, for fully leveraging the benefits of AI. Research suggests that China has reaped immense benefits from AI, primarily due to its extensive and accessible IT infrastructure (Rasheed et al. 2021).

The UAE is also well-equipped in terms of healthcare research centres. The region's largest and most technologically advanced Omics facility, the Omics Centre of Excellence, serves as the backbone of the DoH's Emirati Genome Program (Department of Health 2021). Furthermore, the region's first AI-led healthcare research laboratory has also been established there, which involves a partnership between American Hospital Dubai and Cerner, a global healthcare technology company (American Hospital Dubai 2022).

However, the UAE is not without its shortcomings. It ranks relatively low at 61st for 'secure internet servers' in a global network readiness index survey (Network Readiness Index 2021 2021). The country therefore needs to establish more secure internet servers to enhance stakeholders' trust. An interviewee from the government sector mentioned that maintaining patient privacy remains a significant concern in AI healthcare applications.

Stakeholder Collaboration and Partnerships. Previous research has highlighted the importance of collaborations and partnerships among stakeholders, from a global perspective, for the successful implementation of healthcare technology, including AI (Kaur et al. 2021; Balasubramanian et al. 2021). The UAE has witnessed significant partnerships on AI implementation within healthcare, particularly during the COVID-19 pandemic. These collaborations involved healthcare providers, technology solution providers, universities and startups. Some of the key partnerships are presented in Table 3. However, no collaboration was observed between individual doctors and AI experts. The value of these collaborations, including those between public and private entities, and local and foreign firms, was emphasised during the interviews. Several interviewees highlighted the role of the UAE government and the Dubai Health Authority (DHA) in actively supporting technology startups (including those focused on AI) through incubator and accelerator programmes. Past studies have emphasised the need for collaboration between doctors and AI experts to better understand, interpret and integrate AI applications into existing healthcare practices (Abdulkareem and Petersen 2021).

Innovation Propensity. As previously discussed, and evidenced by the launch of the 'UAE Artificial Intelligence Strategy 2031' in 2017, AI is central to the UAE government's strategic plans. The government has also appointed a Minister of State for Artificial Intelligence, making the UAE the first country in the world to do so. The vision is to establish the country as the most competitive globally by its 100th birthday (UAE Centennial 2071 2021), with innovation and world-class healthcare as two of the six main pillars. Notably, the UAE also has a Fourth Industrial Revolution Strategy that aims to strengthen the UAE's position as a global hub for Industry 4.0 technologies, and it is also underpinned by AI. At the emirate level, interviewees highlighted initiatives such as the Dubai Health Strategy and the Abu Dhabi Healthcare Strategic Plan (for developing a world-class healthcare ecosystem) as evidence of strong innovation propensity. This is also seen through the innovations at the government and hospital levels discussed earlier and seen in Table 3. The results are consistent with the view in the literature that innovation propensity is a key enabler of technology adoption in healthcare (Balasubramanian et al. 2021).

4.2.2. Benefits of AI in the UAE's healthcare sector (Answer to RQ4)

Most interviewees emphasised AI's importance in curbing COVID-19's spread and reducing healthcare professionals' workload at the time. In the words of the UAE's Minister of State for Artificial Intelligence,

> The adoption of AI was central to the UAE's response to the pandemic, including in the development of the Alhosn public health application, which allowed for rapid innovation in testing and tracking for COVID. Based on AI simulations, the government could anticipate what would be needed at various stages of the pandemic, such as the required number of ventilators and vaccines. (Al-Monitor 2021)

Another benefit of AI highlighted by the interviewees was its ability to reduce the time taken for clinical tests. This is particularly relevant for diabetic retinopathy tests, given that 40% of the population in the UAE are either diabetic or pre-diabetic. Several proofs of concept for AI-based tests have been explored by the Dubai Health Authority (in partnership with Artelus), where the time taken could be reduced from four days to 10 min (Gupta 2019). This supports the idea expressed in the literature that AI can help save time by accurately predicting a patient's diagnosis and prognosis (Shah et al. 2021).

AI for chest x-ray scan assessment has also been tried; it could improve the workflow and assessment rate, reduce human errors and provide 95% accuracy in disease detection. Similarly, medical chatbots based on AI have automated the patient booking process, thereby improving cost efficiency as well as patient convenience (i.e. the quality aspect of patient care experience) (Daoud 2019). As noted by the Director-General of DHA, AI in a healthcare setting improves efficiencies and facility management, but most importantly, patient care through diagnosis and treatment as well (Gupta 2019). This reinforces the findings in the literature that AI can achieve accuracy on par with or even surpassing human/manual approaches, while delivering results more quickly and at a lower cost (Shah et al. 2021; Jabarulla and Lee 2021).

According to our respondents, AI also improved predictive capability. For example, AI-based machine learning models could accurately predict the probability of a COVID-19 patient requiring intensive care; models could also stratify the population into priority groups for vaccination, and predict oncoming waves of infection. This finding supports the view that AI prediction tools can optimise the use of resources, as was seen during the COVID-19 pandemic. For example, ICU beds and ventilators could be optimally allocated based on the early detection of breathing problems associated with COVID-19 (Alhasan and Hasaneen 2021).

Lastly, AI also benefits the healthcare system by detecting fraud, waste and abuse. According to the CEO of UAE-based IRIS Health Services, their clients in the UAE, Oman and other Middle Eastern countries could avoid healthcare fraud by integrating emerging technologies like AI, blockchain and deep learning into their operations, saving USD 10 million in the process (Unlock Media 2019). Patients can also benefit from AI, especially in quality terms, through personalised medicine and genomics (The Emirati Genome Program), clinical cobots (collaborative robots) and nanobots, and connected care (via wearable and implantable technologies) (UAE Ministry of Cabinet Affairs and the Future 2017). The literature suggests that AI has the potential to offer personalised care while also saving patients time and money (Jabarulla and Lee 2021).

4.2.3. Challenges of AI in the UAE's healthcare sector (Answer to RQ5)

The interviewees identified significant challenges to the adoption of AI in the UAE's healthcare sector. Greatest among these are privacy and security concerns, which are a challenge for both healthcare providers and technology solution providers. A respondent from a technology solution provider noted the lack of secure internet servers in the country, as most data is hosted on third-party servers in other countries. This is not surprising given the UAE's relatively low global rank for 'secure internet servers' as discussed earlier. Another interviewee (a chief technology architect at a multinational hospital) underscored the challenge of ensuring patient data security in a data-sharing environment. He explained that a patient with a chronic or terminal illness may not want his medical condition to be known, which the healthcare provider needs to respect. Previous studies have also reported privacy and security to be the main challenges in applying AI in healthcare (Khan et al. 2021).

Another challenge identified was the reluctance of hospitals and clinics to share data due to patient confidentiality and trust issues. Given that data limitations, such as only using data from one or a few hospitals, can limit the generalisability of the AI models developed and in turn lower AI adoption, building trust among hospitals and other stakeholders is vital. One solution is federated learning, whereby AI scientists provide training algorithms to healthcare institutions to train models locally; this option is becoming increasingly popular. As AI primarily relies on data and access to that data, any related privacy, security, trust or sharing issues could hinder its progress (Swayamsiddha et al. 2021).

Finally, most interviewees expressed a preference for tried and tested AI solutions or pre-trained models rather than developing new ones, due to a lack of AI expertise in their organisations. This could explain the more widespread use of computer vision and medical chatbots, which require less programming, compared to other, more complex AI models that rely on heterogeneous and unstructured datasets.

