Cognitive Analytics-enabled Responsible Artificial Intelligence for Business Model Innovation: A Multilayer Perceptron Neural Networks Estimation

Abstract

Cognitive analytics employs and analyses complex and heterogeneous data sources generating deeper insights that mimic the natural intelligence of the human brain. Cognitive analytics-enabled Artificial Intelligence (AI) that promotes Business Model Innovation (BMI) for the efficiency of the healthcare system is a nascent and undertheorized domain. Within the healthcare management systems, stakeholders' engagement with AI, particularly with responsible AI, to optimize BMI and improve business performance is bounded by several caveats. Using the Technology Acceptance Model (TAM) and Social Network Theory (SNT) as our conceptual foci, we empirically examine through the Multilayer Perceptron Neural Network the extent to which responsible AI leads to Business Model Innovation (BMI) through the stakeholders' engagement. Our contributions are novel which demonstrate that cognitive analytics-enabled responsible AI is central to innovation, and healthcare stakeholders exhibit a robust propensity to reorientate and innovate their existing BMI to achieve improved business performance. It has significant implications for innovation, AI and cognitive analytics literature.

Keywords: Cognitive Analytics, RAI, Responsibility of Innovation, Business Model Innovation (BMI), Healthcare, Stakeholders, Multilayer Perceptron Neural Network (MLP NN)

Cognitive analytics-enabled Responsible Artificial Intelligence for Business Model Innovation: A Multilayer Perceptron Neural Network Estimation

1. Introduction

Cognitive analytics enables the integration of human and machine functioning that facilitates where computers mimic the human brain's functionality for the decision-making process through a self-learning feedback loop (Charles et al., 2022; Behera et al., 2019). Cognitive analytics-enabled AI can comprehend, reason, and assist people in broadening their knowledge base, increasing productivity, and strengthening their expertise resulting in enhancing business performance (Davenport, 2018). Data analytics has progressed over time from descriptive (what happened) to diagnostic (why did it happen) to predictive (what could happen) to prescriptive (what action could be taken) (Cognitive Analytics Research Lab, 2022; Charles et al., 2022; Gudivada et al., 2016). The next major paradigm shift is cognitive analytics, which capitalizes on advanced high-performance computing by fusing Artificial Intelligence (AI) algorithms with data analytics approaches (Mariani & Wirtz, 2023). Cognitive Analytics is an evolution of AI-based algorithms and systems that include natural language processing (NLP), hypothesis generation and evaluation, with dynamic learning using AI (Ahmed et al., 2017; Marshall, 2017; Hair, Harrison, & Ajjan, 2022). Previous studies refer to descriptive and exploratory analytics and, and some extent predictive analytics for this purpose (Mariani & Baggio, 2022), but relatively very few studies use cognitive analytics based on AI (Mariani & Wirtz, 2023).

Studies available refer to stakeholders and AI engagement (Di Vaio, et al., 2020), but offer a limited understanding of BMI and cognitive analytics (de Oca Munguia et al., 2021; Milkau, 2019), societal well-being and cognitive analytics (Mikalef et al., 2022), TMT and cognitive analytics (Keiningham et al., 2020 and Li, Chen, Yi, Mao, & Liao, 2019) for healthcare (Trocin et al., 2021; Barredo Arrieta, Díaz-Rodríguez, Del Ser, Bennetot et al., 2020), but fail to explain the impact of incorporate responsibility aspect into AI for BMI. Our study addresses this gap from the perspective of stakeholder engagement.

Scholars studying changes in Business Model Innovation (BMI) through cognitive analytics with the use of AI for enhanced business performance are increasingly reimaging how a platform-based digital ecosystem can optimize perceived usefulness (PU) and perceived ease of use (EU) for various stakeholders, particularly, within the healthcare management system (Shah & Chircu, 2018; Nambisan, Zahra & Luo, 2019; Chen et al., 2019). However, the extent to which stakeholders will benefit from the evolved platform-based digital ecosystem (Laplume, Petersen, & Pearce, 2016) and what theoretical priors can reframe our understanding of BMI in a digital setting (Banalieva & Dhanaraj, 2019; Teece, 2018; Brouthers, Geisser, & Rothlauf, 2016) remains to be an area less explored. Despite a concerted effort to reevaluate dominant management theories in a digital setting (Banalieva & Dhanaraj, 2019; Teece, 2018), the prevailing concepts relating to BMI and business performance continue to be undertheorized (Sjödin et al., 2021; Hennart, 2019; Chen, Baird & Straub 2019). Specifically, the literature fails to explain the role of stakeholders' engagement in adopting BMI for enhanced business performance through cognitive analytics such as AI, in particular responsible AI (Fukuda-Parr & Gibbons, 2021). Therefore, it is critical to understand the process and purpose of the platform ecosystem through the lens of cognitive analytics, specifically responsible AI for BMI. Our research argues that Responsible AI empowers organisations and enhances societal well-being by bringing in responsible principles and eliminating biases with the help of AI algorithms (Mikalef et al., 2022). These algorithms of AI include a sub-index that quantifies the degree to which AI and responsible AI principles are adopted by the BMI (IDRC, 2020), thereby, reflecting the need to address BMI in relation to cognitive analytics based on a responsible AI paradigm. Our research contributes to existing literature from several aspects including (1) the relationship between the adoption of AI-enabled innovation in healthcare management systems through digital diffusion and new business model innovation; (2) the impact of BMI through cognitive analytics (i.e., responsible AI) on healthcare stakeholders; (3) the impact of regulatory factors on responsible AI-enabled BMI; (4) the impact between the responsible use of AI on BMI. Underpinning our conceptualization into Technology Acceptance Model (TAM) (Davis, 1986, 1989) and Social Network Theory (SNT) (Granovetter, 1973, 1983, 1985), our study argues that cognitive analytics can revolutionize BMI in the healthcare management system by integrating responsible AI through stakeholders' engagement for improving business performance, particularly, enhancing perceived usefulness (PU) and perceived ease of use (EU) resulting in smart healthcare provisions. With the responsible use of cognitive analytics, health information sharing is enhanced to improve patient outcomes. Advances in the responsible use of data availability, connectivity, and cognitive computing enable doctors, researchers, and other health professionals to examine how ever-growing patient-related information is outpacing human cognitive capacity and proving impossible to fully integrate without new computing models (Ahmed et al., 2017; Marshall, 2017; Gudivada et al., 2016).

In explaining cognitive analytics-enabled responsible AI-generated value creation in the platform ecosystem, extant studies have predominantly focused on specific business models undertaking physical entity views (Garbuio & Lin, 2019). Unlike prevailing views, we adopt TAM and SNT proposing how value is created through stakeholders' engagement, involving cognitive analytics-enabled responsible AI. TAM was chosen because it helps to explain how users would perceive the value of a product which is heavily reliant on healthcare delivery models when individual skills and needs are continually shifting. As a result, social network platforms and stakeholders have to acknowledge and allow technological innovation to happen, and also safeguard the ethical aspects of AI (Du & Chunyan, 2021; Tanniru et al., 2021). SNT was chosen as the network strategy which provides details for a more complete understanding of the fitness consequences of social organization at the individual and community levels (Krause et al., 2007; Kumar & Rathore, 2016). These two theories help answer our research questions and the relevance of understanding various stakeholders' perceptions of responsible AI, as the theories are also directly linked to business performance. Particularly, we examine technological acceptance through which social network platforms introduce new value-creation and efficient mechanisms in the healthcare management system, their facilitators, activities and antecedent effects. Specifically, we show the extent to which social network platforms through technological acceptance and social network relations unwrap conventional ties and modify value-generating structures in the healthcare management system. We also show cognitive analytics-enabled AI is central to stakeholders' sensitivity to innovation, and stakeholders exhibit a robust propensity to reorientate their existing BMI to accommodate smart healthcare management systems for achieving improved business performance. Based on stakeholders' insights, we demonstrate that the BMI model has the relational capacity to improve the platform-based ecosystem and can offer usefulness and ease of use to the end-users leading to enhanced business performance. Our study provides evidence that the stakeholders' engagement through responsible cognitive analytics-enabled AI advances BMI. We outline, referring to various stakeholders, a summarized overview of the key studies relating to AI and responsible AI within the healthcare management system in Table 1. Our study contributes to the relevant research area by providing several important theoretical contributions in the innovation and cognitive analytics field. In particular, Business model innovation in healthcare management is becoming increasingly important for stakeholder engagement as it helps to improve business performance and provide easy-to-use services to end users, and responsible AI is of great importance in the healthcare industry as it facilitates business model innovation.

[Insert Table 1 here]

The paper is organised as follows. In the next section, we reviewed the literature focusing on the theoretical framework and developed six hypotheses. We then outlined the research setting and data followed by our empirical specification. Next, we presented the results obtained from our empirical analysis. In the following sections, we presented a discussion, implications of this study, conclusions, limitations, and future avenues for study.

2. Review of literature

2.1 Cognitive analytics

The simulation of human intelligence processes by machines, particularly by platform-based computer systems, is known as AI (Al-Dhaen et al., 2021; Huang & Rust, 2018). AI is a network of analytic algorithms based on machine learning that aims to mimic human abilities to interpret data, detect patterns, forecast outcomes, and recommend actions without explicit human instructions (Charles et al., 2022; Dignum, 2017; Huang & Rust, 2018). Such AI-based analytics are illustrated by their orientation framework, i.e., descriptive, diagnostic, predictive, prescriptive, and cognitive. In contrast, most orientation taxonomies involve descriptive, diagnostic, predictive, and prescriptive analytics, but cognitive analytics is a "smarter intelligence" that adapts and continues learning through interactions between machines and humans (Charles et al., 2022). Particularly, cognitive analytics-enabled AI differs from traditional predictive and prescriptive analytics in two ways, first, by its ability to self-learn for decision-making and second, by its ability to understand communicative natural language (Someh et al., 2020; Al-Dhaen et al., 2021). Cognitive computing, based on machine learning, refers to a class of analytics that can be taught or learned. Cognitive computing systems continuously learn from the data fed into them by mining these disparate streams of information for relevant streams of information (Di Vaio et al., 2020; Ahmed et al., 2017). Besides, AI on the platform-based ecosystem has transformed the way organisations create value. For example, social network platforms such as Facebook have built on the personal data that users generate and use to create personalized services or give pinpoint advertising space to other businesses (Gleiss et al., 2021). Furthermore, A large amount of data about patients is being collected, including electronic health records, genomic data, and exogenous data (data originating from wearable devices such as the Apple Watch, Fitbit, medical devices, smartphones, and more). It further allows healthcare providers to make better, faster, and more cost-effective decisions while also providing individuals with the information they need to understand their health and receive truly personalized care.

The increasing use of cognitive analytics-enabled AI on social networks has prompted a growing need for research in identifying and examining the multitiered effect of AI on the functional behaviour of organisations and individuals (Di Vaio, Hassan & Alavoine, 2022). However, emerging ethical concerns, raised by stakeholders, related to the use of cognitive analytics-enabled AI warrant further scrutiny, which can help organisations to achieve trust, minimize privacy invasion, and eventually facilitate responsible and accountable AI-enabled social network operations. Often usage of AI compromises the moral consequences and ethical principles (Trocin et al, 2021; Martin, 2019) as machines do not recognize boundaries. This raises substantial ethical enquiry concerning how a platform-based ecosystem should be utilized (Floridi & Taddeo, 2016; Pavlović & Hafner, 2023). Responsible AI within cognitive analytics is about answering who determines what the alternatives are and how to implement AI proportionately for ethical decision-making that is consistent with societal, ethical, and legal requirements in a transparent, unbiased and equitable way (Liu et al., 2021; Huang & Rust, 2018; Kumar, 2014; Micu et al. 2018; Arasu et al., 2020). Particularly, cognitive analytics-enabled responsible AI coupled with the healthcare management system leads to innovation (Shah & Chircu, 2018; Nambisan, Zahra & Luo, 2019; Chen et al., 2019) that reflects technological acceptance (Deng, Hong, Ren, Zhang & Xiang, 2018) and explains the purpose of the social networks through reasoned action (Buabeng-Andoh, Yaokumah & Tarhini, 2019; Trocin, Mikalef, Papamitsiou & Conboy, 2021).

2.2 Theoretical framework

Underpinning two complementing theoretical premises, i.e., the Technology Acceptance Model (TAM) (Davis, 1986, 1989) and Social Network Theory (SNT) (Granovetter, 1973, 1983, 1985), we contend that cognitive analytics, such as responsible AI can revolutionize BMI in the healthcare management system through stakeholders' engagement by improving business performance, particularly, enhancing perceived usefulness (PU) and perceived ease of use (EU) resulting in smart healthcare provisions (Zhang, Xia & Huang, 2023). With the responsible use of cognitive analytics, health information sharing is enhanced to improve patient outcomes. Advances in the responsible use of data availability, connectivity, and cognitive computing enable doctors, researchers, and other health professionals to examine how ever-growing patient-related information is outpacing human cognitive capacity and proving impossible to fully integrate without new computing models (Charle et al., 2022; Ahmed et al., 2017; Marshall, 2017; Gudivada et al., 2016). Prior studies have examined the affiliation of BMI for achieving higher business performance in several industries within the digital setting for various stakeholder communities, i.e., customers, top management teams, and the chief operating officers (Keiningham et al., 2020; Li, Chen, Yi, Mao, & Liao, 2019, Nambisan, Zahra, & Luo, 2019). However, studies on stakeholders' engagement within the healthcare management system to advance BMI and enhance business performance remain relatively sparse (Chen et al., 2019, Trocin et al., 2021). As such, platform ecosystem-based responsible cognitive analytics, particularly responsible AI, is central to data sensitivity and structural transferability (Morley, Machado, Burr et al., 2020) and reduces biases heightening the interpretability of outcomes through stakeholders' engagement in the healthcare management system offering efficient healthcare management system to the society (Trocin et al., 2021; Barredo Arrieta, Díaz-Rodríguez, Del Ser, Bennetot et al., 2020; Chen et al., 2019). In addition, corruption and lack of policy guidance through regulatory framework remain dominant barriers to implementing BMI for the improved business performance and functional well-being of society (Borda et al., 2022; Golbin et al., 2020; Merhi, 2022; Kumar, Dwivedi & Anand, 2021; Du and Chunyan's, 2021). Our study underscores theorizing the TAM and SNT propensity on the BMI, the process of value creation by cognitive analytics such as responsible AI, innovation as a process-value outcome, and smart BMI for better business performance on the platform ecosystem for the efficient healthcare management system. Particularly, we began by exploring the extent to which responsible AI-enabled social networks introduce new value-creation on the platform ecosystem, which, in turn, influences the efficiency of the healthcare management system. As such, at the early stage of innovation diffusion, when the digital integration of innovation, e.g., cognitive analytics-enabled AI, on the healthcare management system, is not fully institutionalized; the end-users, including stakeholders, become concerned about its perceived usefulness and perceived ease of use (Choi et al., 2020; de Oca Munguia et al., 2021; Lin, 2019; and Milkau, 2019).

3. Hypothesis development

3.1 Value creation for the healthcare management System through cognitive analytics-enabled responsible AI: Technology Acceptance Model (TAM)

AI through alternative and innovative business models such as the Internet of Medical Things (IoMT), Remote Patient Monitoring (R\PM) and Electronic Health Records (HER) has generated substantial benefits for the end-users in making self-decision and replacing human interaction with intelligent machine learning, however, such platform-based networks are yet to be transparent and safe (Al-Dhaen et al., 2021; Haaker et al., 2021). Recently, the NIHR (National Institute of Health and Care Research), UK reported that AI is primarily used for generative and predictive purposes.[1] Particularly,

[1] https://evidence.nihr.ac.uk/collection/artificial-intelligence-10-promising-interventions-for-healthcare/ Accessed 18th December 2023

if AI deviates from the transparency, accountability and trustworthiness of the end-users (Scott & Yampolskiy, 2019; Shah & Chircu, 2018), and the regulatory framework lacks administrative and enactment capacity (Golbin et al., 2020; Kumar, Dwivedi & Anand, 2021), the end-users do not receive the perceived benefits. The platform-based ecosystems, i.e., AI algorithms do not always create tangible products or intangible services, they offer a new type of data-driven value generation. Value creation through AI 'without production' differentiates the creation of value as an economic exchange between several stakeholders that substantially shifts the business model within a digital setting (Milkau, 2019; Arasu et al., 2020; Gupta & Kanungo, 2022). Lately, the evolutionary growth of cognitive analytics-enabled AI as a network-driven innovation has led to BMI which has extensively improved business performance. Particularly, cognitive analytics-enabled AI-enabled platforms have not been discussed by traditional economic theories but they can be applied to predict future business models in a digital setting (Milkau, 2019; Kumar, 2014; Micu et al., 2018; Arasu et al. 2020). However, most of the prior studies on innovation in digital settings within healthcare management have undertaken a routine held view from patients' perspectives (Garbuio & Lin, 2019; Harris & Rogers, 2021) and made limited attempts to explore BMI orientation for business performance on the platform-based ecosystem, i.e., AI algorithms with stakeholders' engagement (Banalieva & Dhanaraj, 2019; Li, Chen, Yi, Mao & Liao, 2019; Trocin, Mikalef, Papamitsiou & Conboy, 2021). The value creation embedded in cognitive analytics-enabled AI has two core components, usefulness and ease of use of technology. Both components are aligned with the behavioural intention of the end user's technological acceptance (Harris & Rogers, 2021; Venkatesh, Thong & Xu, 2012). Focusing on stakeholders and referring to cognitive analytics-enabled responsible AI, we argue that AI-enabled technological acceptance procreates value and extends BMI in the healthcare management system by improving business performance. Value creation through cognitive analytics-enabled AI has the potential to renew the healthcare management system (Kulkov, 2021; Trocin et al., 2021; Kumar, Dwivedi & Anand, 2021; Du Chunyan, 2021). This is because cognitive analytics-enabled AI promotes various types of decision-making data analytics including data mining, cognitive modelling, business intelligence, simulation modelling and optimization (Saggi & Jain, 2018). Various digital platforms, i.e., Google, Apple, Facebook, Amazon, and Microsoft, without generalizing, indicate that usage of such platform-based AI algorithms are channels for innovative value creation and continue the value creation from a holistic standpoint (Gleiss et al., 2021). Although, in the healthcare management system, prior studies have attempted to address the engagement of cognitive analytics-enabled AI by capturing patients' and healthcare providers' focus (Garbuio & Lin, 2019; Nambisan, Zahra & Luo, 2019; Trocin et al., 2021), but not the extent to which technological acceptance interplays with various stakeholders' engagement.

The Technology Acceptance Model (TAM) which surrounds perceived usefulness and perceived ease of use was initially introduced in 1986 and further refined in 1989 (Davis, 1986, 1989), and subsequently extended to the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al. 2003). The extended TAM incorporated the Theory of Planned Behavior, Social Cognitive Theory, Diffusion of Innovations Theory, and later hedonic motivation, price value and habit as predictors of technology acceptance in UTAUT leading to the UTAUT2 model (Harris & Rogers, 2021; Venkatesh, Thong & Xu, 2012). Despite several modifications, the core precepts of the TAM remained unchanged. The TAM has emerged as an innovative and evolutionary model for understanding and anticipating human behaviour regarding the prospective adoption or rejection of technology (Liu et al., 2021; Harris & Rogers, 2021). The dominant concept of TAM refers to how users perceive the value of a service provider that is significantly reliant on care delivery models where the user capabilities and expectations are dynamic and continue to change, irrespective of the platform-based ecosystems, for example, the onset of AI and responsible AI being less flexible (Tanniru et al., 2021). Therefore, the level of technology the stakeholders should need to accept and accommodate innovation and embrace the process of continuous technological changes (Li et al., 2019; Kumar, 2014, Micu et al., 2018) while supporting regulatory requirements in maintaining the ethical aspects of AI (Du & Chunyan, 2021) remains critical for healthcare settings. As such, the cognitive analytics-enabled AI-embedded digital settings allow technological changes to be adaptive by fast-tracking changing client expectations such as the real-time monitoring and feedback control systems (Tanniru et al., 2021). Particularly, a higher degree of adoption and, simultaneously, an increasing level of diffusion in innovation, as argued by Kumar (2014), is decisive for technological acceptance through cognitive analytics-enabled AI.

Lately, technological shifts have widely been embraced by consumers and the stakeholders of healthcare. Specifically, adaptive cognitive analytics-enabled AI tools became key to the improved productivity of the technological ecosystem creating significant economic influence (Micu et al., 2018). Although the healthcare industry has a lower technological acceptance threshold and is cautious in adopting new technologies and practices, digital data such as structured and unstructured data, self-monitoring health data, real-time sensor devices, images, videos, various reports, and document visualization facilitated innovations in the healthcare industry have diffused through cognitive analytics-enabled AI into the mainstream market through value-added digital transformations (Saggi & Jain, 2018; Teece, 2018). Particularly, the technological evolution of social networks data analytics using cognitive analytics-enabled AI-enabled healthcare innovation has been instrumental in predicting end-users buying, using and purchasing intentions and desires (Arasu et al., 2020), which is consistent with the TAM. Similarly, in healthcare management, innovation in drug discovery, face recognition, verification of signatures, fingerprint and iris scanning are highly reliant on technological acceptance and have enhanced the technological usefulness and ease of use (Saggi & Jain, 2018; Nambisan, Zahra & Luo, 2019). Also, patient case history, physician notes, lab reports, X-ray reports, diet rules, list of doctors and nurses in a given hospital, health registration data, and medicine and surgical instrument expiry date identification based on RFID (Radio Frequency Identification) data are maintained through technological-based Big Data repository (Saggi & Jain, 2018), that suggest the level of technological acceptance at the organisational level, and at the same time refers to the responsibility of ethical issues relating to regulatory enactment (Kumar, Dwivedi & Anand 2021; Du & Chunvan, 2021). Besides, an AI-embedded platform can advance intelligent solutions as how to prevent, diagnose, treat health conditions and offer a prognosis, renewing the future of the healthcare management system (Garbuio & Lin, 2019; Kumar, Dwivedi & Anand 2021; Du & Chunvan, 2021) but remains surrounded by responsible use of it.[2] Within the TAM context, cognitive analytics-enabled AI, particularly responsible AI, can transform the way healthcare practitioners and executives, as stakeholders, gather data and interact with patients and their families, as well as document and scrutinize clinical and operational personnel data while maintaining ethical standards. For example, AI platforms are created for cloud computing, deep learning in medical imaging, clinical trial patient selection optimization, telemedicine and diagnostic services, virtual assistance, or image recognition. However, cognitive analytics based on AI-embedded applications without accountability and transparency can affect the interpretability and explainability of medical outcomes, as well as compromise moral and ethical consequences for stakeholders of healthcare management and raise concerns about implementing regulatory framework (Trocin et al., 2021; Morley et al., 2020; Dignum, 2019; Li, Chen, Yi, Mao & Liao, 2019; Kumar, Dwivedi & Anand, 2021; Du Chunvan, 2021; Kumar, 2014 and Micu et al., 2018). In addition, identifying the nexus between ethics and responsible AI is becoming a growing concern for stakeholders. Despite stakeholders' engagement, the risk of implementing BMI in the healthcare management system through cognitive analytics-enabled responsible AI remains challenging (Fadul, 2021; Chen et al., 2019; Deng et al., 2018). Particularly, how the regulatory and ethical factors affect the responsible AI-enabled BMI depends on how innovation is optimized and aligned with the existing business system to attain superior business performance (Golbin et al., 2020). Thus, we have proposed the following three hypotheses. In addition, we have illustrated our hypothesis development process in Panel A of Table 2.

H1: *Ceteris paribus, cognitive analytics-enabled AI-led innovation significantly improves the healthcare management system through digital diffusion.*

H2: *Ceteris paribus, business model innovation through cognitive analytics-enabled responsible AI is significantly important for healthcare stakeholders.*

H3: *Ceteris paribus, regulatory factors significantly affect cognitive analytics-enabled responsible AI-led business model innovation.*

---

[2] https://evidence.nihr.ac.uk/collection/artificial-intelligence-10-promising-interventions-for-healthcare/ Accessed 18th December 2023

[Insert Table 2 here]

3.2 Cognitive analytics-enabled responsible AI-enabled innovation in the healthcare management system: Social Network Theory (SNT)

The concept of the social network was formalized to explain the fundamental socio-psychological objectivity of social circles and groups to show the behavioural dependencies and interaction of social entities (Tabassum et al., 2018; Borgatti & Ofem, 2010). The social network carries substantial relevance in understanding the individual and various stakeholders of an assigned group through their interconnectivity and collective dynamics (Borda et al., 2022; Barabási, 2003; Kumar & Rathore, 2016). One of the distinct features of social networks is that they can considerably influence the relationship between country-level administrative effectiveness and dimensions of corruption (Arayankalam, Khan & Krishnan, 2021; Borda et al., 2022) impacting stakeholders' engagement (Berger, 2014; Nundy, Desiraju & Nagral, 2018). In addition, social networks identify behavioural patterns in health practices and management of healthcare informatics (Smith & Christakis, 2008) and help improve homogeneity in social network marketization (Zhang, Liu & Miao, 2021). Social network theory provides a different insight and set of tools for appreciating media effects, allowing for the examination of how micro-and macrosocial structures mediate and moderate media effects (Liu et al., 2017). The media effects can optimize the interaction between participating individuals and groups as agents (Bullmore & Sporns, 2009), and support a platform-based ecosystem to bring in BMI (Fadul, 2021; Gkikas & Theodoridis, 2019; Banalieva & Dhanaraj, 2019), for example, use of AI in health informatics and analytics to reimagine BMI. Social network theory suggests that supply network complexity can potentially promote innovation, for example, an entity occupying a specific position in the network may be able to manage the behaviour of its supply partners and be in a better position to gain access to a broader knowledge base leading to BMI (Kano et al., 2020; Li, 2019). However, social barriers like corruption and rent-seeking often impede the adoption of BMI and adversely impact business performance (Arayankalam, Khan & Krishnan, 2021). Innovation in the platform-based ecosystem through technologies including social networking sites, microblogging tools, online health recommendation systems, and web analytics led by cognitive analytics-enabled AI-embedded business intelligence provide exciting new prospects for applying and expanding social network theory in the context of platform-based media influence (Liu et al., 2017; Arasu et al. 2020). Particularly, the social network utilizes its key notions to uncover opportunities, whether it is at the individual, organisational, inter-organisational, or inter-geographical level (Cuypers et al., 2020).

Recently, the unrelenting surge of the pandemic, combined with stringency and isolation measures, has increased the need for technology-enhanced support and solutions within the healthcare management system (Gleiss et al., 2021; Choi et al, 2020; deOca Munguia et al., 2021; Garbuio & Lin, 2019; Milkau, 2019). As such, among all other curated data, social network data primarily includes the patients' affective and cognitive data, which offer insights into patient health behaviour and patterns. Particularly, healthcare data is processed and leveraged by social network teams, health practitioners and medical companies to forecast and innovate clinical trial outcomes, speed up the drug discovery process and generate a medical knowledge hub. In addition, cognitive analytics-enabled AI-driven social networks contribute to various levels of health marketization and awareness which essentially add value to stakeholders' engagement, customer knowledge, user knowledge and external market knowledge (Paschen et al., 2019). Particularly, AI can introduce new standards in digital healthcare, such as customization, targeting high conversion rates and high ROIs (Gkikas & Theodoridis, 2019). In essence, cognitive analytics-enabled AI-led social networks have substantially improved the performance of the workforce, created health innovation, enhanced workplace connectedness and reduced the workforce size (Basri, 2020). Simultaneously, social networks are becoming instrumental in advancing business model innovation through technological leverage by adopting AI-enabled platforms (Shen et al., 2020; Choi et al., 2020). However, the level of corruption, implicitly connected to social networks, undermines such elements of progress in the healthcare management system and affects various stakeholders (Borda et al., 2022; Park & Kim, 2020; Srivastava & Teo, 2007)

For healthcare management, each social network platform service is typically ascribed to different healthcare phases, i.e., prevention, treatment, care, after-care, and support either directly or indirectly, such as documentation, diagnosis, and monitoring. (Gleiss et al., 2021). For different cognitive analytics-enabled AI-led healthcare management systems, there are three design themes based on design elements and frames, including improved access to healthcare, responsiveness and privacy, i.e., secured data procession diagnostics, therapy or drug discovery (Kulkov, 2021). These three themes respectively contribute to value creation in healthcare decision support, assistance in the absence of necessary specialists, the speed of service, load reduction and cost reduction, and secured data procession. When patients are offered various forms of new services and channels through AI-enabled platforms to manage their health conditions, patients' choices drive the emergence of new business models (Gleiss et al., 2021). As such, approximately 72% of US internet users look for health information online, while 16% look for peers who have similar health concerns (Pew Research Center, 2013). Typically, the healthcare management system is limited in providing clinical as well as therapeutic supports, such as hospitalization, ambulatory care, drugs, treatments, and preventative care, whereas not providing a sense of holistic well-being for the patients (Joiner & Lusch, 2016). Thus, to meet their increasing necessity for diverse health-related issues, patients engage with platform-based media for health information and peer-to-peer interaction to find solutions from similar patient experiences (Van Oerle et al., 2016).

The adoption of AI on platform-based social networks, such as cognitive analytics-based speech robots and recognitions, AI-enabled diagnostic algorithms and AI-led personalized Medicare can remodel healthcare management and improve users' perceptions of service outcomes (Wang, Teo, & Janssen, 2021; He, Baxter, Xu, Xu, & Zhou, 2019; Wang, Kung, & Byrd, 2018). However, users often fail to realize the benefits due to rampant corruption in the healthcare management system (Berger, 2014; Nundy, Desiraju & Nagral, 2018). Cognitive analytics based on AI-enabled applications assist patients in finding the most relevant health information, such as how to stay healthy or to better understand their symptoms (Garbuio & Lin, 2019). For instance, AI-enabled tools aid patients in completing a preliminary diagnosis on their own. AI also prompts patients to improve their behavioural patterns based on the analysis of huge data from patients with a specific ailment (e.g., heart failure) and data obtained through a remote monitoring system. In addition, AI provides solutions to diagnostic difficulties and offers decision support for specialists, eliminates factors that have a negative impact on medical treatment, and gives hospitals and insurance companies predictable results and cost savings (Kulkov, 2021). However, since AI-enabled platforms within healthcare management systems involve several stakeholders, their roles and interests should not be ignored but balanced. In addition, the ethical and moral concerns regarding AI remain a challenge and must be addressed in a responsible and accountable way to offer best-perceived usefulness (PU) and perceived ease of use (EU) to the end-users, i.e., stakeholders (Vayena, Blasimme & Cohen, 2018). In particular, the issues surrounding corruption in the healthcare management system that remain contentious for the end users should be tackled (Berger, 2014; Nundy, Desiraju & Nagral, 2018). In addition, increasing digital diffusion may increase corruption (Park & Kim, 2020). Therefore, implementing cognitive analytics-enabled responsible AI-led BMI through stakeholders' engagement should not only be a self-benefiting exercise for the institutions but to realize better business performance (Srivastava, Teo & Devaraj, 2016). Cognitive analytics-enabled AI-led platforms to facilitate remote and continuous client monitoring on social networks generate massive amounts of data, reconfigure the way to identify changing customer needs and adapt digital services accordingly (Tanniru et al., 2021; Choi et al., 2020; de Oca Munguia et al., 2021; Garbuio & Lin, 2019; Milkau, 2019). Chronic patients often prefer to choose social network platforms such as Facebook or WhatsApp to communicate with physicians or other fellow patients (Gleiss et al., 2021). However, there are growing concerns regarding fairness, accountability, transparency and unbiased usage of such a considerable amount of information responsibly (Vayena et al., 2021). These concerns have raised renewed demands for cognitive analytics-based responsible AI designers and social network managers to look into patients' journeys and unfulfilled needs in leveraging new forms of technologies, business model innovation and responsible usage of AI-enabled platform ecosystems.