In conclusion, the case study findings, in line with our second research objective, have demonstrated the applicability of our framework in a real-world setting.

5. Discussion and conclusion

The healthcare sector has increasingly adopted disruptive Industry 4.0 technologies (Healthcare 4.0) since the start of the COVID-19 pandemic in an effort to manage therapeutic processes and outcomes more efficiently and effectively (Tonetto et al. 2021; Tortorella et al. 2022a; 2022b). Of these technologies, AI is considered to have the greatest potential. This study focused on developing a novel AI application framework for the sector, and then establishing its validity and applicability by applying it to the UAE's healthcare sector. The findings meet most of the requirements for framework validity, such as credibility, transferability, dependability, confirmability, fairness and authenticity, which will help improve understanding and stimulate and empower action (Creswell and Miller 2000; Balasubramanian et al. 2021).

The study results confirm healthcare as one of the most promising sectors for AI application. Although the research was conducted during COVID-19, the framework's application and lessons learned extend far beyond addressing the challenges of this present pandemic. Specifically, they provide insights into the different implementation layers of AI, namely the data layer, the computation layer and the application layer. Regarding the data layer, the results demonstrate the importance of using diverse (clinical, epidemiological, locational, behavioural and genomic) and heterogeneous data (e.g. video, audio, images and text) for training, testing and developing AI models. The results also reveal the multifaceted nature of AI computation techniques, specifically machine learning, deep learning, natural language processing and computer vision, which are used to develop AI applications from the micro (molecular) to the macro (population) level. The macro-level applications include public health surveillance for detection, diagnosis, prognosis and vaccine development. With regards to stakeholders, it is clear that the government is the most important of them. It not only benefits from AI by applying it to public health management, but also acts as an enabler of AI by devising and enforcing relevant industry standards, policies and regulations. To facilitate AI adoption, it is critical to have a regulatory and legal environment that ensures transparency, safety/security, privacy, ethics and accountability for key healthcare stakeholders, including healthcare providers, end-users, professionals, pharmaceutical companies, insurance companies and researchers. The government also needs to collaborate and forge partnerships with the private sector on AI.

The technology infrastructure in clinics and hospitals – such as electronic health records, security and cloud infrastructure, and internet bandwidth – directly affects AI adoption. For some AI applications (e.g. contact tracing), consumers' technology readiness and access to smartphones and high-speed internet are also critical. Our findings confirm the need for strong collaboration among stakeholders on AI. One example of such a collaboration involved Apple, the Centers for Disease Control, the Federal Emergency Management Agency, and the White House coronavirus task force working together to develop the AI-based Health Check app (Kaur et al. 2021). Furthermore, as seen in the UAE's case, countries with a higher propensity for innovation, such as those having a clear national-level strategy on AI, Industry 4.0 and other innovations, are more likely to adopt AI technologies in healthcare than those without one.

Our findings also confirm the numerous operational, quality and social benefits of applying AI in healthcare. Operationally, AI-enabled automation can enhance the speed, efficiency and scalability of healthcare processes (Fruehwirt and Duckworth 2021). For instance, the Abu Dhabi Health Services Company (SEHA), the UAE's largest healthcare network, was able to reduce retinal image reading and assessment time from three days to three seconds through AI (Zawya 2022). The associated reduction in staff workload and stress was also beneficial. The predictive capability of AI algorithms, which enables more optimal resource allocation and priority treatment for sicker patients, was also highlighted. In addition, the reduction in time for drug/vaccine development through the use of AI was emphasised. For example, in drug repurposing, AI-based models can scan drug and disease databases containing terabytes of published and unpublished data to construct a biomedical knowledge graph, featuring over 31 million biomedical disease and drug concepts (Surianarayanan and Chelliah 2021).

In terms of quality benefits, AI's ability to reduce diagnostic errors was emphasised. For instance, AI-based medical imaging can provide similar or superior diagnostic accuracy compared to experienced radiologists (Alhasan and Hasaneen 2021), even detecting features that some radiologists might overlook (Naseem et al. 2020). AI also enables advanced diagnostic and treatment options that are not feasible with conventional approaches.

Lastly, regarding social benefits, the study demonstrates AI's crucial role in public health management. The predictive capability of AI algorithms in healthcare prognosis can also significantly reduce the mortality rate. For instance, the machine learning algorithm XGBoost supervised classifier could predict individuals' mortality more than ten days in advance with 90% accuracy (Surianarayanan and Chelliah 2021). Other notable contributions made by AI include the development of personalised medicines and preventive programmes tailored to an individual's unique genetic makeup, as was suggested by the Emirati Genomic Program (Department of Health 2019), as well as remote patient care using clinical data captured through smartphones.

However, several challenges to AI adoption need to be addressed, such as data privacy and security, and the lack of AI model generalisability. A significant factor contributing to the former is the increased use of credit card transaction and mobile phone activity-related data in AI models. Moreover, in a dynamically changing environment with mutating viruses like COVID-19, the data used to train AI models may quickly become outdated, compromising their practical performance. Therefore, efforts must be made to develop robust, pre-trained, and cross-validated AI models to enhance generalisability. Other concerns involve data or algorithmic bias and the absence of data standards. For example, AI models developed to diagnose whether a person is infected or not (binary classifier) should use unbiased data proportionate to both classes, which may not always be feasible in practice (Shah et al. 2021). Lastly, there is a challenge with the availability of large-scale data that is well-annotated (e.g. by doctors, researchers and other experts) and standardised (Pankhania 2021; Albalawi and Mustafa 2022).

5.1. Future prospects of AI in healthcare

Despite these challenges, the future prospects of AI in healthcare are promising. First, AI applications could be used to predict viral mutational landscapes, and they could help analyse the effectiveness of currently available medications on future variants to develop effective options (Sarker et al. 2021). Next, different AI techniques could be combined to form hybrids that are more robust and accurate in different settings. For example, a combination of machine learning and deep learning was found to be more effective in diagnosing COVID-19 (Rasheed et al. 2021). Similarly, a combination of computer vision and deep learning algorithms in public health surveillance yielded superior results (Shah et al. 2021). Likewise, a multimodal AI framework that uses different data types can be more robust, as demonstrated by several studies that combined clinical and image features (CT scans and CXR images) for the diagnosis and prognosis of COVID-19 (Adamidi, Mitsis, and Nikita 2021; Arora et al. 2021). Future AI models are also more likely to use federated learning to address data privacy and trust issues among institutions. However, most federated learning approaches operate on a centralised server, where hacking or data leakage is possible. Blockchain-based federated learning for training ML or DL models offers a potential solution and can be expected to gain more traction in the future (Jabarulla and Lee 2021). AI applications in healthcare can also be enhanced and made more secure and private through integration with alternative blockchain technologies (Jabarulla and Lee 2021; Lotfi et al. 2022b). Similarly, AI and cloud computing technologies can be integrated to address data storage and computational capability-related problems, and to generate faster outputs (Shah et al. 2021; Nguyen et al. 2021). AI and vision-based robotic solutions can also be combined for more effective public health surveillance (Sarker et al. 2021).