Thus, we have proposed the following three hypotheses. In addition, we have illustrated our hypothesis development process in Panel B of Table 2.

H4: *Ceteris paribus, cognitive analytics-enabled responsible AI significantly promotes business model innovation through social network platforms.*

H5: *Ceteris paribus, cognitive analytics-enabled responsible AI creates significant value for healthcare stakeholders.*

H6: *Ceteris paribus, corruption significantly constraints cognitive analytics-enabled responsible AI-led innovations that improve business model innovation.*

In line with our hypotheses, we have developed and presented our conceptual framework in Figure 1.

[Insert Figure 1 here]

4. Data and empirical specification

4.1 Research setting and data

Unlike following a tradition of secondary data collection, we view the legitimacy and scholarly purpose of our study will be better served using a questionnaire survey (Plakoyiannaki & Budhwar, 2021; Doz, 2011; Birkinshaw, Brannen & Tung, 2011). Considering epistemological and practical concerns often seen in questionnaire surveys (Robinson, 2014), we followed strict guidelines consistent with Morrison, Dillman & Christian (2010) for designing and administering our questionnaire covering five key stakeholders of the healthcare management system, i.e., doctors, clinical professionals associated with the healthcare system, administrative professionals associated with the healthcare system, patients and non-patients from India. The identified categories are the most commonly accepted key stakeholders of the healthcare management system (Li, Chen, Yi, Mao, & Liao 2019, Nambisan, Zahra, & Luo, 2021; Chen et al., 2019, Trocin et al., 2021).

We used purposive sampling in line with Glaser and Strauss (2009) to avoid heterogeneous variability among our groups of participants and to limit any potential bias (Patton, 1990). Our sample selection was based on the following criteria: 1) all the participants are at least 20 years old, 2) they are at least educated to a degree level so that we can understand the context of interview questions and respond accordingly, 3) they are involved with the healthcare management system in different capacities, all of them have substantive experience, at least 5 years, of professional healthcare experience, and a clear understanding of the application of AI and ethics associated with it (i.e., responsible AI practices). 4) they are using some form of social network platform to engage with the healthcare system 5) include patients with health-related issues, i.e., chronic health conditions for around 5 years and non-patients having secondary health-related experience, i.e., care responsibilities for not less than 5 years. All the participants were briefed about the purposes of the study and provided with supplementary materials if they needed any further clarifications. Our questions were primarily based on AI and responsible AI for three pertinent and relevant reasons:

1) Cognitive analytics is fundamentally based on AI (Hair, Harrison, & Ajjan, 2022).
2) A sizable corpus of studies has used descriptive, exploratory analytics, and to a lesser extent predictive analytics (Mariani & Baggio, 2022), whereas studies using cognitive analytics based on AI are comparatively limited (Mariani & Wirtz, 2023).
3) The role of stakeholders in adopting BMI using cognitive analytics such as AI, in particular responsible AI, is relatively very less studied and sparse (Fukuda-Parr & Gibbons, 2021).

The questions included in the questionnaire and their sources are presented in Table 3. We administered 700 sets of online questionnaires to our sample groups in India covering a period from December 2021 to June 2022 and received a 67% response rate, i.e., in total of 472 completed questionnaires. Our questionnaire design was primarily based on the protocol proposed by Robinson (2014), Van Oerle et al. (2016), and McColl-Kennedy et al. (2017). We used 10 key questions on a five-point Likert scale to elicit data from the participants. The details of the questionnaire validation process are outlined in Table 4

[Insert Table 3 here]

[Insert Table 4 here]

A brief including ethical aspects of the survey was attached to the online questionnaire. The sample distribution is presented in Table 5. We aimed to generate data covering the rationale of adopting AI and responsible AI and the details of BMI induced by AI and responsible AI for improved business performance, thereby obtaining a rich understanding of AI and responsible AI within the platform-based digital ecosystem in the healthcare management system.

[Insert Table 5 here]

Our selection of an emerging market like India as our sample source was based on several socio-economic and healthcare attributes, i.e., a rising middle class having higher disposable income to meet greater demand for goods and services (Kumar & Srivastava, 2020), increasing healthcare expenditure and growing innovation in healthcare management (Agarwal, Brem & Grottke, 2018), expanding digitalization and usage of AI-enabled digital setting (Claessens et al., 2018), expanding home healthcare (HHC) demand and increasing morbidity due to non-communicable diseases (Gupta, Randhawa & Nandraj, 2023) and economic development and progressive liberalization (Kumar & Srivastava, 2020). Particularly, India has lately witnessed an increasing emphasis on the digital healthcare system, i.e., increasing adoption of cognitive analytics-enabled AI Medicare (Kumar, Vrontis & Pallonetto, 2023) and the Indian healthcare system is devolved, i.e., the federal healthcare system, which is managed both at central and state levels giving a higher degree of engagement to various stakeholders. In addition, the healthcare utilization capacity is rapidly developing in India due to several policy measures (Tikkanen et al., 2020).

4.2 Empirical specification: Multilayer Perceptron (MLP) Neural Network

We applied a Multilayer Perceptron (MLP) Neural Network to examine our questionnaire survey dataset. Particularly, for the reason that the underlying process of the neural network falls within the cognitive analytics algorithms for intelligent decision-making (Guan & Chen, 2021). Particularly, artificial intelligence closely imitates cognitive analytics of the human brain, and its learning regularity can be modulated to enhance the accuracy of outputs (Desai & Shah, 2021). Contrary to other multivariate approaches, this approach continually adjusts the weights of nodes, i.e., the causal connections in the network to reduce the difference between the actual output vector of the network and the desired output vector leading to more accurate estimations of complex and multi-level phenomena (Park & Lek, 2016) similar to our study where we explore various causal interactions arising from our participants' responses. In addition, for three relevant reasons, we include MLP Neural Network as our estimation method, i.e., 1) Artificial Neural Network is widely used in healthcare management systems for its algorithmic and predictive capacity offering accurate and reliable outputs (Naraei, Abhari &

Sadeghian, 2016; Desai & Shah, 2021), 2) The MLP Neural Network is a variant of feedforward artificial Neural Network that, unlike conventional quantitative methods, efficiently detects any non-linearity patterns in the dataset (Naraei, Abhari & Sadeghian, 2016) and accurately predicts the complex interaction of the variables (Meyer-Baese & Schmid, 2014), and 3) MLP Neural Network, contrary to other empirical specifications, has robust extractive potential to unravel the hidden meaning of interactions (Krishna & Reddy, 2019) Since we strive to explore and understand the stakeholders' engagement using cognitive analytics-led AI, MLP Neural Network seemed as our logical parametric choice (Wu, Ma & Olson, 2022)

The MLP Neural Network (NN) uses several algorithms to apply a non-linear function that maps an input variable (independent variable, i.e., each questionnaire item represents an independent variable) to an output variable (dependent variable, i.e., five categories of stakeholders involved with the healthcare management system) by classifying outputs (Nassif, Ho & Capretz, 2013; Desai & Shah, 2021). The MLP NN includes layers of nodes where each node is assigned individual weighting. Weight outputs are aggregated at each node and inputted to an activation function to generate an output of that node (Nassif et al., 2013). The mathematical specification of the MLP NN model is illustrated as:

$$y(t)=f[\sum_{i=1}^{n} w_i x_i - w_0] \tag{1}$$

where x_i represents neuron inputs, w_i represents the weights and $f[\sum_{i=1}^{n} w_i x_i - w_0]$ represents activation functions. Here, x_i denotes our independent variables. We outline below the mathematical derivation of MLP Neural Network that is consistent with Ettaouil, Lazaar & Ghanou (2013) and Ramchoun et al. (2016) work. Assuming an input layer with n_0 neurons represents $X = (x_0, x_1, \cdots, x_n)$ where the sigmoid activation function is

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

Each output was computed at each unit of x_i for each layer to obtain the final network output. This means our dependent variable, i.e., five categories of stakeholders was computed reiteratively for each independent variable to arrive at the final network output. With a set of hidden layers $(h_1, h_2, \cdots, h_n)$, where n_i is the number of neurons for each hidden layer h_i. This gives output for the first hidden layer

$$h_i^j = f\left(\sum_{k=1}^{n_{i-1}} w_{k,j}^0 x_k\right), j = 1,2,3 \cdots, n_i \tag{3}$$

h_i^j as outputs of neurons in the hidden layers are computed as:

$$h_i^j = f\left(\sum_{k=1}^{n_{i-1}} w_{k,j}^{i-1} h_{i-1}^k\right), i = 2, \cdots, N \text{ and } j = 1,2,3, \cdots, n_i \tag{4}$$

Where the weight between the neuron k in the hidden layer i and the neuron j in the hidden layer +1 is denoted by $w_{k,j}^i$, and n_i represents the number of neurons in the i^th^ hidden layer. The output for i^th^ hidden layer is presented as:

$$h_i = {}^t\left(h_i^1, h_i^2, \cdots h_i^{n_i}\right) \tag{5}$$

This leads to the final network output

$$y_t = f\left(\sum_{k=1}^{n_N} w_{k,j}^N h_N^k\right), \; Y = \left(y_{1,} \cdots, y_j, \cdots, y_{N+1}\right) = F(W, X) \tag{6}$$

Where Y is the vector of the output layer, w is the matrix of weights, $w_{k,j}^N$ denotes weight between the neuron k within N^th^ hidden layer referring to the neuron j in the output layer. n_N represents the total number of neurons in the N^th^ hidden layer. The matrix of weights w can be written as

$$W = \left[W^0, \cdots, W^j, \cdots, W^N\right]$$

$$W^i = \left(w_{j,k}^i\right), 0 \le i \le N, 1 \le j \le n_{i+1}, 1 \le k \le n_i \tag{7}$$

To make the specification simpler, we write $n = n_i$ and $\forall i = 1, \cdots, N$ for all the hidden layers. Where X is the input of the neural network and f is the activation function and W^i denotes the matrix of weights between the i^th^ hidden layer and the $\left(i + 1^{th}\right)$ hidden layer for $i = 1, \cdots, N-1, W^0$ is the matrix of weights between the input and the first hidden layer, and W^N denotes a matrix of weights between the N^th^ hidden layer and the output layer. The final network output shows the normalised importance of our independent variables.

To start with the model building, we began applying various combinations of nodes using one and two hidden layers. We then applied different random partition rates to the dataset having various combinations for training, testing, and holdout, i.e., 50%–30%–20%, 60%–20%–20%, and 70%–20%–10%. We do so since NN builds through training to establish a correlation between a dependent variable with independent variables as the Neural Network has the ability to contrast the predicted values with the observed values. The following equation was used to ascertain the number of hidden layers necessary to achieve an approximation order (Rumelhart & Hinton, 1988, pp 50-72).

$n \geq 2\sqrt{\binom{N+n_0}{n_0} + 2(n_0+1)} - n_0 - 3$, where N is an approximation order for all functions, and n_0 represents hidden units (Trenn, 2008).

5. Discussion of results

Our findings demonstrate how stakeholders' engagement impacts business model innovation via cognitive analytics, in particular, with the use of AI as well as responsible AI. Using the technology acceptance model (TAM) and social network theory (SNT), we have elicited data from five key stakeholders of the healthcare management system based on AI and responsible AI usage in the healthcare sector. In the following session, a summary of statistics of the data set and results from MLP Neural Network are presented.

5.1 Summary statistics

The summary statistics of the dataset are presented in Table 6. Estimated statistics are at a 95% confidence interval and the table includes the overall reliability for internal consistency measure, i.e., Cronbach's Alpha score for each question. The overall Cronbach's Alpha score is above 0.8, indicating the high internal reliability of our questionnaire items (Bland & Altman, 1997). Most of the variables show their mean values above 4, therefore, suggesting that the respondents mostly agreed or strongly agreed with the questions. Particularly, questions involving "Responsible AI have significantly improved medical innovation", "Responsible AI carries material importance for its usefulness", and "AI through innovation has improved healthcare management systems" show stronger agreement from respondents. However, the "Responsible AI has created value for the stakeholders and improved the efficiency of the business model in the healthcare management system" and "The adoption of responsible AI has led to the smart healthcare business model where the stakeholders have been the beneficiaries of the improved business model" questions, i.e., Q6 and Q7 exhibit marginally lower mean values, i.e., 3.93 and 3.87 respectively.

[Insert Table 6 here]

The correlation matrix of the dataset is presented in Table 7. The questionnaire items show a significant positive relationship with the dependent variable, i.e., stakeholders. Particularly, the new business models in healthcare management are becoming increasingly important for the stakeholders for their usefulness and for serving the end users with ease of use ($r = 0.463$, $p < 0.05$), AI has improved the healthcare management and delivery system ($r = 0.413$, $p < 0.01$), the adoption of responsible AI has led to the improved healthcare business model where the stakeholders have been the beneficiaries of the business model innovation ($r = 0.411$, $p < 0.05$), and responsible AI has created value for the stakeholders and improved the efficiency of the business model in the healthcare management system ($r = 0.408$, $p < 0.05$). The statistically significant correlation between stakeholders and response items suggests that healthcare stakeholders benefit through cognitive analytics-enabled AI as well as responsible AI in advancing BMI for improved business performance. This further demonstrates that responsible AI creates value and reorients BMI for enhanced business performance, whereas regulatory framework and corruption are significant countervailing factors in predicting stakeholders' engagement involving AI and responsible AI for BMI which is broadly consistent with Borda et al. (2022) and Golbin et al. (2020).

[Insert Table 7 here]

5.2 Results from MLP Neural Network

We used an MLP Neural Network, unlike various multivariate analyses, to obtain deeper and more complex interaction of our independent variables with the dependent variable. Through MLP Neural Network, our independent variables capture their initial weights, then turn them into a weighted sum under an activation function leading to a layer, and each layer feeds to the next layer as their internal representation of the data (Trenn, 2008; Apicella et al., 2021). Consequently, the collective feedback gets transmitted through the hidden layers to the output variable, producing an accurate causality between the output layers, i.e., the dependent variable and input layers, i.e., independent variables (Islam, Chen & Jin, 2019; Wong & Nandi, 2001). The observed and predicted classification of the dataset is presented in Table 8. The correct classification for each category of stakeholders on the training and testing of MLP Neural Network broadly indicates the classificatory success of the architectural model. The results show that at the training the overall percentage the model correctly predicts is 91.1% and at the testing, it correctly predicts 78.2% of the model classification. At the testing, the stakeholders, i.e., doctors (74.2%), non-patients (73.0%), patients (70.7%), the administrative professionals associated with the healthcare (62.1%) and the clinical professionals associated with the healthcare (60.3%) correctly predict the classification of the model architecture, respectively.