5.2. Theoretical implications

The implications of this study are manifold. Our proposed framework is, arguably, the first of its kind in enabling AI for healthcare; it is comprehensive and incorporates both technology and management levers. To a great extent, it fills the gap in the literature concerning a comprehensive AI application framework. Additionally, the study offers in-depth empirical insights into AI adoption in healthcare from a holistic, country-level perspective, particularly in an advanced setting like the UAE. These insights are both novel and significant. We anticipate that they will encourage more holistic, country-level research on AI adoption in healthcare in other advanced, emerging, and developing nations. The development and validation of this framework contribute to establishing a robust theoretical foundation that can steer both future research and the practical applications resulting therefrom.

5.3. Practical implications

The framework and findings reveal the considerable potential of AI to revolutionise the healthcare sector in the UAE and other countries with similar aspirations. This transformation could involve addressing various inefficiencies and enhancing the effectiveness, safety, accessibility and delivery of services, in addition to providing evidence-based quality of care in diagnosis, prognosis, personalisation and prevention. The framework presented in this study can aid healthcare stakeholders in identifying the most pertinent AI applications, computational techniques and data requirements, as well as their associated challenges, benefits and enablers. This comprehensive understanding can pave the way for more effective strategies for AI adoption and its integration into healthcare systems.

Healthcare policymakers can leverage the framework to promote AI technologies and facilitate their adoption through supportive regulations, policy interventions and support mechanisms. The insights gained from the use of AI applications during the COVID-19 pandemic could enhance preparedness and response measures for future pandemics and outbreaks, enabling healthcare systems to better mitigate their impacts. The framework and findings of this study contribute to the management of healthcare systems in several ways, including:

- Accelerated drug and vaccine development and production: AI can expedite the drug and vaccine development process, leading to faster discovery and approval of new medications and therapies, benefiting patients and society beyond the COVID-19 pandemic.
- Mass customisation of drugs: AI algorithms can analyse genomic data to identify specific genetic variants or biomarkers associated with an individual's unique response to medication. This information can then be used to manufacture personalised drugs tailored to the individual's genetic makeup.
- Supply chain optimisation: AI can optimise the medicine supply chain by predicting drug and vaccine demand. This will ensure the efficient production, distribution and delivery of the medicines, helping to reduce waste, minimise production and inventory costs, and ensure that patients receive their medications in a timely manner.
- Increased collaboration among stakeholders: The AI application framework can serve as a basis for collaboration among different healthcare stakeholders, including governments, hospitals, pharmaceutical companies and patients. This collaboration can lead to a more unified approach to AI adoption in healthcare, promoting innovation, adoption and standardisation.

5.4. Implication for managers

For managers, this research provides a structured approach for understanding and implementing AI solutions in healthcare. It highlights the importance of responsible AI adoption, drawing attention to major challenges such as data privacy, security and algorithmic bias. Addressing these issues is essential for the ethical deployment of AI in healthcare. Furthermore, the study underscores the importance of promoting stakeholder collaboration and partnerships to share insights, data and best practices. Finally, the different AI-related solutions discussed allow managers to streamline operations, optimise resources and even predict outbreaks, offering cost-saving opportunities without compromising quality.

5.5. Limitations and future research

This study has some limitations. While the proposed framework was developed through an extensive literature review, it may not cover every aspect enabling AI adoption, and makes several assumptions. Additionally, the framework was tested in the context of only one country, mostly using a qualitative approach, which may not provide precise statistical or quantitative understanding. Further, not all stakeholders were considered in the study, so future research could include extended healthcare stakeholders such as insurance providers and the manufacturers and suppliers of medical equipment. Additional future research could explore how AI models could be used in healthcare projects, such as hospital construction, to minimise costs and maximise quality (Lotfi et al. 2022b; 2023). It could also examine improving vendor-managed inventory models for hospitals and pharmacies, particularly in light of the significant impact COVID-19 has had on overall supply chains (Lotfi et al. 2022a; 2022c). Finally, AI models also have the potential to enhance medical waste management practices, including those dealing with infectious, hazardous and radioactive waste (Lotfi et al. 2022d).

Despite these limitations, this study is timely as the healthcare sector is attempting to recover from the COVID-19 pandemic. In future research, more rigour should be added to the investigation by conducting a large-scale survey to test the statistical appropriateness and generalisability of the framework. The framework could also be applied and tested in different national settings to further refine and validate it. Finally, given its conceptual comprehensiveness and generic nature, researchers across various industries can adapt and apply the framework to their specific contexts. Healthcare encompasses numerous sectors, such as manufacturing (of drugs and medical equipment), services (e.g. insurance and ambulatory transportation), and research and development (e.g. clinical trials and laboratory experiments) (Balasubramanian et al. 2021). As such, the framework has significant potential applicability in other sectors, provided it is carefully tailored and contextualised for each case.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributor

Dr. Sreejith Balasubramanian is the Associate Professor, and the Head of the Centre for Supply Chain Excellence at Middlesex University, Dubai. He is also the Chair of the Office of Research. His main research areas are green supply chain management and Industry 4.0 technologies. His other areas of expertise include operations management, disruptive technologies, sustainability, and knowledge management. He has been a consultant for several public and private sector entities and intergovernmental organisations including Bridgestone, Abu Dhabi Chamber of Commerce, and Mekong Institute. He has also received project funding from global bodies such as the International Organization for Migration (IOM), and Mekong – Korea Cooperation Fund (MKCF), and UN Office for South-South Cooperation (UNOSSC). Sreejith has over 60 publications in leading academic and practitioner-focused journals, including Supply Chain Management: An International Journal; Production, Technological Forecasting and Social Change, IEEE Transactions on Engineering Management, Planning & Control; Business Strategy and the Environment, and Journal of Knowledge Management. Before moving to academia, Sreejith had several years of industry experience in the telecom sector in senior roles as an IT project consultant and project manager.

Vinaya Shukla is a Senior Lecturer in Operations and Supply Chain Management at Middlesex University Business School in London. He earned his PhD from Cardiff Business School, UK. Before venturing into academia, he spent many years as a Management Consultant, advising clients on enhancing their operations performance. His research interests encompass Industry 4.0 and Blockchain, supply chain sustainability, supply chain systems, and supply chain risk management. He has published articles in several prestigious journals, including the International Journal of Production Economics, International Journal of Production Research, Supply Chain Management: An International Journal, Production Planning and Control, International Journal of Logistics Management, and Journal of Manufacturing Technology Management.

Nazrul Islam is a Professor of Business & Director of Research Degrees at the University of East London. He holds a PhD in innovation management. His research interests include innovation in high-tech industries and the management of emerging and discontinuous innovations. His work has been published in leading international journals, and he has also authored three books. His research has received several awards, including the 'Brad Hosler Award for Outstanding Paper' from the USA and the 'Pratt & Whitney Canada Best Paper Award' from Canada. He serves as Associate Editor (Lead Bureau Editor for Emerging Technologies) for Technological Forecasting and Social Change, Department Editor for IEEE Transactions on Engineering Management, and Editor-in-Chief for International Journal of Technology Intelligence and Planning.

Arvind Upadhyay is a Professor of Operations, Logistics and Supply Chain Management at Guildhall School of Business and Law at London Metropolitan University, London, UK. Professor Upadhyay's research, consulting, and teaching stretch across the management spectrum, with an emphasis on integrating operations and supply chain with other management subject areas. He is a Senior Fellow of the Higher Education Academy (SFHEA), UK. Professor Upadhyay has taken an active role in the research and publications. The output from his work, which has involved collaboration with colleagues across multiple disciplines, has been published in a range of leading international peer-reviewed journals. His research has been published in the Journal of Business Research, International Journal of Production Research, Production Planning and Control, Technological Forecasting and Social Change, Business Strategy and the Environment, Journal of Cleaner Production, and Resources Policy, amongst others.