[Insert Table 8 here]

The parameter estimation results are presented in Table 9 showing the number of neurons in the hidden layers and input layers for 10 independent variables, i.e., each questionnaire item. An automated architecture was built in designing the MLP Neural Network with 4 nodes with 9 hidden layers consistent with Park & Lek, (2016) and Uzair & Jamil (2020). The MLP Neural Network explains the stakeholders' engagement corresponding to each questionnaire item. Two different functions were used for different layers, i.e., for the hidden layers, the *hyperbolic tangent* was used as the activation function and for the output layers, the *softmax* function was used (Ganea, Bécigneul & Hofmann, 2018; Trenn, 2008). The model was validated by using cross-entropy as the error function (Ramchoun et al., 2016). For all hidden layers, Q2, Q3, Q4, and Q7 emerge as the most important variables that explain the stakeholders' engagement, whereas for some hidden layers Q8 and Q9 reasonably explain the stakeholders' engagements. These findings suggest with regard to BMI that innovation through digital diffusion is rapidly increasing in the healthcare management system through social networks and BMI in healthcare management are becoming increasingly important for the stakeholders' engagement for its usefulness for improving business performance and for serving the end users with ease of use. Cognitive analytics-enabled responsible AI has led to the reimagined BMI where the stakeholders have been the beneficiaries of the improved business model, and cognitive analytics-enabled responsible AI in the healthcare industry promotes BMI for better business performance. The results simultaneously indicate that stakeholders perceive that the regulatory factors affect responsible AI-enabled BMI and corruption, as a barrier, constrains responsible AI-enabled BMI. The hypothesis results are reported in Table 10.

[Insert Table 9 here]

[Insert Table 10 here]

The influence of each independent variable on the dependent variable, i.e., categories of stakeholders is displayed in Table 11 illustrating their relative and normalized importance obtained through MLP Neural Network. In addition, Figure 2 illustrates the normalized importance by order. The results show that cognitive analytics-enabled responsible AI has led to the reimagined healthcare business model where the stakeholders have been the beneficiaries of the improved business model (with the highest normalized importance, i.e., 100% among all other variables). Other predictor variables in terms of their normalized importance are: the new business models in healthcare management are becoming increasingly important for the stakeholders for their usefulness and for serving the end users with ease of use (68.10%), responsible AI has created value for the stakeholders and improved the efficiency of the business model in the healthcare management system (64.2%), corruption is one of the barriers that constrain responsible AI-enabled innovations to improve (56.9%), adoption of innovation through digital diffusion is rapidly increasing in the healthcare management system through the social networks that is influencing the evolution of the new business model (54.30%), AI has improved the healthcare management and delivery system (39.50%), responsible AI has significantly improved medical diagnosis and prescriptive innovation process (37.80%), responsible AI in the healthcare industry has substantial importance due to its usefulness that promotes business model innovation (37.50%), regulatory factors affect responsible AI-enabled BMI (28.70%) and recently several changes through innovations have been taking place in my organisation and industry that are directly improving the healthcare business model (22.70%). Collectively, the levels of their normalized importance suggest that not only AI and responsible AI have been instrumental in BMI orientations but also in improving business performance in healthcare management systems.

[Insert Table 11 here]

[Insert Figure 2 here]

Figure 3 displays the predicted pseudo-probabilities for response categories, i.e., dependent variable categories, where the predicted response categories are computed as the cluster variables through the marginal survival function (Zhao & Feng, 2020). The chart shows that particularly the doctors, non-patients, and administrative people involved with healthcare management mostly explain the association of the independent variables. Figure 4 displays the sensitivity and specificity chart for the five categories of stakeholders obtained through training and testing of the MLP Neural Network. The diagonal line characterizes the model architecture of randomly guessing the categories. The more the curves move away from the diagonal line, the more the precision of classification. Thus, doctors, clinical professionals and patients indicate higher classification accuracy. The gain chart displayed in Figure 5 shows how to identify the level of gain. In view of the baseline and curves position, the MLP Neural Network shows an overall higher gain and explains the perfect performance for the five categories of the stakeholders at 50% and above partitions. The lift chart shown in Figure 6 provides a graphical illustration of model classification mostly consistent with the gain chart. Particularly, the lift chart extracts a part of the data to justify the advantages of using the specified model contrary to not using the model (Trenn, 2008, Bekesiene, Smaliukiene & Vaicaitiene, 2021). The lift aspect is highest for the patients (100%/1.1 = 90.9%), followed by doctors (100%/1.2 = 83.3%), administrative professionals associated with healthcare management (100%/1.5 = 66.6%), non-patients (100%/1.8 = 55.5%) and clinical professions (100%/2.6 = 34.4%), respectively. This suggests that the above stakeholders are the principal beneficiaries, respectively, through cognitive analytics-enabled responsible AI-led BMI, and implicitly indicates that these stakeholders carry considerable relevance for improving the business performance.

[Insert Figures 3-6 about here]

6. Contributions

We adopt the Technology Acceptance Model (TAM) and Social Network Theory (SNT) lenses to bring new insights into the discussion regarding the extent to which AI and responsible AI contributed to Business Model Innovation (BMI) through the stakeholders' engagement. Examining our central inquiry by using a Multilayer Perceptron Neural Network, we add to the body of knowledge of cognitive analytics literature with reference to the BMI.

Our study substantively contributes to the cognitive analytics literature, more specifically to the knowledge of AI and responsible AI literature. Although developing AI technology responsibly has been discussed previously in the relevant literature, its impact on engagement levels and business performance is underexplored (Al-Dhaen, Hou & Rana, 2021; Barredo Arrieta et al., 2020; Mikalef et al., 2022; Kumar, Dwivedi & Anand, 2021). There is an urgency to expand our knowledge of how these improvised solutions can be successful and how to properly manage them. In healthcare settings, such as patients' decision-making and smart healthcare provisions, the courses of health information-sharing events inevitably produce unexpectedness. Thus, learning cognitive analytics techniques, through channels of AI, to deal with unforeseen situations is essential to business model innovation (Arasu et al., 2020; Fadul, 2021). Our study shows that cognitive analytics-enabled AI and responsible AI lead to smart BMI, stakeholders become beneficiaries of improved business models, and cognitive analytics-enabled responsible AI in the healthcare industry promotes BMI to improve business performance.

We further show that innovation through digital dissemination is rapidly increasing in healthcare management systems via a higher degree of technological acceptance and social networks, and BMI in healthcare management is becoming increasingly important for stakeholder engagement as it helps to improve business performance and enhance perceived ease of use and higher usefulness to the end users. Given that a deeper knowledge of AI and responsible AI would be beneficial for healthcare administrators and shareholders (Trocin et al., 2021), it is imperative to understand them through cognitive analytics applicability. Thus, the healthcare professionals would be capable of delivering high-quality and cost-effective healthcare services to a varied community and stakeholders. Our study, in particular, would provide them with knowledge of balancing growth and sustainability, which would benefit wider societal causes. Additionally, new business models in healthcare management are increasingly important to stakeholders because of their usefulness and ease of use for end users, and the use of cognitive analytics-enabled AI and responsible AI creates value for stakeholders and improves the efficiency of business performance in healthcare management systems. For instance, the responsible use of AI significantly improves medical diagnostics and prescribing innovation processes.

Concerning the BMI literature, first, our data reinforces the understanding of stakeholders' engagement in adopting business model innovation for enhanced business performance in a digital setting (Hennart, 2019; Laplume, Petersen, & Pearce, 2016; Kumar, Dwivedi & Anand, 2021), and clarifies the role of stakeholders' engagement in adopting business model innovation for enhanced business performance through cognitive analytics-enabled AI and responsible AI (Fukuda-Parr & Gibbons, 2021). Viewing professional stakeholders' responses to how responsible AI influences market-based performance through different levels of patients' engagement, it unveils the role of the different types of stakeholders, regulatory factors and corruption. Most innovation literature (Kumar, Dwivedi & Anand, 2021), particularly the BMI literature, is mostly concentrated on fixing the immediate issue and disguising the underlying concerns that hurt the system as an entirety. On the contrary, our study reveals the recurring issues regarding BMI implementations and underscores the relevance of understanding the stakeholders' engagement with the digital platform, through technological acceptance and social networks as this is also directly linked to business performance (Di Vaio, et al., 2020). In summary, our study contributes to the existing knowledge by providing clarity about the extent to which cognitive analytics-enabled AI and responsible AI lead to improved healthcare business models in which stakeholders have become the beneficiaries.

6. Implications of the study

6.1 Academic implications

Within our theoretical framework of TAM and SNT, we extend our knowledge and show that cognitive analytics-enabled responsible AI has led to significant orientation in BMI and enhanced business performance through stakeholders' engagement. As such, through digital platforms, BMI can harness value co-creation for various stakeholders (Schiavone et al., 2021). Thus, AI and responsible AI-enabled BMI has the ability to improve stakeholders' engagement, while improving business performance which is broadly consistent with Alsheibani et al. (2020) and Åström (2020). Particularly, responsible AI can create value for the stakeholders and improve the efficiency of BMI while maintaining innovation through technological acceptance by diffusion and social networks. Resonating with TAM, we demonstrate that the stakeholders as beneficiaries, strive to achieve reoriented BMI for its usefulness and for serving the end users with ease of use so that better business performance can be achieved. We further contribute to cognitive analytics-enabled responsible AI and healthcare management literature by illustrating that responsible AI can improve healthcare management and delivery systems through medical diagnosis, drug delivery, treatment, and drug innovation processes. This has both theoretical and material relevance as healthcare management and the delivery system largely suffer from these issues (Bucciol, Camboni & Valbonesi, 2020; Agarwal, Brem & Grottke, 2018).

6.2 Practical implications

Our practical contribution is related to two largely dominant issues, i.e., corruption and regulations associated with the healthcare management system, particularly, in emerging countries like India (Berger, 2014; Nundy, Desiraju & Nagral, 2018). The access to copious health data that was previously hidden now enables us to have a greater understanding of the healthcare industry (Manogaran et al., 2018). From personal fitness trackers and mobile apps to electronic medical records and genomic and clinical research, humans generate a massive amount of health-related data (Witt et al., 2019). Nevertheless, much of this data is discarded or underutilized, and sometimes misused and manipulated and the vast majority of patients do not even have access to their data (Ahmed et al., 2017; Parry et al., 2021) due to lack of regulatory and governance measures, making this a practical challenge as to how to overcome such issues. Our finding unveils the extent to which this can be moderated with stakeholder engagement.

We have further evidence that corruption substantially constrains responsible AI-enabled innovations to improve the BMI in the healthcare management system. This also shows corruption can effectively distress business performance. Considering, the Indian healthcare system is largely privatized, the cost of corruption and rent-seeking is exorbitant (Berger, 2014), thus, the stakeholders perceive corruption as a barrier to implementing BMI through responsible AI.

6.3 Political implications

One of the key areas of concern is the regulatory framework in the healthcare management system (Golbin et al., 2020). The Indian healthcare system is heterogeneous, where public healthcare is poorly organized in contrast to private ones (Hunter, Murray & Marathe, 2022). Currently, the state's capacity to renew existing regulatory frameworks is gaining traction in India (Patel et al., 2021). We show that the regulatory factors affect AI and responsible AI-enabled business model innovation. Thus, regulatory factors which are reliant on political approval can broadly impact the expected business performance. Given the nature of complexities associated with healthcare management regulations, i.e., political dialogues and consensus, civil society movement, financial capital, trust, institutional auditors, insurers and technological affordance, it is highly likely that the healthcare stakeholders find that the regulatory framework can affect the BMI and it is unlikely that better business performance can be achieved if an unbiased and effective regulatory framework is not enacted through political goodwill. This has profound socio-economic and political implications since enacting policy through a regulatory framework is central to an enhanced healthcare management system (Schiavone et al., 2021). We further demonstrate that the adoption of innovation through digital diffusion is rapidly increasing in the healthcare management system through the social networks that is influencing the evolution of the new business model. This reveals the significance of the social network that aligns with SNT. Social networks, as such, represent an innovative paradigm for the healthcare systems and tie with Sustainable Development Goals (Blanchet & James, 2012), which has potential policy and political implications.

7. Conclusion and prospects for future research

We underpin the Technological Acceptance Model (TAM) and Social Network Theory (SNT) to examine cognitive analytics-enabled AI and responsible AI for BMI in healthcare management system through stakeholders' engagement and assess business performance in digital platforms. We focus on explaining the relationship between "AI along with responsible AI-enabled BMI for improving business performance" and "healthcare stakeholders" using an MLP Neural Network. MLP Neural Network offers higher predictive and classificatory accuracy (Trenn, 2008) and has been used in several healthcare studies (Bekesiene, Smaliukiene & Vaicaitiene, 2021; Shah & Chircu, 2018; Vayena, Blasimme & Cohen, 2018). Our results evidence that technological acceptance and social networks disrupt conventional ways of value-creation in the healthcare management system and reimage cognitive analytics-enabled AI and responsible AI-enabled BMI for improving business performance. We show, AI, particularly, responsible AI improves stakeholders' engagement with innovation, and stakeholders are inclined to renew their existing BMI in healthcare management at the institutional level for enhanced business performance. Particularly, the adoption of responsible AI has led to BMI reorientation where the stakeholders have been the beneficiaries of the improved business performance and the improved BMI in healthcare management is becoming increasingly important for the stakeholders for their usefulness and for serving the end users with ease of use (Bhattacherjee & Hikmet, 2007). Simultaneously, responsible AI has created value for the stakeholders and improved the efficiency of the BMI in the healthcare management and delivery system leading to better business performance (Kumar et al., 2019). This is happening because innovation through digital diffusion is rapidly increasing in the healthcare management system through social networks and is influencing the evolution of the new business model (Schiavone et al., 2021). Whereas the stakeholders find that cognitive analytics-enabled responsible AI has significantly improved medical diagnosis and prescriptive processes. Nevertheless, corruption is seen as a barrier that constrains responsible AI-enabled innovations to improve the existing business model in the healthcare management system and regulatory factors affect responsible AI-enabled business model innovation (Schiavone et al., 2021; Golbin et al., 2020).

For future studies, examining diverse social and cultural contexts, i.e., the gender divide among stakeholders and the cultural orientation of various stakeholders can extend our view of responsible AI-enabled BMI within healthcare management and the role of stakeholders. Regardless of examining corruption and regulatory framework in our study, issues surrounding ethics and ecology can be further explored to understand the socio-moralistic dimensions of future studies.

8. Limitations of the study

Despite novel contributions to the AI literature and the use of non-traditional analytics like MLP Neural Network, our study has certain limitations that need further investigation. We have examined through the theoretical lenses of TAM and SNT the extent to which cognitive analytics-enabled responsible AI-led BMI can achieve better business performance through stakeholders' engagement. However, alternative theories such as the Matching Person and Technology Model (MPT), the Hedonic-Motivation System Adoption Model (HMSAM), and the Social Economics theory can potentially be used to explore the research context. In addition, our study is based on one emerging country, i.e., India. Although India offers a parsimonious representation of data, examining other emerging countries and contrasting with the developed countries could produce a better and more nuanced understanding of stakeholders' engagement, cognitive analytics based on responsible AI and BMI-led business performance.

References

Adlassnig, K. (2009). An analysis of personal medical information disclosed in YouTube videos created by patients with multiple sclerosis. In *Medical Informatics in a United and Healthy Europe: Proceedings of MIE 2009, the XXII International Congress of the European Federation for Medical Informatics* (pp. 292-296). Los Press.

Agarwal, N., Brem, A., Grottke, M. (2018). Towards a higher socio-economic impact through shared understanding of product requirements in emerging markets: The case of the Indian healthcare innovations. *Technological Forecasting and Social Change*, *135*, 91-98.

Agnihotri, R. (2020). Social networks, customer engagement, and sales organizations: A research agenda. *Industrial Marketing Management*, *90*, 291-299.

Ahmed, M. N., Toor, A. S., O'Neil, K., & Friedland, D. (2017). Cognitive computing and the future of health care cognitive computing and the future of healthcare: the cognitive power of IBM Watson has the potential to transform global personalized medicine. *IEEE pulse*, *8*(3), 4-9.