Dr Linh N K Duong is a Senior Lecturer in Operations Management at Bristol Business School, University of the West of England, UK. His current research interests focus on sustainable and resilient supply chain management with the link to digital transformation, innovation, and collaboration among supply chain partners. He focuses on vulnerable contexts such as the agri-food industry, tourism industry, or small and medium enterprises (SMEs).

Data statement

The participants of this study did not give written consent for their identifying data to be shared publicly, so due to the sensitive nature of the research, supporting data is not available.

ORCID

Sreejith Balasubramanian http://orcid.org/0000-0002-0475-7305
Linh Duong http://orcid.org/0000-0002-9415-1082

References

Abdulkareem, Musa, and Steffen E. Petersen. 2021. "The Promise of AI in Detection, Diagnosis, and Epidemiology for Combating COVID-19: Beyond the Hype." *Frontiers in Artificial Intelligence* 4 (652669): 1–18.

Abu Dhabi Government Media Office. 2021. *Department of Health - Abu Dhabi authorizes the use of EDE scanners to detect COVID-19 infections*. https://www.mediaoffice.abudhabi/en/health/department-of-health-abu-dhabi-authorises-the-use-of-ede-scanners-to-detect-COVID-19/.

Adamidi, E. S., K. Mitsis, and K. S. Nikita. 2021. "Artificial Intelligence in Clinical Care Amidst COVID-19 Pandemic: A Systematic Review." *Computational and Structural Biotechnology Journal* 19: 2833–2850. https://doi.org/10.1016/j.csbj.2021.05.010

Albalawi, U., and M. Mustafa. 2022. "Current Artificial Intelligence (AI) Techniques, Challenges, and Approaches in Controlling and Fighting COVID-19: A Review." *International Journal of Environmental Research and Public Health* 19 (5901): 1–24.

Alhasan, M., and M. Hasaneen. 2021. "Digital Imaging, Technologies and Artificial Intelligence Applications During COVID-19 Pandemic." *Computerized Medical Imaging and Graphics* 91 (101933): 1–22.

Ali, O., W. Abdelbaki, A. Shrestha, E. Elbasi, M. A. A. Alryalat, and Y. K. Dwivedi. 2023. "A Systematic Literature Review of Artificial Intelligence in the Healthcare Sector: Benefits, Challenges, Methodologies, and Functionalities." *Journal of Innovation & Knowledge* 8 (1): 100333. https://doi.org/10.1016/j.jik.2023.100333

Allied Market Research. 2021. *AI in Healthcare Market*. https://www.alliedmarketresearch.com/artificial-intelligence-in-healthcare-market.

Al-Monitor. 2021. "AI played 'big role' in approach to pandemic, says UAE artificial intelligence minister". November 19, 2021. https://www.al-monitor.com/originals/2021/11/ai-played-big-role-approach-pandemic-says-uae-artificial-intelligence-minister.

Al Zahra Hospital Dubai. 2020. *Artificial Intelligence Elevating Patient Communication and Access to Care*. https://azhd.ae/artificial-intelligence-elevating-patient-communication-and-access-to-care/.

American Hospital Dubai. 2022. *First AI-led research lab in the region*. https://www.ahdubai.com/research-innovation-hub.

Arora, G., J. Joshi, R. S. Mandal, N. Shrivastava, R. Virmani, and T. Sethi. 2021. "Artificial Intelligence in Surveillance, Diagnosis, Drug Discovery and Vaccine Development Against COVID-19." *Pathogens (basel, Switzerland)* 10 (1048): 1–21.

Aruleba, R. T., T. A. Adekiya, N. Ayawei, G. Obaido, K. Aruleba, I. D. Mienye, I. Aruleba, and B. Ogbuokiri. 2022. "COVID-19 Diagnosis: A Review of Rapid Antigen, RT-PCR and Artificial Intelligence Methods." *Bioengineering* 9 (153): 1–18.

Balasubramanian, S., V. Shukla, N. Islam, and S. Manghat. 2022. "Construction Industry 4.0 and Sustainability: An Enabling Framework." *IEEE Transactions on Engineering Management*, 1–19. https://doi.org/10.1109/TEM.2021.3110427

Balasubramanian, S., V. Shukla, J. S. Sethi, N. Islam, and R. Saloum. 2021. "A Readiness Assessment Framework for Blockchain Adoption: A Healthcare Case Study." *Technological Forecasting and Social Change* 165 (120536): 1–16.

Bayanat. 2022. "The UAE Open Data Portal". https://bayanat.ae/.

Baz, M., S. Khatri, A. Baz, H. Alhakami, A. Agrawal, and R. A. Khan. 2022. "Blockchain and Artificial Intelligence Applications to Defeat COVID-19 Pandemic." *Computer Systems Science and Engineering* 40 (2): 691–702. https://doi.org/10.32604/csse.2022.019079

BodyO. 2022. "AiPod & Health Lounge". https://bodyo.com/step-1-know-yourself/.

Carriere, J., H. Shafi, K. Brehon, K. Pohar Manhas, K. Churchill, C. Ho, and M. Tavakoli. 2021. "Case Report: Utilizing AI and NLP to Assist with Healthcare and Rehabilitation During the COVID-19 Pandemic." *Frontiers in Artificial Intelligence* 4 (613637): 1–7.

Cerner. 2021. "American Hospital Dubai Accelerates UAE's Health Care Transformation Through the Development of Next-Generation Intelligence in Collaboration with Cerner". January 3, 2021. https://www.cerner.com/ae/en/blog/american-hospital-accelerates-the-uaes-health-care-transformation-in-collaboration-with-cerner.

Clinical Trials Arena. 2020. *China's Sinopharm Launches Phase III Trial of Covid-19 Vaccine in UAE*. https://www.clinicaltrialsarena.com/news/sinopharm-covid-vaccine-uae-trial/.

Creswell, J. W., and D. L. Miller. 2000. "Determining Validity in Qualitative Inquiry." *Theory Into Practice* 39 (3): 124–130. https://doi.org/10.1207/s15430421tip3903_2

Daoud, Andre. 2019. "Medcare Launches Chatbots to Assist Patients". *Zawya* April 1, 2019. https://www.zawya.com/en/life/medcare-launches-chatbots-to-assist-patients-dj90eavx.

de Leon, Pamella. 2021. "UAE-Based Prognica Labs Uses Artificial Intelligence To Detect Masses In Mammography Screenings". *Entrepreneur Middle East*, January 24, 2021. https://www.entrepreneur.com/article/363990.

Deloitte. 2020. *Thriving in the era of pervasive AI. Deloitte Insights*. Deloitte AI Institute and Deloitte Center for Technology, Media and Telecommunications https://www2.deloitte.com/content/dam/insights/us/articles/6462_state-of-ai-in-the-enterprise/DI_State-of-AI.pdf.

Department of Health. 2018. "Policy on Use of Artificial Intelligence (AI) in the Healthcare Sector of the Emirate of Abu Dhabi". https://www.doh.gov.ae/-/media/E9C1470A575146B18015DEBE57E47F8D.ashx.