Al-Dhaen, F., Hou, J., Rana, N.P. (2021). Advancing the Understanding of the Role of Responsible AI in the Continued Use of IoMT in Healthcare. *Information System Frontiers*. https://doi.org/10.1007/s10796-021-10193-x

Alsheibani, S. A., Cheung, Y., Messom, C., & Alhosni, M. (2020). Winning AI Strategy: Six-Steps to Create Value from Artificial Intelligence. Retrieved from:

https://aisel.aisnet.org/amcis2020/adv_info_systems_research/adv_info_systems_research/1.Accessed October 24, 2022.

Apicella, A., Donnarumma, F., Isgrò, F., & Prevete, R. (2021). A survey on modern trainable activation functions. *Neural Networks*, *138*, 14-32.

Arasu, B. S., Seelan, B. J. B., & Thamaraiselvan, N. (2020). A machine learning-based approach to enhancing social network marketing. *Computers & Electrical Engineering*, *86*, 106723.

Arayankalam, J., Khan, A., & Krishnan, S. (2021). How to deal with corruption? Examining the roles of e-government maturity, government administrative effectiveness, and virtual social networks diffusion. *International Journal of Information Management*, *58*, 102203.

Åström, J. (2020). Value creation and value capture in AI offerings: A process framework on business model development. (Master dissertation, Luleå University of Technology).

Banalieva, E. R. & Dhanaraj, C. (2019). Internalization theory for the digital economy. *Journal of International Business Studies*, *50*(8), 1372-87.

Barabási, A. L. (2003). Linked: The new science of networks. *American Journal of Physics*. *71*, 409. Chicago.

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, *58*, 82-115.

Basri, W. (2020). Examining the impact of artificial intelligence (AI)-assisted social networks marketing on the performance of small and medium enterprises: toward effective business management in the Saudi Arabian context. *International Journal of Computational Intelligence Systems*, *13*(1), 142-152.

Bhattacherjee, A., & Hikmet, N. (2007). Physicians' resistance toward healthcare information technology: a theoretical model and empirical test. *European Journal of Information Systems*, *16*(6), 725-737.

Behera, R. K., Bala, P. K., & Dhir, A. (2019). The emerging role of cognitive computing in healthcare: a systematic literature review. *International journal of medical informatics*, *129*, 154-166.

Bekesiene, S., Smaliukiene, R., Vaicaitiene, R. (2021). Using Artificial Neural Networks in Predicting the Level of Stress among Military Conscripts. *Mathematics*, *9*(6), 626-643.

Berger, D. (2014). Corruption ruins the doctor-patient relationship in India. *British Medical Journal*, *348*.

Birkinshaw, J., Brannen, M. & Tung, R. (2011). From a distance and generalizable to up close and grounded: Reclaiming a place for qualitative methods in international business research. *Journal of International Business Studies, 42,* 573–581. https://doi.org/10.1057/jibs.2011.19

Blanchet, K., & James, P. (2012). How to do (or not to do) a social network analysis in health systems research. *Health policy and planning*, *27*(5), 438-446.

Bland J, Altman D. (1997). Statistics notes: Cronbach's alpha. *British Medical Journal*, 314(7080),572

Borda, A., Molnar, A., Neesham, C., & Kostkova, P. (2022). Ethical Issues in AI-Enabled Disease Surveillance: Perspectives from Global Health. *Applied Sciences*, *12*(8), 3890.

Borgatti, S. P., & Ofem, B. (2010). Social network theory and analysis. *Social network theory and educational change*, 17-29.

Brouthers, K., Geisser, K., & Rothlauf, F. (2016). Explaining the internationalization of ibusiness firms. *Journal of International Business Studies*, 47(5), 513-534.

Brtnikova, M., Crane, L. A., Allison, M. A., Hurley, L. P., Beaty, B. L., & Kempe, A. (2018). A method for achieving high response rates in national surveys of US primary care physicians. *PloS one*, *13*(8), e0202755.

Buabeng-Andoh, C., Yaokumah, W., & Tarhini, A. (2019). Investigating students' intentions to use ICT: A comparison of theoretical models. *Education and Information Technologies*, 24(1), 643-660.

Bucciol, A., Camboni, R., Valbonesi, P. (2020). Purchasing medical devices: The role of buyer competence and discretion. *Journal of Health Economics, 74,* 102370.

Bullmore, E., & Sporns, O. (2009). Complex brain networks: graph theoretical analysis of structural and functional systems. *Nature Reviews Neuroscience, 10(3),* 186-198.

Chatfield, C. (2016). *The analysis of time series: an introduction.* Chapman and Hall/CRC.

Charles, V., Emrouznejad, A., Gherman, T., & Cochran, J. (2022). Why data analytics is an art. Significance, 19(6), 42-45. https://doi.org/10.1111/1740-9713.01707.

Chen, L., Baird, A., & Straub, D. (2019). An Analysis of the Evolving Intellectual Structure of Health Information Systems Research in the Information Systems Discipline. *Journal of the Association for Information Systems*, 1023–1074.

Cheng, S., & Long, J. S. (2007). Testing for IIA in the multinomial logit model. *Sociological methods & research*, *35(4),* 583-600.

Cho, H., Kwon, J. (2021). Pandemic and hospital avoidance: Evidence from the 2015 Middle East respiratory syndrome outbreak in South Korea. *Economics Letters, 203*, 109852.

Choi, D., Chung, C. Y., Seyha, T., & Young, J. (2020). Factors affecting organizations' resistance to the adoption of Blockchain Technology in Supply Networks. *Sustainability, 12(21),* 8882.

Claessens, S., Jon Frost, J., Grant Turner, G., Zhu, F. (2018). Fintech credit markets around the world: size, drivers and policy issues. *BIS Quarterly Review, 12(2)*, 15-28.

Courbage, C., Peter, R. (2021). On the effect of uncertainty on personal vaccination decisions. *Health Economics*, 1-6.

Cognitive Analytics Research Lab, 2022. Cognitive Analytics - combining Artificial Intelligence (AI) and Data Analytics, Available at: https://www.ulster.ac.uk/cognitive-analytics-research/cognitive-analytics, Accessed October 31, 2022.

Cuypers, I. R., Ertug, G., Cantwell, J., Zaheer, A., & Kilduff, M. (2020). Making connections: Social networks in international business. *Journal of International Business Studies, 51*, 714-736, Daniels, N. (2001). Justice, Health, and Healthcare. *The American Journal of Bioethics, 1(2)*, 2-16.

Davis, F. D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results (Doctoral dissertation, Massachusetts Institute of Technology).

Davis, F. D. (1989). "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly, 13 (3):* 319-340.

Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics*, *1*(2), 73-80.

de Oca Munguia, O. M., Pannell, D. J., Llewellyn, R., & Stahlmann-Brown, P. (2021). Adoption pathway analysis: Representing the dynamics and diversity of adoption for agricultural practices. *Agricultural Systems, 191,* 103173.

Deng, Z., Hong, Z., Ren, C., Zhang, W., & Xiang, F. (2018). What predicts patients' adoption intention toward mHealth services in China: Empirical study. *JMIR mHealth and uHealth, 6(8),* e172. https://preprints.jmir.org/preprint/9316

Desai, M., & Shah, M. (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.

Di Vaio, A., Boccia, F., Landriani, L., & Palladino, R. (2020). Artificial intelligence in the agri-food system: Rethinking sustainable business models in the COVID-19 scenario. *Sustainability*, *12*(12), 4851.

Doz, Y. (2011). Qualitative research for international business. *Journal of International Business Studies, 42,* 582–590. https://doi.org/10.1057/jibs.2011.18

Du, S., & Xie, C. (2021). Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities. *Journal of Business Research*, *129*, 961-974.

Ettaouil, M., Lazaar, M., & Ghanou, Y. (2013). Architecture optimization model for the multilayer perceptron and clustering. *Journal of Theoretical & Applied Information Technology*, *47(1)*. 2012-243.

Fadul, W. (2021). Data-Driven Health Services: an Empirical Investigation on the Role of Artificial Intelligence and Data Network Effects in Value Creation. (Unpublished dissertation, Upssala University).

Floridi, L., & Taddeo, M. (2016). What is data ethics? *Philosophical Transactions of the Royal Society A: Mathematical Physical and Engineering Sciences, 374(2083),* 20160360. https://doi.org/10.1098/rsta.2016.0360.

Fukuda-Parr, S., & Gibbons, E. (2021). Emerging Consensus on 'Ethical AI': Human Rights Critique of Stakeholder Guidelines. *Global Policy*, *12*, 32-44.

Ganea, O., Bécigneul, G., & Hofmann, T. (2018). Hyperbolic neural networks. *Advances in neural information processing systems*, *31*.

Garbuio, M., & Lin, N. (2019). Artificial intelligence as a growth engine for health care startups: Emerging business models. *California Management Review*, *61(2)*, 59-83.

Gkikas, D. C., & Theodoridis, P. K. (2019). Artificial Intelligence (AI) Impact on Digital Marketing Research. In *Strategic Innovative Marketing and Tourism* (pp.1251-1259). Springer, Cambridge.

Glaser, B. G., & Strauss, A. L. (2009). The discovery of grounded theory: Strategies for qualitative research. Transaction Publishers.

Gleiss, A., Kohlhagen, M., & Pousttchi, K. (2021). An apple a day-how the platform economy impacts value creation in the healthcare market. *Electronic Markets*, 1-28.

Golbin, I., Rao, A. S., Hadjarian, A., & Krittman, D. (2020). Responsible AI: a primer for the legal community. In *2020 IEEE International Conference on Big Data (Big Data)*, 2121-2126.

Granovetter, M. (1973). Granovetter — *Strength of Weak Ties*. *American Journal of Sociology*, *78(6),* 1360-1380.

Granovetter, M. (1983). *The Strength of Weak Ties: a network theory revisited. Sociological Theory, 1,* 201-233.

Granovetter, M. (1985). *Economic Action and Social Structure: The Problem of Embeddedness, American Journal of Sociology, 91(3),* 481-510.

Guan, Y., & Chen, Q. (2021). Research on Intelligent Perception and Cognitive Computing of Information Security System Based on Computer Big Data. *Wireless Communications and Mobile Computing*, *2021*. https://doi.org/10.1155/2021/3281825.

Gudivada, V. N., Irfan, M. T., Fathi, E., & Rao, D. L. (2016). Cognitive analytics: Going beyond big data analytics and machine learning. In *Handbook of Statistics* (Vol. 35, pp. 169-205). Elsevier.

Gupta, S., & Kanungo, R. P. (2022). Financial inclusion through digitalisation: Economic viability for the bottom of the pyramid (BOP) segment. *Journal of Business Research*, *148*, 262-276.

Gupta, P., Randhawa, S., & Nandraj, S. (2023). The Home Healthcare Boom: Opportunities and Obstacles in India's Changing Healthcare Landscape. *Home Health Care Management & Practice*, 10848223231196301.

Haaker, T., Ly, P. T. M., Nguyen-Thanh, N., & Nguyen, H. T. H. (2021). Business model innovation through the application of the Internet-of-Things: A comparative analysis. *Journal of Business Research*, *126*, 126-136.

Hair, J.F., Harrison, D. E., Ajjan, H., (2022). *Essentials of Marketing Analytics*. New York: McGraw Hill.

Hannan, E. J., Rissanen, J. (1982). Recursive estimation of mixed autoregressive-moving average order. *Biometrika*, *69,* 81-94.

Harris, M., & Rogers, W. (2021). Developing a Healthcare Technology Acceptance Model (H-TAM) for Older Adults with Hypertension. *Ageing and Society*, 1-21.

He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. *Nature Medicine, 25(1),* 30–36.

Heisterkamp, S. H., Dekkers, A. L. M., Heijne, J. C. M. (2006). Automated detection of infectious disease outbreaks: hierarchical time series models. *Statistics in Medicine, 25(41),* 79-96.

Hennart, J. F. (2019). Digitalized service multinationals and international business theory. *Journal of International Business Studies, 50(8),* 1388-1400.

Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression (Vol. 398).* John Wiley & Sons.

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21(2),* 155-172.

Hunter, B. M., Murray, S. F., Marathe, S., Chakravarthi, I. (2022). Decentred regulation: The case of private healthcare in India. *World Development*, *155*, 105889.

IDRC. (2020). *2020 government AI readiness index: Governments must prioritise responsible AI use*. https://www.idrc.ca/en/news/2020-government-ai-readiness-index-governments-must-prioritise-responsible-ai-use [Google Scholar]

Islam, M., Chen, G., & Jin, S. (2019). An overview of neural network. *American Journal of Neural Networks and Applications*, *5*(1), 7-11.

Jirotka, M., Procter, R., Hartswood, M., Slack, R., Simpson, A., Coopmans, C., ... & Voss, A. (2005). Collaboration and trust in healthcare innovation: The eDiaMoND case study. *Computer Supported Cooperative Work (CSCW)*, 14(4), 369-398.

Joiner, K. A., & Lusch, R. F. (2016). Evolving to a new service-dominant logic for health care. *Innovation and Entrepreneurship in Health*, *3*(3), 25-33.

Kano, L., Tsang, E. W., & Yeung, H. W. C. (2020). Global value chains: A review of the multi-disciplinary literature. *Journal of international business studies*, *51*(4), 577-622.

Keiningham, T., Aksoy, L., Bruce, H. L., Cadet, F., Clennell, N., Hodgkinson, I. R., & Kearney, T. (2020). Customer experience driven business model innovation. *Journal of Business Research*, *116*, 431-440.

Kernick, D. P. (2000). The impact of health economics on healthcare delivery. A primary care perspective. *Pharmacoeconomics. 18(4),* 311-315.

Korda, R. J., & Butler, J. R. G. (2006). Effect of healthcare on mortality: trends in avoidable mortality in Australia and comparisons with Western Europe. *Public health*, *120(2),* 95-105.

Krishna, C. L., & Reddy, P. V. S. (2019, February). An efficient deep neural network multilayer perceptron based classifier in healthcare system. In *2019 3rd International Conference on Computing and Communications Technologies (ICCCT)* (pp. 1-6). IEEE.

Krause, J., Croft, D. P., & James, R. (2007). Social network theory in the behavioural sciences: potential applications. *Behavioral Ecology and Sociobiology*, 62, 15-27.

Kulkov, I. (2021). Next-generation business models for artificial intelligence start-ups in the healthcare industry. *International Journal of Entrepreneurial Behaviour & Research*. 1355-2554.

Kumar, A., and Rathore, N. (2016). Improving attribute inference attack using link prediction in online social networks. *Recent Advances in Mathematics, Statistics and Computer Science*. 494–503.

Kumar, P., Dwivedi, Y. K., & Anand, A. (2021). Responsible artificial intelligence (AI) for value formation and market performance in healthcare: The mediating role of patient's cognitive engagement. *Information Systems Frontiers*, 1-24.

Kumar, V. (2014). Understanding cultural differences in innovation: A conceptual framework and future research directions. *Journal of International Marketing*, *22(3),* 1-29.

Kumar, V., & Srivastava, R. (2020). New perspectives on business model innovations in emerging markets. *Journal of the Academy of Marketing Science*. *48,* 815-825.

Kumar, P., Vrontis, D., & Pallonetto, F. (2023). Cognitive engagement with AI-enabled technologies and value creation in healthcare. *Journal of Consumer Behaviour*, 1–16. https://doi.org/10.1002/cb.2196

Laplume, A. O., Petersen, B., & Pearce, J. M. (2016). Global value chains from a 3D printing perspective. *Journal of International Business Studies, 47(5),* 595-609.

Levine, L. (2019). Digital trust and cooperation with an integrative digital social contract. *Journal of Business Ethics*, *160(2),* 393-407.

Li, J., Chen, L., Yi, J., Mao, J., & Liao, J. (2019). Ecosystem-specific advantages in international digital commerce. *Journal of International Business Studies*, *50(9),* 1448-63.

Litewka, S. G., Heitman, E. (2020). Latin American healthcare systems in times of pandemic. *Developing World Bioethics, 20(2),* 69-73.

Liu, W., Sidhu, A., Beacom, A. M., & Valente, T. W. (2017). Social network theory. *The International Encyclopaedia of Media Effects*, 1-12.

Manogaran, G., Vijayakumar, V., Varatharajan, R., Malarvizhi Kumar, P., Sundarasekar, R., & Hsu, C. H. (2018). Machine learning based big data processing framework for cancer diagnosis using hidden Markov model and GM clustering. *Wireless personal communications*, *102*, 2099-2116.

Mariani, M. and Baggio, R. (2022). Big data and analytics in hospitality and tourism: a systematic literature review. *International Journal of Contemporary Hospitality Management*, *34(1)*, 231-278.

Mariani, M. M., & Wirtz, J. (2023). A Critical Reflection on Analytics and Artificial Intelligence-based Analytics in Hospitality and Tourism Management Research. *International Journal of Contemporary Hospitality Management*, Forthcoming.

Marshall, T., Champagne-Langabeer, T., Castelli, D., & Hoelscher, D. (2017). Cognitive computing and eScience in health and life science research: artificial intelligence and obesity intervention programs. *Health information science and systems*, *5*(1), 1-11.

Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of Business Ethics*, 160(4), 835-850.

McClelland, J. L., Rumelhart, D. E., & Hinton, G. E. (1986). The appeal of parallel distributed processing. *MIT Press, Cambridge MA*, *3*, 44.

McColl-Kennedy, J. R., Hogan, S. J., Witell, L., & Snyder, H. (2017). Cocreative customer practices: Effects of health care customer value cocreation practices on well-being. *Journal of Business Research*, *70*, 55-66.

Merhi, M. I. (2022). An Assessment of the Barriers Impacting Responsible Artificial Intelligence. *Information Systems Frontiers*, 1-14.

Meyer-Baese, A., & Schmid, V. (2014). Chapter 7 - Foundations of Neural Networks. Editor(s): Anke Meyer-Baese, Volker Schmid, Pattern Recognition and Signal Analysis in Medical Imaging (Second Edition), Academic Press, 197-243.

Micu, A., Capatina, A., & Micu, A. E. (2018). Exploring Artificial Intelligence Techniques' Applicability in Social networks Marketing. *Journal of Emerging Trends in Marketing and Management*, *1(1)*, 156-165.

Mikalef, P., Conboy, K., Lundström, J. E., & Popovič, A. (2022). Thinking responsibly about responsible AI and 'the dark side'of AI. *European Journal of Information Systems*, *31*(3), 257-268.

Milkau, U. (2019). Value Creation within AI-enabled Data Platforms. *Journal of Creating Value, 5(1),* 25-39.

Morley, J., Machado, C. C. V., Burr, C., Cowls, J., Joshi, I., Taddeo, M., & Floridi, L. (2020). The ethics of AI in health care: A mapping review. *Social Science & Medicine*, *260,* 113172.

Morrison, R. L., Dillman, D. A., & Christian, L. M. (2010). Questionnaire design guidelines for establishment surveys. *Journal of Official Statistics*, *26(1)*, 43.

Nambisan, S., Zahra, S. A., & Luo, Y. (2019). Global platforms and ecosystems: Implications for international business theories. *Journal of International Business Studies*, 50(9), 1464-86. org/10.1016/j.inffus.2019.12.012.

Naraei, P., Abhari, A., & Sadeghian, A. (2016). Application of multilayer perceptron neural networks and support vector machines in classification of healthcare data. *2016 Future Technologies Conference (FTC)*, 848-852.

Nassif, A. B., Ho, D., & Capretz, L. F. (2013). Towards an early software estimation using log-linear regression and a multilayer perceptron model. *Journal of Systems and Software*, *86(1),* 144-160.

Nundy, S., Desiraju, K., & Nagral, S. (2018). *Healers or Predators?: Healthcare Corruption in India*. Oxford University Press.

Park, Y. S., & Lek, S. (2016). Artificial neural networks: Multilayer perceptron for ecological modeling. In *Developments in environmental modelling* (Vol. 28, pp. 123-140). Elsevier.

Park, C. H., & Kim, K. (2020). E-government as an anti-corruption tool: Panel data analysis across countries. *International Review of Administrative Sciences*, *86*(4), 691-707.

Parry, G., Bennett, D., Roth, A. D., & Kellett, S. (2021). Developing a competence framework for cognitive analytic therapy. *Psychology and Psychotherapy: Theory, Research and Practice*, *94*, 151-170.

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business & Industrial Marketing*. 1410–1419.

Patel, V., Mazumdar-Shaw, K., Kang, G., Das, P., & Khanna, T. (2021). Reimagining India's health system: a Lancet Citizens' Commission. *The Lancet*, *397*(10283), 1427-1430.

Patton, M. Q. (1990). *Qualitative evaluation and research methods*. SAGE Publications, inc.

Plakoyiannaki, E., & Budhwar, P. (2021). From convention to alternatives: rethinking qualitative research in management scholarship. *British Journal of Management*, *32(1),* 3-6.

Ramchoun, H., Ghanou, Y., Ettaouil, M., & Idrissi, M., A. (2016). Multilayer Perceptron: Architecture Optimization and Training. *International Journal of Interactive Multimedia and Artificial Intelligence, 4(1)*, 26-30.

Reddy, S., Fox, J., & Purohit, M. P. (2019). Artificial intelligence-enabled healthcare delivery. *Journal of the Royal Society of Medicine*, *112(1),* 22-28.

Robinson, O. C. (2014). Sampling in interview-based qualitative research: A theoretical and practical guide. *Qualitative research in psychology*, *11(1),* 25-41.

Saggi, M. K., & Jain, S. (2018). A survey towards an integration of big data analytics to big insights for value-creation. *Information Processing & Management*, 54(5), 758-790.

Saqib, M., & Benhmad, F. (2021). Updated meta-analysis of environmental Kuznets curve: Where do we stand?. *Environmental Impact Assessment Review, 86*, 106503.

Schiavone, F., Mancini, D., Leone, D., & Lavorato, D. (2021). Digital business models and ridesharing for value co-creation in healthcare: A multi-stakeholder ecosystem analysis. *Technological Forecasting and Social Change*, *166*, 120647.

Scott, P., & Yampolskiy, R. (2019). Classification schemas for artificial intelligence failures. *Delphi - Interdisciplinary Review of Emerging Technologies*, 2(4), 186–199.

Shah, R., & Chircu, A. (2018). IoT and AI in healthcare: A systematic literature review. *Issues In Information Systems*, 19(3), 33-41.

Shen, C. W., Luong, T. H., Ho, J. T., & Djailani, I. (2020). Social networks marketing of IT service companies: Analysis using a concept-linking mining approach. *Industrial Marketing Management*, *90*, 593-604.

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research*, *134*, 574-587.

Smith, K. P., & Christakis, N. A. (2008). Social networks and health. *Annual Review Sociology*, *34*, 405-429.

Someh, I., Wixom, B., & Zutavern, A. (2020, January). *Overcoming organizational obstacles to artificial intelligence value creation: propositions for research.* Proceedings of the 53rd Hawaii International Conference on System Sciences.

Srivastava, S. C., & Teo, T. S. (2007). E-government payoffs: Evidence from cross-country data. *Journal of Global Information Management*, *15*(4), 20-40.

Srivastava, S. C., Teo, T. S., & Devaraj, S. (2016). You Can't Bribe a Computer. *Mis Quarterly*, *40*(2), 511-526.

Tabassum, S., Pereira, F. S., Fernandes, S., & Gama, J. (2018). Social network analysis: An overview. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *8*(5), e1256.

Tanniru, M. R., Agarwal, N., Sokan, A., & Hariri, S. (2021). An agile digital platform to support population health—A case study of a digital platform to support patients with delirium using IoT, NLP, and AI. *International journal of environmental research and public health*, *18*(11), 5686.

Teece, D. J. (2018). Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Journal of Research Policy*, 47(8), 1367-1387.

Tikkanen, R., Osborn, R., Mossialos, E., Djordjevic, A.., & Wharton, G. (2020). *International Profiles of Health Care Systems, The Commonwealth Fund.* Retrieved from https://www.commonwealthfund.org/sites/default/files/2020-12/International_Profiles_of_Health_Care_Systems_Dec2020.pdf Accessed November 30, 2021.

Tjondronegoro, D., Yuwono, E., Richards, B., Green, D., & Hatakka, S. (2022). Responsible AI Implementation: A Human-centered Framework for Accelerating the Innovation Process. arXiv preprint arXiv:2209.07076.

Trenn, S. (2008). Multilayer Perceptrons: Approximation Order and Necessary Number of Hidden Units. *IEEE Transactions on Neural Networks,* 19(5), 836-44.

Trocin, C., Mikalef, P., Papamitsiou, Z., & Conboy, K. (2021). Responsible AI for digital health: a synthesis and a research agenda. *Information Systems Frontiers*, 1-19.

Uzair, M., & Jamil, N. (2020, November). Effects of hidden layers on the efficiency of neural networks. In *2020 IEEE 23rd international multitopic conference (INMIC)* (pp. 1-6). IEEE.

Van Oerle, S., Mahr, D., & Lievens, A. (2016). Coordinating online health communities for cognitive and affective value creation. *Journal of Service Management. 27(4),* 481-506.

Vayena, E., Blasimme, A., & Cohen, I. G. (2018). Machine learning in medicine: Addressing ethical challenges. PLoS Medicine, 15(11), 4–7. https://doi.org/10.1371/journal.pmed.1002689.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Venkatesh, V, Thong, JYL and Xu, X (2012) Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly,* 36, 157–178.

Wang, C., Teo, T. S., & Janssen, M. (2021). Public and private value creation using artificial intelligence: An empirical study of AI voice robot users in Chinese public sector. *International Journal of Information Management*, *61*, 102401.

Wang, Y., Kung, L. A., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change,* 126, 3–13.

Wearn, O. R., Freeman, R., & Jacoby, D. M. (2019). Responsible AI for conservation. *Nature Machine Intelligence*, *1*(2), 72-73.

Witt, D. R., Kellogg, R. A., Snyder, M. P., & Dunn, J. (2019). Windows into human health through wearables data analytics. *Current opinion in biomedical engineering*, *9*, 28-46.

Wong, M. D., & Nandi, A. K. (2001). Automatic digital modulation recognition using spectral and statistical features with multi-layer perceptrons. In *Proceedings of the sixth international symposium on signal processing and its applications (Cat. No. 01EX467)*, 390-393). IEEE.

Wu, D., Ma, X., & Olson, D. L. (2022). Financial distress prediction using integrated Z-score and multilayer perceptron neural networks. *Decision Support Systems*, *159*, 113814.

Zhang, P., Liu, Y. & Miao, L. (2021). Impacts of social networks on floating population wages under different marketization levels: empirical analysis of China's 2016 national floating population dynamic monitoring data, *Applied Economics*, 53:22, 2567-2583.

Zhao, L., & Feng, D. (2020). Deep Neural Networks for Survival Analysis Using Pseudo Values. IEEE Journal of Biomed Health Inform, *24*(11), 3308-3314.

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research*, *121*, 283-314.

Di Vaio, A., Hassan, R., & Alavoine, C. (2022). Data intelligence and analytics: A bibliometric analysis of human–Artificial intelligence in public sector decision-making effectiveness. *Technological Forecasting and Social Change*, *174*, 121201.

Pavlović, P., & Hafner Fink, M. (2023). New ethnographic perspective on relational ethics in the field of Artificial intelligence. *Quality & Quantity*, 1-19.

Zhang, Z., Xia, E., & Huang, J. (2022). Impact of the moderating effect of national culture on adoption intention in wearable health care devices: Meta-analysis. *JMIR mHealth and uHealth*, *10*(6), e30960.

Table 1: Key Studies on AI and responsible AI in the healthcare management system

Author(s)	Research context	Data and Methodology	Research Gaps	Major stakeholders	Key contributions
Van Oerle et al. (2016)	50 online health communities	Data from 50 English-language online health communities. (Qualitative and quantitative techniques)	Previous research remained inconclusive regarding the synergistic or conflicting nature of cognitive and affective value creation, but this research demonstrates that cognitive value creation is an enabler of affective value creation.	Involved patients, professionals, and other stakeholders	(1) Four community configurations were found: basic information provider, advanced patient knowledge aggregator, systematic networked innovator, and uncomplicated idea sharer. (2) Online communities can be categorized into two knowledge creation dimensions: knowledge externalization and knowledge internalization. (3) Online health communities have the power to fulfil unmet patient needs while also promoting patient involvement in service delivery and medical decision-making.
McColl-Kennedy et al. (2017)	six separate samples of 1151 healthcare customers	health care customer diaries (content analysis) questions on how often the health care customers visit the medical centre and how long they have had the ongoing illnesses. (Quantitative method, Partial Least Squares (PLS) test.)	Much less is known about the process of customer value cocreation and the effects of customer value cocreation practices on well-being.	Medical staff at the Medical Centre, other patients, friends and family	(1) While positive connections with medical professionals (doctors) promote well-being by cocreating therapeutic approaches, interactions with friends and family and their accompanying cocreated activities have an even higher favourable effect on well-being. (2) Other customer-directed actions have good indirect benefits as well.
Garbuio & Lin (2019)	AI-driven healthcare startups	Second-hand data & one interview (Theory development)	We do not know whether startups that solve different problems share common business models. Nor do we know what value is created for stakeholders, ranging from clinicians, patients, health care administrators, insurance companies, and government agencies	clinicians, patients, health care administrators, insurance companies, and government agencies.	(1) AI in health care will eliminate information asymmetries between clinicians, payers, and patients. (2) Patients are the objects of a value chain system; AI enables people to take greater responsibility for their health. (3) AI could revolutionize clinical staff access to information as well as resources and financial outcomes. (4) Finding innovative solutions to security and privacy issues will allow companies to handle large volumes of digital data more easily.
Fadul (2020)	The healthcare sector	Interview data (Semi-structured interviews)	(1) there is a knowledge gap in how eHealth and mobile applications can be designed, developed, and delivered to create new values for patients as well as help healthcare providers deliver better services. (2) there are several developed applications and platforms but still, there is a gap between commercially available applications and scientifically	AI experts, users, and AI service providers.	(1) Training the AI capabilities with high-quality data and an adequate volume of data will guide service providers to reduce the utilization of resources, time, and effort, and boost efficiency, for example, doctors' and nurses' time as a primary resource in health care. (2) It can also lessen the danger of clients switching to competitors and introduce AI-enabled uniqueness, which is seen as a competitive advantage among competitors.

			validated and developed applications (3) the data network effects (DNE) model is a new concept that was not empirically tested and validated in AI-driven health offerings.		
Someh et al. (2020)	53 executives representing 50 large companies headquartered globally	Online discussion data (Thematic content analysis)	The literature currently sheds less light on organisational reasons for slow AI adoption; information systems research on the topic, for example, is scant and mostly anecdotal in nature.	Internal and external stakeholders such as AI talent and top management.	AI research is required to investigate how companies can prevent bias in training datasets; how to best explain, communicate, and/or justify algorithmic decisions; the substitutive and complementary roles of domain and algorithm experts; acceptable data use governance, including extending oversight of data projects beyond regulatory and legal compliance; AI talent requirements for companies, and how to build effective new talent strategies, portfolios, and management programs.
Åström (2020)	A market-leading telecom provider of AI-related services	3 interviews were held with the case company (Thematic analysis)	Previous researches fall short in understanding how firms successfully operationalize AI solutions through their business models, especially concerning technological advancements in the AI sphere.	Customers, AI service providers	(1) To build AI solutions, AI providers must first identify the prerequisites for value creation, then connect value creation with value capture opportunities, and finally design the value offering. (2) To successfully operationalize AI, AI providers must design and manage numerous business models at the same time.
Alsheiabni et al. (2020)	Top 100 AI organisations including healthcare companies.	Top AI actual use cases analysis across 7 industries and systematization of the existing literature (Content analysis)	AI technology is immature, with known challenges in the areas of data quality, talent, transparency, and interoperability with other systems. Many business leaders and investors are still unsure about how AI technology can translate into revenues for organisations that adopt intelligent commerce.	Top management, AI talent	Six challenges of AI at the organisation level have emerged from the analysis: AI business case, Relative benefits of AI, Top management support, Effective use of data, AI talent, and AI compatibility.
Tanniru et al. (2021)	Dynamic software ecosystems	Conceptual analysis	The adaptation of value cycles to address the rapid changes in customer expectations requires agile digital platforms with dynamic software ecosystems interacting with multiple actors. How can we build an agile digital platform to support healthcare delivery in a client ecosystem?	Machine actors (i.e., systems), human actors (i.e., nursing staff)	(1) Services need to be considered when leveraging technologies accessible to customers to fulfil their values. (2) An agile digital platform can help satisfy changing customers' needs and dynamic context quickly to fulfil the value.