Department of Health. 2019. "Department Of Health Unveils World's Most Comprehensive Genome Program, Transforming Health and Well-Being with Genomics and Artificial Intelligence, the Nation's Leading Strengths". December 10, 2019. https://www.doh.gov.ae/en/news/Department-Of-Health-unveils-worlds-most-comprehensive-Genome-Program.

Department of Health. 2021. "DoH Chairman inaugurates G42 Healthcare's Omics Centre of Excellence, the region's largest and most advanced Omics facility". January 25, 2021. https://www.doh.gov.ae/en/news/DoH-Chairman-inaugurates-G42-Healthcares-Omics-Centre.

Desai, M., and M. Shah. 2021. "An Anatomization on Breast Cancer Detection and Diagnosis Employing Multi-Layer Perceptron Neural Network (MLP) and Convolutional Neural Network (CNN)." *Clinical EHealth* 4: 1–11. https://doi.org/10.1016/j.ceh.2020.11.002

Dicuonzo, G., F. Donofrio, A. Fusco, and M. Shini. 2023. "Healthcare System: Moving Forward with Artificial Intelligence." *Technovation* 120: 102510. https://doi.org/10.1016/j.technovation.2022.102510

Digital Dubai. 2022. "Artificial Intelligence Principles & Ethics". https://www.digitaldubai.ae/initiatives/ai-principles-ethics.

Dubai Police. 2020. *Safety and Security Monthly Bulletin*. June 2020, Issue 221. https://www.dubaipolice.gov.ae/Magazines/Safety%20and%20Security/2020/pages/June/S_S%20June%202020.pdf.

EIT (European Institute of Innovation & Technology). 2021. *Emerging Artificial Intelligence and Data Driven Business Models in EU*. https://eit.europa.eu/sites/default/files/emerging_ai_and_data_driven_business_models_in_europe_final.pdf.

El-Sherif, Dina M., Mohamed Abouzid, Mohamed T. Elzarif, Alhassan A. Ahmed, Ashwag Albakri, and Mohamed M. Alshehri. 2022. "Telehealth and Artificial Intelligence Insights Into Healthcare During the COVID-19 Pandemic." *Healthcare* 10 (385): 1–15.

FCSC (Federal Competitiveness and Statistics Centre). 2022. "Latest United Arab Emirates COVID-19 Data". United Arab Emirates Ministry of Cabinet Affairs. https://fcsc.gov.ae/en-us/Pages/COVID19/UAE-COVID-19-Updates.aspx.

Forbes. 2018. "How To Keep Your AI Algorithms Accurate And Adaptable". July 17, 2018. https://www.forbes.com/sites/intelai/2018/07/17/keep-your-ai-algorithms-accurate-and-adaptable/?sh = 5776a0f363a4.

Fruehwirt, W., and P. Duckworth. 2021. "Towards Better Healthcare: What Could and Should Be Automated?" *Technological Forecasting and Social Change* 172: 120967. https://doi.org/10.1016/j.techfore.2021.120967

G42. 2020. "World's First Phase III Clinical Trial of COVID-19 Inactivated Vaccine Begins in UAE". https://g42.ai/news/healthcare/worlds-first-phase-iii-clinical-trial-COVID-19-inactivated-vaccine-begins-in-uae/.

G42. 2021a. "G42 announces new JV with Sinopharm CNBG to produce Hayat-Vax vaccine in the UAE". https://g42.ai/news/g42/g42-announces-new-jv-with-sinopharm-cnbg-to-produce-hayat-vax-vaccine-in-the-uae/.

G42. 2021b. "Emirati Genome Program opens additional sample collection centers across Abu Dhabi". Available at https://g42.ai/news/healthcare/emirati-genome-program-adds-sample-collection-centers/.

George, G., V. Sahar, S. Dani, and A. Grigoris. 2019. "Supply Chain Risk Management and Artificial Intelligence: State of the Art and Future Research Directions." *International Journal of Production Research* 57 (7): 2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Ghasemi, P., F. Goodarzian, A. Gunasekaran, and A. Abraham. 2021. "A bi-Level Mathematical Model for Logistic Management Considering the Evolutionary Game with Environmental Feedbacks." *The International Journal of Logistics Management*. Advance Online Publication. https://doi.org/10.1108/IJLM-04-2021-0199.

Google. 2022a. "Building a responsible regulatory framework for AI". https://ai.google/static/documents/building-a-responsible-regulatory-framework-for-ai.pdf.

Google. 2022b. "Recommendations for Regulating AI". https://ai.google/static/documents/recommendations-for-regulating-ai.pdf.

Government of Dubai Media Office. 2020. "Dubai Silicon Oasis Authority partners with Derq to deploy AI-based solutions to monitor adherence to COVID-19 guidelines". June 8, 2020. https://mediaoffice.ae/en/news/2020/June/08-06/Dubai%20Oaisis%20Selicon.

Gupta, K. 2019. "Dubai to Deploy Cutting-Edge AI devices in Healthcare". *Omnia Health*. December 18, 2019. https://insights.omnia-health.com/hospital-management/dubai-deploy-cutting-edge-ai-devices-healthcare#: ∼ :text = %E2%80%9CBodyo%20has%20developed%20mobile%20AI,13%20minutes%20the%20first%20time.

Ho, D. 2020. "Addressing COVID-19 Drug Development with Artificial Intelligence." *Advanced Intelligent Systems* 2 (5): 2000070. https://doi.org/10.1002/aisy.202000070

Hosseini, S., H. Ahmadi Choukolaei, P. Ghasemi, H. Dardaei-beiragh, S. Sherafatianfini, and A. Pourghader Chobar. 2022. "Evaluating the Performance of Emergency Centers During Coronavirus Epidemic Using Multi-Criteria Decision-Making Methods (Case Study: Sari City)." *Discrete Dynamics in Nature and Society* 6074579: 1–13. https://doi.org/10.1155/2022/6074579

Ipsos. 2019. "Global Citizens & Data Privacy". Ipsos-World Economic Forum: Global Citizens & Data Privacy. Davos 2019. https://www.ipsos.com/sites/default/files/global-citizens-data-privacy.pdf.

Issa, H., R. Jabbouri, and M. Palmer. 2022. "An Artificial Intelligence (AI)-Readiness and Adoption Framework for AgriTech Firms." *Technological Forecasting and Social Change* 182: 121874. https://doi.org/10.1016/j.techfore.2022.121874

Jabarulla, M. Y., and H. N. Lee. 2021. "A Blockchain and Artificial Intelligence-Based, Patient-Centric Healthcare System for Combating the COVID-19 Pandemic: Opportunities and Applications." *Healthcare* 9 (1019): 1–22.

Jahangiri, S., M. Abolghasemian, P. Ghasemi, and A. P. Chobar. 2023. "Simulation-based Optimisation: Analysis of the Emergency Department Resources Under COVID-19 Conditions." *International Journal of Industrial and Systems Engineering* 43 (1): 1–19. https://doi.org/10.1504/IJISE.2023.128399

Johnson, M., A. Albizri, and S. Simsek. 2022. "Artificial Intelligence in Healthcare Operations to Enhance Treatment Outcomes: A Framework to Predict Lung Cancer Prognosis." *Annals of Operations Research* 308 (1-2): 275–305. https://doi.org/10.1007/s10479-020-03872-6

Kamran, M. A., R. Kia, F. Goodarzian, and P. Ghasemi. 2023. "A new Vaccine Supply Chain Network Under COVID-19 Conditions Considering System Dynamic: Artificial Intelligence Algorithms." *Socio-Economic Planning Sciences* 85 (101378): 1–24.