Gleiss et al. (2021)	Google, Apple, Facebook, Amazon, and Microsoft (GAFAM)	The GAFAM-impact on the healthcare market (Value network analyses)	There is comparatively little knowledge and theoretical conceptualization from a holistic standpoint on how and to what extent big digital platforms redesign entire ecosystems and markets. In particular, research has not studied the potential strategic economic and technological impact of the big digital platforms on healthcare.	Patients, physicians, nurses, clerks, application, system, and database.	(1) GAFAM platforms impact value creation in healthcare in many ways, as they encroach on current structures not only by enabling transaction and engagement but also by offering content and products. (2) Platforms have complete control over consumer interactions and network structures. (3) By introducing new roles to the value network, digital platforms centralize the client relationship while also modularizing value generation in healthcare.
Kulkov (2021)	Nine European start-ups developing AI healthcare solutions.	Interview data (A multiple case study method)	There are no studies that analyze the transformation of business processes that are inherent in the pharmaceutical industry under the influence of AI.	Patients, physicians, hospitals and insurance, pharma ad biotechnology companies.	(1) Clarify the value generation of applying AI by evaluating business models that generate healthcare solutions: present value to the market; give value to the consumer; communicate with consumers. (2) Specialized start-ups fundamentally concentrate on particular themes: improved access to healthcare, responsiveness and privacy design.

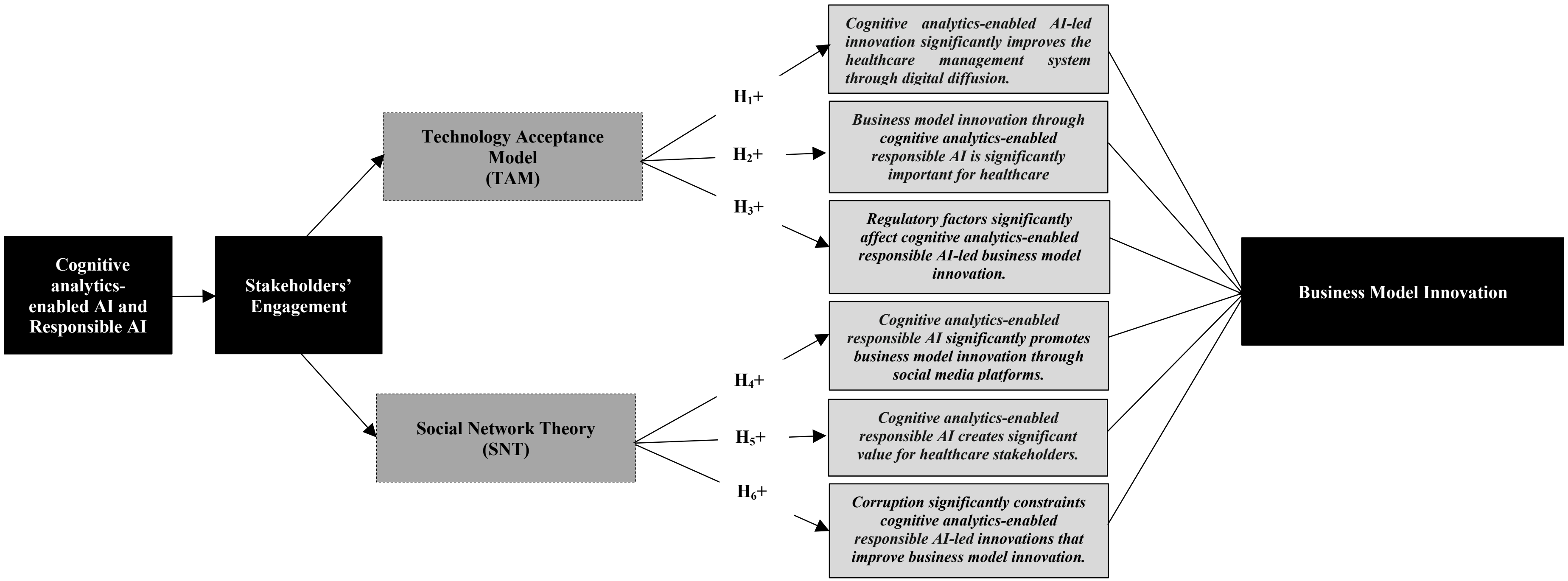

Figure 1: Conceptual Framework

Table 2: Hypothesis development process

Hypotheses	Key Sources	Rationale
Panel A		
H1: Innovation and AI-enabled innovation → digital diffusion → significant improvement of the healthcare management	This hypothesis is developed based on the review of the literature on innovation (e.g., Banalieva & Dhanaraj, 2019; Teece, 2018), particularly, AI-enabled innovation within the healthcare management system (Morley et al., 2020).	Innovation as a process-value outcome diffuses through different channels, particularly through digital platforms. Responsible AI driven by innovation leads to healthcare management improvement (Shah & Chircu, 2018). However, the extent to which innovation through digital diffusion brings in improvement for healthcare management remains less explored.
H2: Responsible AI → the BMI → importance for healthcare stakeholders	This hypothesis is developed based on several studies that explore the role of stakeholders in healthcare management (Li, Chen, Yi, Mao, & Liao 2019, Nambisan, Zahra, & Luo, 2019). Particularly, studies on stakeholders' engagement within the healthcare management system to advance the BMI remain relatively sparse (Chen et al., 2019, Trocin, Mikalef, Papamitsiou, & Conboy, 2021)	Most of the prior studies on innovation in digital settings within healthcare management have undertaken a routinely held view from patients' perspectives (Garbuio & Lin, 2019; Harris & Rogers, 2021) and made limited attempts to explore BMI orientation relating to healthcare stakeholders' collective engagement. In addition, the role of responsible AI in reorienting healthcare BMI and its derived benefits are not fully studied.
H3: Regulatory factors → significant effect → the responsible AI-enabled BMI	This hypothesis is conceptualized from the enquiry that regulatory factors significantly affect responsible AI-enabled business model innovation. Particularly, it broadly refers to Kumar, Dwivedi & Anand's (2021) work and evaluates some of the regulatory challenges illustrated in Du & Chunyan's (2021) study.	Regulatory concerns surrounding AI and responsible AI are crucial to understand as regulations influence the implementation of BMI. Despite the collective efforts of various healthcare stakeholders to formalize the regulatory framework, the risk of implementing BMI in the healthcare management system through responsible AI remains challenging. The extent to which regulatory factors affect the responsible AI-enabled BMI depends on several caveats, i.e., how uncertainty and risk are managed, how organisational capabilities are upscaled, and how to optimize innovation and align it with existing business eco-system etc.
Panel B		
H4: Responsible AI → Social networks platform→significantly promotes BMI	This hypothesis is developed taking a baseline perspective from several studies (Kumar, 2014; Micu et al., 2018), with some support from existing literature. Arasu et al., (2020) show that social networks platforms using AI can promote BMI. Particularly, AI-enabled healthcare innovations have been instrumental in predicting end-users' behaviour.	The increasing use of AI through social networks has prompted a growing need for research in identifying and examining the multitiered effect of AI on the functional behaviour of organisations to adopt BMI. In the healthcare management system, prior studies have attempted to address the engagement of AI by capturing patients' and healthcare providers' focus (Garbuio & Lin, 2019), but not in the social networks context and with various stakeholders' engagement.
H5: Responsible AI → significant value → for healthcare stakeholders	This hypothesis is developed based on a number of studies (Choi et al., 2020; de Oca Munguia et al., 2021; Garbuio & Lin, 2019; Milkau, 2019) that shed light on the value-creation through AI, with some support from existing literature. We conceptualize that AI, in specific, responsible AI creates significant value for healthcare stakeholders.	Responsible AI through digitalization can transform the way organisations create value. Most studies have focused on specific business models undertaking physical entities views (Garbuio & Lin, 2019), whereas we adopt TAM and SNT proposing how value is created through stakeholders' engagement. Particularly, we show value as the usefulness and ease of use of BMI for the stakeholders.
H6: Corruption → significantly constraints → responsible AI-enabled innovations that improve the BMI	This hypothesis is developed based on the perspective that corruption is one of the dominant barriers to implementing BMI through responsible AI, broadly consistent with using the Technology-Organisation-Environment framework (Merhi, 2022). We argue that the purpose of improving BMI for the benefit of stakeholders can be constrained by corruption.	The nexus between corruption and innovation is well-documented. However, different stakeholders have their perspectives on how corruption constrains innovation. In specific, to what extent corruptions act as an intervention that constraints responsible AI-enabled innovation regarding BMI is relatively less explored.

Table 3: Questionnaire Items

No.	Questionnaire items	Sources
Q1	Recently several changes through innovations have been taking place in my organisation and industry that are directly improving the healthcare business model.	Jirotka et al. (2005)
Q2	The adoption of innovation through digital diffusion is rapidly increasing in the healthcare management system through the social network that is influencing the evolution of the new business model.	Schiavone et al. (2021)
Q3	The new business models in healthcare management are becoming increasingly important for the stakeholders for their usefulness and serving the end users with ease of use.	Bhattacherjee & Hikmet (2007)
Q4	Given the growing significance of innovation, AI has improved the healthcare management and delivery system.	Reddy et al. (2019)
Q5	The role of AI, particularly responsible AI, in the healthcare industry has substantial importance due to its usefulness that promotes business model innovation.	Wearn et al. (2019)
Q6	Responsible AI has created value for the stakeholders and improved the efficiency of the business model in the healthcare management system.	Kumar et al. (2019)
Q7	The adoption of responsible AI has led to the smart healthcare business model where the stakeholders have been the beneficiaries of the improved business model.	Tjondronegoro et al. (2022)
Q8	Regulatory factors affect the responsible AI-enabled business model innovation.	Golbin et al. (2020)
Q9	Corruption is one of the barriers that constrain responsible AI-enabled innovations to improve the existing business model in the healthcare management system.	Borda et al. (2022)
Q10	Responsible AI has significantly improved medical diagnosis, drug delivery, treatment, and drug innovation process.	Oliveira (2020)

Table 4: Questionnaire Validation Procedure

Pre-test	To set the questionnaire, we first identified the context of each question and closely matched them with studies in line with the literature review (Table 1). Next, we elicited feedback from a panel of academics actively researching in the areas including AI, responsible AI, Healthcare and Stakeholders to ensure that the questions are consistent and can seek answers to the research hypotheses. No issues were reported by the panel; however, some minor changes were made, i.e., the online layout of the questionnaire was revised to make it more presentable. In addition, a question referring to corruption, as suggested by the panel, was added since corruption in India is one of the barriers in the healthcare sector to business model innovation.
Pilot Study	Covering the five best-performing Indian states based on the healthcare system, we conducted a pilot study via an online platform using a representative sample of 250 sets of questionnaires to ensure our questionnaire is clear and understandable to the participants. Five states, i.e., Kerala (74.01%), Andhra Pradesh (65.13%), Maharashtra (63.99%), Gujarat (63.52%) and Punjab (63.01%) were chosen based on their overall healthcare management performance as reported by the second edition of NITI Aayog's Health Index, 2021 (http://social.niti.gov.in/hlt-ranking). The key performance indicators include the proportion of medical staff, specified medical facilities, usage of the digital platform, innovation in healthcare management, and utilization of advanced diagnostics etc.
Main Data Collection	We administered 700 sets of online questionnaires to our sample groups (five groups of stakeholders) using convenience sampling, covering the period from December 2021 to June 2022 across the above five states and received a 67% response rate, i.e., in total 472 completed questionnaires. Our response rate is deemed high for any traditional healthcare management study (Brtnikova et al., 2018). The distribution of demographic characteristics, i.e., age, level of education and categories of stakeholders is presented in Table 5. In addition, we ran our reliability check to assess the consistency of the questions. The results indicated a high level of internal consistency, i.e., Cronbach Alpha's > 0.80 (Table 6).

Table 5: Sample Distribution

		N	Percentage
Stakeholders	Doctors	93	19.7%
	Clinical professionals associated with the healthcare	49	10.4%
	Administrative professionals associated with the healthcare	115	24.4%
	Patients	92	19.5%
	Non-Patients	123	26.1%
Age	20-29	71	15.0%
	30-29	108	22.9%
	40-49	150	31.8%
	50-59	97	20.6%
	60 and above	46	9.7%
Education	Degree	190	40.3%
	Masters	139	29.4%
	PhD	118	25.0%
	Others	25	5.3%
Total		472	100%

Table 6: Summary Statistics and Internal Consistency Check

	Variables	Mean[a]	Std. Dev.	Confidence level (95%)	Cronbach's Alpha[b]
Q1	Recently several changes through innovations have been taking place in my organisation and industry that are directly improving the healthcare business model.	4.07	.750	0.127	0.833
Q2	The adoption of innovation through digital diffusion is rapidly increasing in the healthcare management system through the social network that is influencing the evolution of the new business model.	4.10	.647	0.148	0.829
Q3	The new business models in healthcare management are becoming increasingly important for the stakeholders for their usefulness and for serving the end users with ease of use.	4.06	.874	0.123	0.821
Q4	Given the growing significance of innovation, AI has improved healthcare management and delivery system.	4.15	.757	0.135	0.830
Q5	The role of AI, particularly responsible AI, in the healthcare industry has substantial importance due to its usefulness that promotes business model innovation.	4.19	.705	0.116	0.825
Q6	Responsible AI has created value for the stakeholders and improved the efficiency of the business model in the healthcare management system.	3.93	.852	0.101	0.826
Q7	The adoption of responsible AI has led to the smart healthcare business model where the stakeholders have been the beneficiaries of the improved business model.	3.87	.644	0.126	0.841
Q8	Regulatory factors affect responsible AI-enabled business model innovation.	4.13	.528	0.159	0.828
Q9	Corruption is one of the barriers that constrain responsible AI-enabled innovations to improve the existing business model in the healthcare management system.	4.10	.742	0.172	0.833
Q10	Responsible AI has significantly improved medical diagnosis, drug delivery, treatment, and drug innovation process.	4.35	.634	0.123	0.834

[a] Mean value of questions based on a 5-point *Likert* Scale

[b] Internal consistency test for the questionnaire items. The overall Cronbach's Alpha score is above 0.8, indicating high internal reliability of our questionnaire items (Bland & Altman, 1997).