Kaur, I., T. Behl, L. Aleya, H. Rahman, A. Kumar, S. Arora, and I. J. Bulbul. 2021. "Artificial Intelligence as a Fundamental Tool in Management of Infectious Diseases and its Current Implementation in COVID-19 Pandemic." *Environmental Science and Pollution Research* 28 (30): 40515–40532. https://doi.org/10.1007/s11356-021-13823-8

Khalilpourazari, S., and H. H. Doulabi. 2021. "Robust Modelling and Prediction of the COVID-19 Pandemic in Canada." *International Journal of Production Research*, 1–17. https://doi.org/10.1080/00207543.2021.1936261

Khalsa, R. K., A. Khashkhusha, S. Zaidi, A. Harky, and M. Bashir. 2021. "Artificial Intelligence and Cardiac Surgery During COVID-19 era." *Journal of Cardiac Surgery* 36 (5): 1729–1733. https://doi.org/10.1111/jocs.15417

Khan, M., M. T. Mehran, Z. U. Haq, Z. Ullah, S. R. Naqvi, M. Ihsan, and H. Abbass. 2021. "Applications of Artificial Intelligence in COVID-19 Pandemic: A Comprehensive Review." *Expert Systems with Applications* 185 (115695): 1–17.

Lotfi, R., E. Haqiqat, M. S. Rajabi, and A. Hematyar. 2023. "Robust and Resilience Budget Allocation for Projects with a Risk-Averse Approach: A Case Study in Healthcare Projects." *Computers & Industrial Engineering* 176 (108948): 1–10.

Lotfi, R., B. Kargar, A. Gharehbaghi, H. Hazrati, S. Nazari, and M. Amra. 2022b. "Resource-constrained Time–Cost-Quality-Energy-Environment Tradeoff Problem by Considering Blockchain Technology, Risk and Robustness: A Case Study of Healthcare Project." *Environmental Science and Pollution Research* 29 (42): 63560–63576. https://doi.org/10.1007/s11356-022-20334-7

Lotfi, R., B. Kargar, A. Gharehbaghi, and G. W. Weber. 2022d. "Viable Medical Waste Chain Network Design by Considering Risk and Robustness." *Environmental Science and Pollution Research* 29: 79702–79717. https://doi.org/10.1007/s11356-021-16727-9

Lotfi, R., B. Kargar, M. Rajabzadeh, F. Hesabi, and E. Özceylan. 2022a. "Hybrid Fuzzy and Data-Driven Robust

Optimization for Resilience and Sustainable Health Care Supply Chain with Vendor-Managed Inventory Approach." *International Journal of Fuzzy Systems* 24 (2): 1216–1231. https://doi.org/10.1007/s40815-021-01209-4

Lotfi, R., M. Rajabzadeh, A. Zamani, and M. S. Rajabi. 2022c. "Viable Supply Chain with Vendor-Managed Inventory Approach by Considering Blockchain, Risk and Robustness." *Annals of Operations Research*, 1–20. https://doi.org/10.1007/s10479-022-05119-y.

Mahboub, B., M. T. A. Bataineh, H. Alshraideh, R. Hamoudi, L. Salameh, and A. Shamayleh. 2021. "Prediction of COVID-19 Hospital Length of Stay and Risk of Death Using Artificial Intelligence-Based Modeling." *Frontiers in Medicine* 8 (592336): 1–9.

Malaffi. 2021. "100% of Abu Dhabi-based Hospitals Connected to Malaffi". October 14, 2021 https://malaffi.ae/2021/10/14/100-of-abu-dhabi-based-hospitals-connected-to-malaffi/.

Malik, Y. S., S. Sircar, S. Bhat, M. I. Ansari, T. Pande, P. Kumar, B. Mathapati, et al. 2021. "How Artificial Intelligence may Help the COVID-19 Pandemic: Pitfalls and Lessons for the Future." *Reviews in Medical Virology* 31 (5): 1–11. https://doi.org/10.1002/rmv.2205

MBZUAI (Mohamed bin Zayed University of Artificial Intelligence). 2022. "Mohamed bin Zayed University of Artificial Intelligence joins forces with SEH A". April 21, 2022 https://mbzuai.ac.ae/news-events/Mohamed-bin-Zayed-University-of-Artificial-Intelligence-joins-forces-with-SEHA.

Microsoft. 2020. "Daman and Microsoft collaborate to introduce Health Bot to fight COVID-19". September 7, 2020. https://news.microsoft.com/en-xm/2020/09/07/daman-and-microsoft-collaborate-to-introduce-health-bot-to-fight-COVID-19/.

Mohamadou, Y., A. Halidou, and P. T. Kapen. 2020. "A Review of Mathematical Modeling, Artificial Intelligence and Datasets Used in the Study, Prediction and Management of COVID-19." *Applied Intelligence* 50 (11): 3913–3925. https://doi.org/10.1007/s10489-020-01770-9

MOI (Ministry of Interior). 2021. "Smart helmet to detect potential cases of COVID-19". January 20, 2021. https://www.moi.gov.ae/en/about.moi/sustainable.development.goals/SmHeDe.aspx.

Müller, A., S. M. Mertens, G. Göstemeyer, J. Krois, and F. Schwendicke. 2021. "Barriers and Enablers for Artificial Intelligence in Dental Diagnostics: A Qualitative Study." *Journal of Clinical Medicine* 10 (1612): 1–13.

Nanath, K., S. Balasubramanian, V. Shukla, N. Islam, and S. Kaitheri. 2022. "Developing a Mental Health Index Using a Machine Learning Approach: Assessing the Impact of Mobility and Lockdown During the COVID-19 Pandemic." *Technological Forecasting and Social Change* 178: 121560. https://doi.org/10.1016/j.techfore.2022.121560

Naseem, M., R. Akhund, H. Arshad, and M. T. Ibrahim. 2020. "Exploring the Potential of Artificial Intelligence and Machine Learning to Combat COVID-19 and Existing Opportunities for LMIC: A Scoping Review." *Journal of Primary Care & Community Health* 11: 1–11. https://doi.org/10.1177/2150132720963634

The National News. 2018. "Dubai hospitals trial latest medical headband technology to cut stroke deaths". https://www.thenationalnews.com/uae/dubai-hospitals-trial-latest-medicals-headband-technology-to-cut-stroke-deaths-1.734241.

The National News. 2021a. "How do Abu Dhabi's EDE COVID scanners work?" https://www.thenationalnews.com/uae/2021/12/16/how-do-abu-dhabis-ede-covid-scanners-work/.

The National News. 2021b. "Abu Dhabi health officials embrace artificial intelligence to assess impact of COVID-19". March 1, 2021. https://www.thenationalnews.com/uae/health/abu-dhabi-health-officials-embrace-artificial-intelligence-to-assess-impact-of-COVID-19-1.1175539.

The National News. 2021c. "How artificial intelligence is boosting the fight against COVID-19". Available at https://www.thenationalnews.com/health/2021/10/07/how-artificial-intelligence-is-boosting-the-fight-against-COVID-19/.

Naz, F., R. Agrawal, A. Kumar, A. Gunasekaran, A. Majumdar, and S. Luthra. 2022. "Reviewing the Applications of Artificial Intelligence in Sustainable Supply Chains: Exploring Research Propositions for Future Directions." *Business Strategy and the Environment* 31 (5): 2400–2423. https://doi.org/10.1002/bse.3034

NCEMA (National Emergency Crisis and Disasters Management Authority). 2022. ALHOSN UAE App. National Emergency Crisis and Disasters Management Authority. https://www.ncema.gov.ae/alhosn/index.html.

Network Readiness Index 2021. 2021. "Benchmarking the Future of the Network Economy". https://networkreadinessindex.org/countries/.

Ngabo, D., W. Dong, E. Ibeke, C. Iwendi, and E. Masabo. 2021. "Tackling Pandemics in Smart Cities Using Machine Learning Architecture." *Mathematical Biosciences and Engineering* 18 (6): 8444–8461. https://doi.org/10.3934/mbe.2021418

Nguyen, D. C., M. Ding, P. N. Pathirana, and A. Seneviratne. 2021. "Blockchain and AI-Based Solutions to Combat Coronavirus (COVID-19)-Like Epidemics: A Survey." *IEEE Access* 9: 95730–95753. https://doi.org/10.1109/ACCESS.2021.3093633

Pankhania, M. 2021. "Artificial Intelligence and Radiology: Combating the COVID-19 Conundrum." *Indian Journal of Radiology and Imaging* 31 (S 01): S4–S10. https://doi.org/10.4103/ijri.IJRI_618_20

Piccialli, F., V. S. Di Cola, F. Giampaolo, and S. Cuomo. 2021. "The Role of Artificial Intelligence in Fighting the COVID-19 Pandemic." *Information Systems Frontiers* 23 (6): 1467–1497. https://doi.org/10.1007/s10796-021-10131-x

Pillai, R., B. Sivathanu, M. Mariani, N. P. Rana, B. Yang, and Y. K. Dwivedi. 2021. "Adoption of AI-Empowered Industrial Robots in Auto Component Manufacturing Companies." *Production Planning & Control*, 1–17.

Rasheed, J., A. Jamil, A. A. Hameed, F. Al-Turjman, and A. Rasheed. 2021. "COVID-19 in the age of Artificial Intelligence: A Comprehensive Review." *Interdisciplinary Sciences: Computational Life Sciences* 13 (2): 153–175. https://doi.org/10.1007/s12539-021-00431-w

Reuters. 2021. Abu Dhabi's lightning-fast COVID-19 scanners raise privacy fears. https://www.reuters.com/article/us-health-coronavirus-emirates-privacy-idUSKCN2EE0RT.

Riayati. 2022. "Transforming the UAE Healthcare Landscape". Ministry of Health and Prevention. https://riayati.mohap.gov.ae/.

Rodríguez-Espíndola, O., S. Chowdhury, A. Beltagui, and P. Albores. 2020. "The Potential of Emergent Disruptive

Technologies for Humanitarian Supply Chains: The Integration of Blockchain, Artificial Intelligence and 3D Printing." *International Journal of Production Research* 58 (15): 4610–4630. https://doi.org/10.1080/00207543.2020.1761565

Roy, Avik. 2021. "Key Findings from the 2021 FREOPP World Index of Healthcare Innovation". *FREOPP.org*. June 25, 2021. https://freopp.org/key-findings-from-the-freopp-world-index-of-healthcare-innovation-cda78938c047.

RTA (Roads and Transport Authority). 2020. "AI in taxis to curb spread of COVID-19". Roads and Transport Authority. June 15, 2020. https://www.rta.ae/wps/portal/rta/ae/home/news-and-media/all-news/NewsDetails/ai-in-taxis-to-curb-spread-of-COVID-19.

Russo, G., P. Reche, M. Pennisi, and F. Pappalardo. 2020. "The Combination of Artificial Intelligence and Systems Biology for Intelligent Vaccine Design." *Expert Opinion on Drug Discovery* 15 (11): 1267–1281. https://doi.org/10.1080/17460441.2020.1791076

Santosh, K. C., S. Ghosh, and D. GhoshRoy. 2022. "Deep Learning for Covid-19 Screening Using Chest X-Rays in 2020: A Systematic Review." *International Journal of Pattern Recognition and Artificial Intelligence* 36 (05): 2252010. http://doi.org/10.1142/S0218001422520103.

SAP. 2022. "What is machine learning?" *SAP Insights*. https://www.sap.com/mena/insights/what-is-machine-learning.html.

Sarker, S., L. Jamal, S. F. Ahmed, and N. Irtisam. 2021. "Robotics and Artificial Intelligence in Healthcare During COVID-19 Pandemic: A Systematic Review." *Robotics and Autonomous Systems* 146: 103902. https://doi.org/10.1016/j.robot.2021.103902.

SAS. 2022. "Machine Learning: What it is and why it matters". *SAS Insights*. https://www.sas.com/en_ae/insights/analytics/machine-learning.html.

Shah, H., S. Shah, S. Tanwar, R. Gupta, and N. Kumar. 2021. "Fusion of AI Techniques to Tackle COVID-19 Pandemic: Models, Incidence Rates, and Future Trends." *Multimedia Systems* 28 (4): 1189–1222. https://doi.org/10.1007/s00530-021-00818-1

Sharma, R., A. Shishodia, A. Gunasekaran, H. Min, and Z. H. Munim. 2022. "The Role of Artificial Intelligence in Supply Chain Management: Mapping the Territory." *International Journal of Production Research* 60 (24): 7527–7550. https://doi.org/10.1080/00207543.2022.2029611.

Shirazi, H., R. Kia, and P. Ghasemi. 2021. "A Stochastic bi-Objective Simulation–Optimization Model for Plasma Supply Chain in Case of COVID-19 Outbreak." *Applied Soft Computing* 112 (107725): 1–25.

Smart Cities World. 2021. "Smart Dubai develops data-driven model to predict the future course of COVID-19". May 4, 2021 https://www.smartcitiesworld.net/news/news/smart-dubai-develops-data-driven-model-to-predict-the-future-course-of-COVID-19-6378.

Snider, M. 2020. "Tests expand on whether wearables could predict coronavirus". *Medical Xpress*, May 28, 2020. https://medicalxpress.com/news/2020-05-wearables-coronavirus.html.

Suliman, Duaa. M., Faisal A. Nawaz, Parvathy Mohanan, Mohamed A. K. A. Modber, Muhammad K. Musa, Mohamed B. Musa, Diala E. Chbib, et al. 2021. "UAE Efforts in Promoting COVID-19 Vaccination and Building Vaccine Confidence." *Vaccine* 39 (43): 6341–6345. https://doi.org/10.1016/j.vaccine.2021.09.015

Surianarayanan, C., and P. R. Chelliah. 2021. "Leveraging Artificial Intelligence (AI) Capabilities for COVID-19 Containment." *New Generation Computing* 39 (3-4): 717–741. https://doi.org/10.1007/s00354-021-00128-0

Swayamsiddha, S., K. Prashant, D. Shaw, and C. Mohanty. 2021. "The Prospective of Artificial Intelligence in COVID-19 Pandemic." *Health and Technology* 11 (6): 1311–1320. https://doi.org/10.1007/s12553-021-00601-2

Tang, G., K. Westover, and S. Jiang. 2021. "Contact Tracing in Healthcare Settings During the COVID-19 Pandemic Using Bluetooth Low Energy and Artificial Intelligence—A Viewpoint." *Frontiers in Artificial Intelligence* 4 (666599): 1–3.

Tonetto, L. M., T. A. Saurin, F. S. Fogliatto, G. L. Tortorella, G. Narayanamurthy, V. M. da Rosa, and J. Tengkawan. 2021. "Information and Communication Technologies in Emergency Care Services for Patients with COVID-19: A Multi-National Study." *International Journal of Production Research*, 1–17. https://doi.org/10.1080/00207543.2021.1967501

Tortorella, G. L., F. S. Fogliatto, S. Kurnia, M. Thürer, and D. Capurro. 2022a. "Healthcare 4.0 Digital Applications: An Empirical Study on Measures, Bundles and Patient-Centered Performance." *Technological Forecasting and Social Change* 181: 121780. https://doi.org/10.1016/j.techfore.2022.121780

Tortorella, G. L., F. S. Fogliatto, V. Sunder M, A. M. Cawley Vergara, and R. Vassolo. 2022b. "Assessment and Prioritisation of Healthcare 4.0 Implementation in Hospitals Using Quality Function Deployment." *International Journal of Production Research* 60 (10): 3147–3169. https://doi.org/10.1080/00207543.2021.1912429

UAE. 2020. "Virtual Doctor for COVID-19". June 9, 2020. https://u.ae/en/information-and-services/justice-safety-and-the-law/handling-the-COVID-19-outbreak/smart-solutions-to-fight-COVID-19/virtual-doctor-for-COVID-19.

UAE. 2021. "Scientific research on prevention and treatment of COVID-19". September 11, 2021. https://u.ae/en/information-and-services/justice-safety-and-the-law/handling-the-COVID-19-outbreak/scientific-research-on-prevention-and-treatment-of-COVID-19.

UAE. 2022. "Smart solutions to fight COVID-19". March 7, 2022 https://u.ae/en/information-and-services/justice-safety-and-the-law/handling-the-COVID-19-outbreak/smart-solutions-to-fight-COVID-19.

UAE Centennial 2071. 2021. https://u.ae/en/about-the-uae/strategies-initiatives-and-awards/federal-governments-strategies-and-plans/uae-centennial-2071.

UAE Ministry of Cabinet Affairs and the Future. 2017. "UAE's Fourth Industrial Revolution Strategy". September 2017 https://u.ae/en/about-the-uae/strategies-initiatives-and-awards/federal-governments-strategies-and-plans/-/media/About-UAE/Strategies/UAE-4-IR-Strategy/En-UAE-4-IR-Strategy.ashx.

Unlock Media. 2019. "IRIS Health UAE uses AI and Blockchain to save than USD 10 million in MENA". August 27, 2019. https://www.unlock-bc.com/news/2019-08-27/iris-health-uae-uses-ai-and-blockchain-to-save-than-usd-10-million-in-mena.

Vaishya, R., M. Javaid, I. H. Khan, and A. Haleem. 2020. "Artificial Intelligence (AI) Applications for COVID-19 Pandemic." *Diabetes & Metabolic Syndrome: Clinical Research & Reviews* 14 (4): 337–339. https://doi.org/10.1016/j.dsx.2020.04.012

Vaka, A. R., B. Soni, and S. Reddy. 2020. "Breast Cancer Detection by Leveraging Machine Learning." *ICT Express* 6 (4): 320–324. https://doi.org/10.1016/j.icte.2020.04.009
van Der Schaar, M., A. M. Alaa, A. Floto, A. Gimson, S. Scholtes, A. Wood, E. McKinney, D. Jarrett, P. Lio, and A. Ercole. 2021. "How Artificial Intelligence and Machine Learning Can Help Healthcare Systems Respond to COVID-19." *Machine Learning* 110 (1): 1–14. https://doi.org/10.1007/s10994-020-05928-x
Verde, L., G. De Pietro, A. Ghoneim, M. Alrashoud, K. N. Al-Mutib, and G. Sannino. 2021. "Exploring the use of Artificial Intelligence Techniques to Detect the Presence of Coronavirus COVID-19 Through Speech and Voice Analysis." *IEEE Access* 9: 65750–65757. https://doi.org/10.1109/ACCESS.2021.3075571
WAM. 2021. "Dubai Health Authority introduces AI policy in healthcare". *Emirates News Agency-WAM*. September 15, 2021. https://www.wam.ae/en/details/1395302970260#:~:text=The%20policy%20mandates%20that%20all,the%20long%20and%20short%20term.%22.
Wang, L., Y. Zhang, D. Wang, X. Tong, T. Liu, S. Zhang, … M. Clarke. 2021. "Artificial Intelligence for COVID-19: A Systematic Review." *Frontiers in Medicine* 8 (704256): 1–5.
Weqaya. 2021a. "UAE becomes world's most vaccinated nation: Bloomberg Tracker". July 5, 2021. https://www.weqaya.ae/en/posts/uae-becomes-world-s-most-vaccinated-nation-bloomberg-tracker.
Weqaya. 2021b. Digital, AI solutions enhanced UAE's fight against COVID-19: Report. https://www.weqaya.ae/en/posts/digital-ai-solutions-enhanced-uae-s-fight-against-COVID-19-report.
Weqaya. 2021c. Smart Dubai, MBRU develop new COVID-19 epidemiological model. Available at https://www.weqaya.ae/en/posts/smart-dubai-mbru-develop-new-COVID-19-epidemiological-model.
Wirtz, B. W., and W. M. Müller. 2019. "An Integrated Artificial Intelligence Framework for Public Management." *Public Management Review* 21 (7): 1076–1100. https://doi.org/10.1080/14719037.2018.1549268
Wirtz, B. W., J. C. Weyerer, and B. J. Sturm. 2020. "The Dark Sides of Artificial Intelligence: An Integrated AI Governance Framework for Public Administration." *International Journal of Public Administration* 43 (9): 818–829. https://doi.org/10.1080/01900692.2020.1749851
Yin, R. K. 2009. *Case Study Research: Design and Methods*. London: SAGE Publications Ltd.
Zawya. 2020. "First Ai Medical Fitness Center in the World Conducts Tests with Minimum Human Intervention". February 23, 2020 https://www.zawya.com/en/press-release/first-ai-medical-fitness-center-in-the-world-conducts-tests-with-minimum-human-intervention-oq8suc3r.
Zawya. 2022. "From Three Days to Three Seconds: SEHA Implements New AI Technology at 11 of Its Centers". June 2, 2022. https://www.zawya.com/en/press-release/government-news/from-three-days-to-three-seconds-seha-implements-new-ai-technology-at-11-of-its-centers-utbu9cfr.

Appendix (Interview Protocol)

- What are the various AI applications and techniques adopted in your organisation and the UAE healthcare sector in general?
- Why did your organisation implement these AI applications and techniques vis-à-vis others?
- Did you face any issues or risk during or post-implementation of AI solutions? If so, what are they?
- Based on your experience or knowledge on AI applications and techniques, what are the key enablers or factors that are critical for the sector-wide adoption of AI in healthcare?
- Based on your experience or knowledge of AI applications and techniques, what are the key barriers/challenges that are hindering the sector-wide adoption of AI in the healthcare sector?
- Based on your knowledge of AI applications and techniques, what are their benefits for the healthcare sector (operational, quality and social)? Please provide a few examples.
- In your opinion, what is the role of government and what should they do to promote AI in the healthcare sector?
- How do you foresee the evolution and impact of AI on health in the next 5 years?