Table 7: Correlations Matrix

	Variables	Stakeholders	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Group	Stakeholders	1										
Q1	Recently several changes through innovations have been taking place in my organisation and industry that are directly improving the healthcare business model.	0.342**	1									
Q2	The adoption of innovation through digital diffusion is rapidly increasing in the healthcare management system through the social network that is influencing the evolution of the new business model.	0.403**	0.432*	1								
Q3	The new business models in healthcare management are becoming increasingly important for the stakeholders for their usefulness and for serving the end users with ease of use.	0.463*	0.565*	0.606**	1							
Q4	Given the growing significance of innovation, AI has improved the healthcare management and delivery system	0.413**	0.248*	0.245**	0.314**	1						
Q5	The role of AI, particularly responsible AI, in the healthcare industry has substantial importance due to its usefulness that promotes business model innovation.	0.392**	0.333**	0.293**	0.300**	0.802**	1					
Q6	Responsible AI has created value for the stakeholders and improved the efficiency of the business model in the healthcare management system.	0.408*	0.220*	0.302**	0.423*	0.431*	0.492**	1				
Q7	The adoption of responsible AI has led to the smart healthcare business model where the stakeholders have been the beneficiaries of the improved business model.	0.411*	0.232*	0.400**	0.301**	0.245**	0.296**	0.386**	1			
Q8	Regulatory factors affect responsible AI-enabled business model innovation.	0.395**	0.359*	0.388**	0.492*	0.311**	0.292**	0.430**	0.373**	1		
Q9	Corruption is one of the barriers that constrains responsible AI-enabled innovations to improve the existing business model in the healthcare management system.	0.401*	0.316**	0.241**	0.298**	0.292*	0.341*	0.366**	0.257*	0.409**	1	
Q10	Responsible AI has significantly improved medical diagnosis, drug delivery, treatment, and drug innovation process.	0.405*	0.304**	0.301*	0.308**	0.414**	0.484**	0.378**	0.130**	0.228**	0.500**	1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 8: Sample Classification

Sample	Observed	Predicted					
		Doctors	Clinical professionals associated with the healthcare	Administrative professionals associated with the healthcare	Patients	Non-Patients	Percent Correct
Training	Doctors	31	11	15	16	18	48.4%
	Clinical professionals associated with the healthcare	13	14	8	18	28	20.0%
	Administrative professionals associated with the healthcare	21	23	26	20	37	31.0%
	Patients	12	14	9	22	43	20.0%
	Non-Patients	9	16	27	21	43	53.8%
	Overall Percent	86.1%	74.0%	76.4%	72.6%	86.3%	91.1%
Testing	Doctors	16	14	10	12	13	32.7%
	Clinical professionals associated with the healthcare	22	16	15	10	14	10.0%
	Administrative professionals associated with the healthcare	17	21	28	21	25	15.8%
	Patients	26	15	23	10	19	30.0%
	Non-Patients	27	12	17	21	28	46.7%
	Overall Percent	74.2%	60.3%	62.1%	70.7%	73.0%	78.2%

Dependent Variable: Stakeholders

Table 9: Parameter Estimation

Predictor		Hidden Layer[a]								
		H(1)	H(2)	H(3)	H(4)	H(5)	H(6)	H(7)	H(8)	H(9)
Input Layer	[Q1=2]	.016	.016	.154	.217	.045	.000	.065	.000	.000
	[Q1=3]	.031	.206	.026	.130	.409	.000	.261	.000	.000
	[Q1=4]	.922	.746	.821	.565	.409	.000	.522	.000	.630
	[Q1=7]	.031	.032	.000	.087	.136	1.000	.152	1.000	.370
	[Q2=1]	.000	.000	.000	.130	.000	.000	.000	.000	.000
	[Q2=2]	.000	.000	.333	.174	.000	.000	.130	.000	.000
	[Q2=3]	.047	.381	.205	.087	.682	.115	.391	.000	.037
	[Q2=4]	.938	.571	.462	.478	.182	.115	.391	.115	.963
	[Q2=7]	.016	.048	.000	.130	.136	.769	.087	.885	.000
	[Q3=8]	.000	.000	.000	.087	.000	.000	.000	.038	.000
	[Q3=2]	.047	.000	.359	.348	.000	.000	.087	.000	.000
	[Q3=3]	.000	.571	.103	.130	.636	.000	.435	.000	.074
	[Q3=4]	.938	.429	.538	.348	.318	.000	.413	.115	.852
	[Q3=7]	.016	.000	.000	.087	.045	1.000	.065	.846	.074
	[Q4=2]	.000	.000	.000	.522	.091	.038	.000	.000	.074
	[Q4=3]	.000	.111	.000	.087	.818	.000	.022	.000	.000
	[Q4=4]	1.000	.841	1.000	.087	.091	.077	.065	.731	.111
	[Q4=7]	.000	.048	.000	.304	.000	.885	.913	.269	.815
	[Q5=2]	.000	.000	.000	.391	.000	.000	.000	.000	.000
	[Q5=3]	.016	.063	.000	.174	1.000	.000	.000	.038	.037
	[Q5=4]	.984	.921	.974	.217	.000	.000	.043	.577	.037
	[Q5=7]	.000	.016	.026	.217	.000	1.000	.957	.385	.926
	[Q6=9]	.000	.000	.000	.000	.000	.000	.000	.038	.000
	[Q6=2]	.000	.000	.436	.304	.000	.000	.065	.000	.000
	[Q6=3]	.047	.302	.128	.043	.818	.000	.109	.000	.000
	[Q6=4]	.938	.603	.436	.609	.182	.000	.130	.769	.630
	[Q6=7]	.016	.095	.000	.043	.000	1.000	.696	.192	.370
	[Q7=8]	.000	.000	.000	.043	.000	.038	.043	.000	.000
	[Q7=2]	.031	.095	.487	.435	.000	.115	.152	.038	.148
	[Q7=3]	.109	.444	.128	.000	1.000	.000	.304	.000	.000
	[Q7=4]	.859	.413	.385	.522	.000	.077	.217	.885	.778
	[Q7=7]	.000	.048	.000	.000	.000	.769	.283	.077	.074
	[Q8=1]	.000	.016	.000	.130	.000	.000	.000	.038	.000
	[Q8=2]	.000	.079	.615	.261	.091	.077	.217	.038	.000
	[Q8=3]	.109	.619	.205	.130	.818	.000	.348	.154	.000
	[Q8=4]	.891	.222	.179	.478	.091	.077	.217	.462	.926
	[Q8=7]	.000	.063	.000	.000	.000	.846	.217	.308	.074
	[Q9=9]	.000	.000	.000	.043	.000	.000	.022	.000	.000
	[Q9=2]	.016	.032	.128	.087	.000	.000	.022	.000	.000
	[Q9=3]	.047	.159	.077	.000	.727	.000	.043	.000	.037
	[Q9=4]	.906	.571	.744	.783	.227	.077	.457	.346	.667
	[Q9=7]	.031	.238	.051	.087	.045	.923	.457	.654	.296
	[Q10=8]	.000	.000	.000	.043	.000	.000	.000	.000	.000
	[Q10=2]	.000	.000	.051	.043	.000	.000	.000	.000	.000
	[Q10=3]	.000	.048	.051	.087	.500	.000	.022	.000	.000
	[Q10=4]	1.000	.587	.744	.652	.364	.000	.130	.231	.222
	[Q10=7]	.000	.365	.154	.174	.136	1.000	.848	.769	.778
Hidden Unit Width		.374	.752	.709	.854	.657	.411	.778	.646	.607

[a] Displays centre vector for each hidden unit

		Output Layer				
		Doctors	Clinical professionals associated with the healthcare	Administrative professionals associated with the healthcare	Patients	Non- Patients
Hidden Layer	H(1)	.271	.074	.235	.096	.324
	H(2)	.214	.176	.224	.205	.181
	H(3)	.403	.098	.238	.205	.056
	H(4)	.167	.090	.375	.138	.230
	H(5)	.276	.109	.153	.061	.401
	H(6)	.120	.063	.209	.210	.398
	H(7)	.188	.070	.231	.192	.318
	H(8)	.043	-.027	.240	.332	.412
	H(9)	.218	-.006	.255	.398	.135

Table 10: Hypothesis results

H1	Ceteris paribus, innovation and AI-enabled innovation significantly improve the healthcare management system through digital diffusion.	Supported
H2	Ceteris paribus, business model innovation through responsible AI is significantly important for healthcare stakeholders.	Supported
H3	Ceteris paribus, regulatory factors significantly affect responsible AI-enabled business model innovation.	Supported
H4	Ceteris paribus, responsible AI significantly promotes business model innovation through social networks platforms.	Supported
H5	Ceteris paribus, responsible AI creates significant value for healthcare stakeholders.	Supported
H6	Ceteris paribus, Corruption significantly constraints responsible AI-enabled innovations that improve business model innovation.	Supported

Table 11: Independent Variable Importance by order

		Importance	Normalized Importance
Q7	The adoption of responsible AI has led to the smart healthcare business model where the stakeholders have been the beneficiaries of the improved business model.	0.196	100.00%
Q3	The new business models in healthcare management are becoming increasingly important for the stakeholders for their usefulness and for serving the end users with ease of use.	0.134	68.10%
Q6	Responsible AI has created value for the stakeholders and improved the efficiency of the business model in the healthcare management system.	0.126	64.20%
Q9	Corruption is one of the barriers that constrains responsible AI-enabled innovations to improve the existing business model in the healthcare management system.	0.112	56.90%
Q2	The adoption of innovation through digital diffusion is rapidly increasing in the healthcare management system through the social network that is influencing the evolution of the new business model.	0.107	54.30%
Q4	Given the growing significance of innovation, AI has improved the healthcare management and delivery system	0.077	39.50%
Q10	Responsible AI has significantly improved medical diagnosis, drug delivery, treatment, and drug innovation process.	0.074	37.80%
Q5	The role of AI, particularly responsible AI, in the healthcare industry has substantial importance due to its usefulness that promotes business model innovation.	0.074	37.50%
Q8	Regulatory factors affect responsible AI-enabled business model innovation.	0.056	28.70%
Q1	Recently several changes through innovations have been taking place in my organisation and industry that are directly improving the healthcare business model.	0.045	22.70%

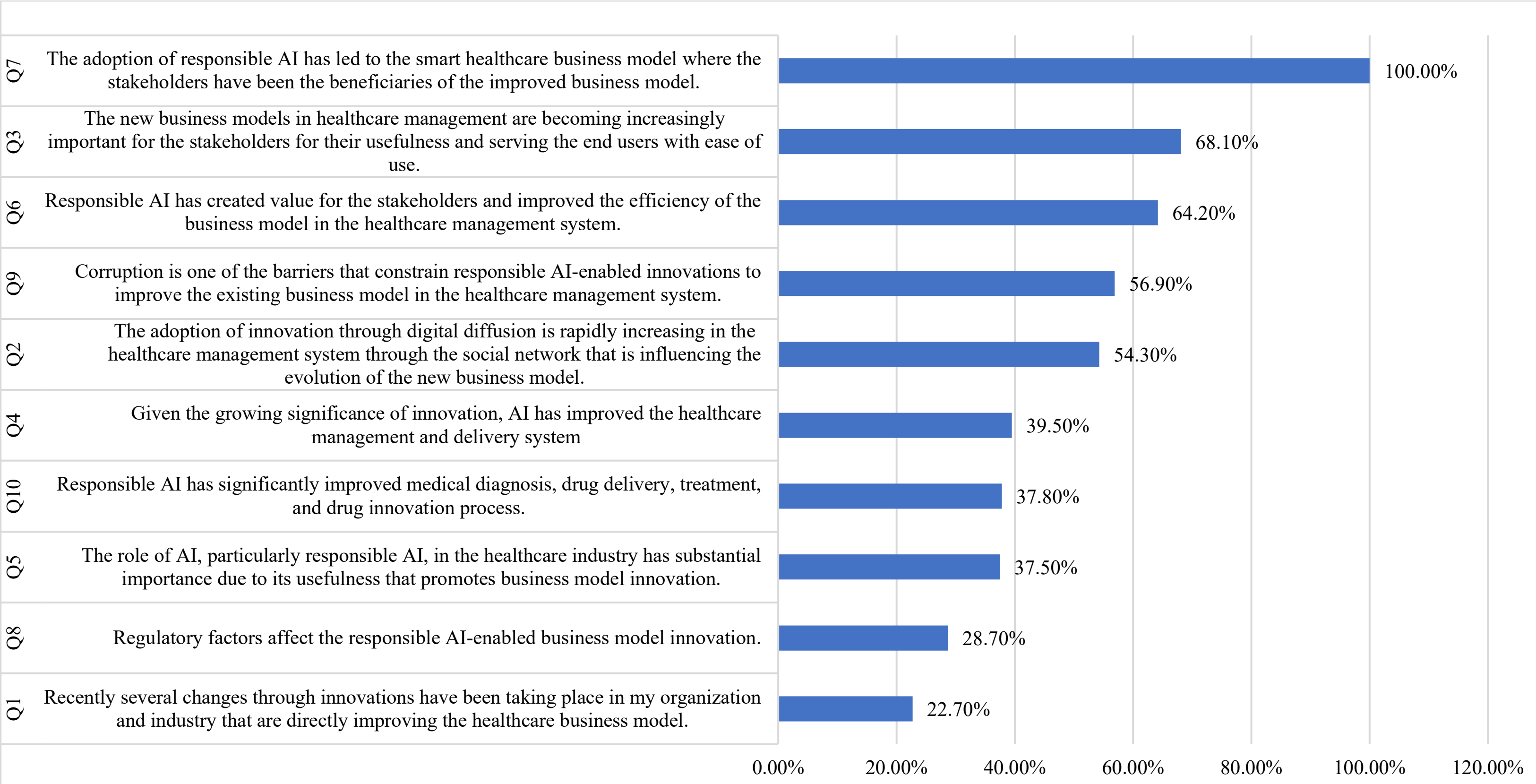

Figure 2: Independent Variable Normalised Importance by order

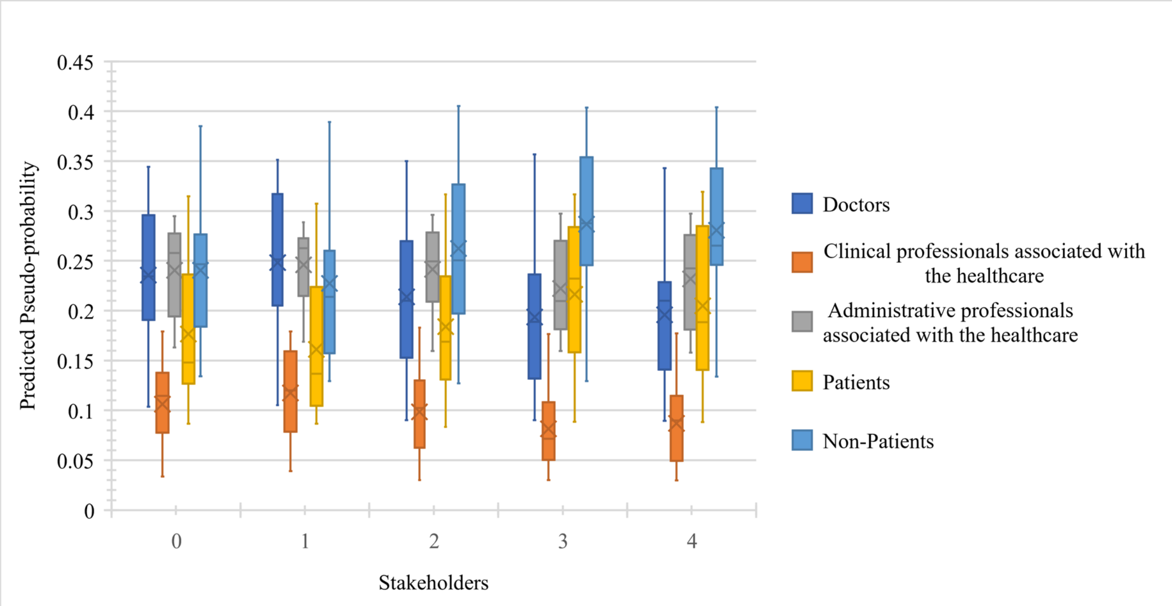

Figure 3: Predictive Pseudo-probability Chart

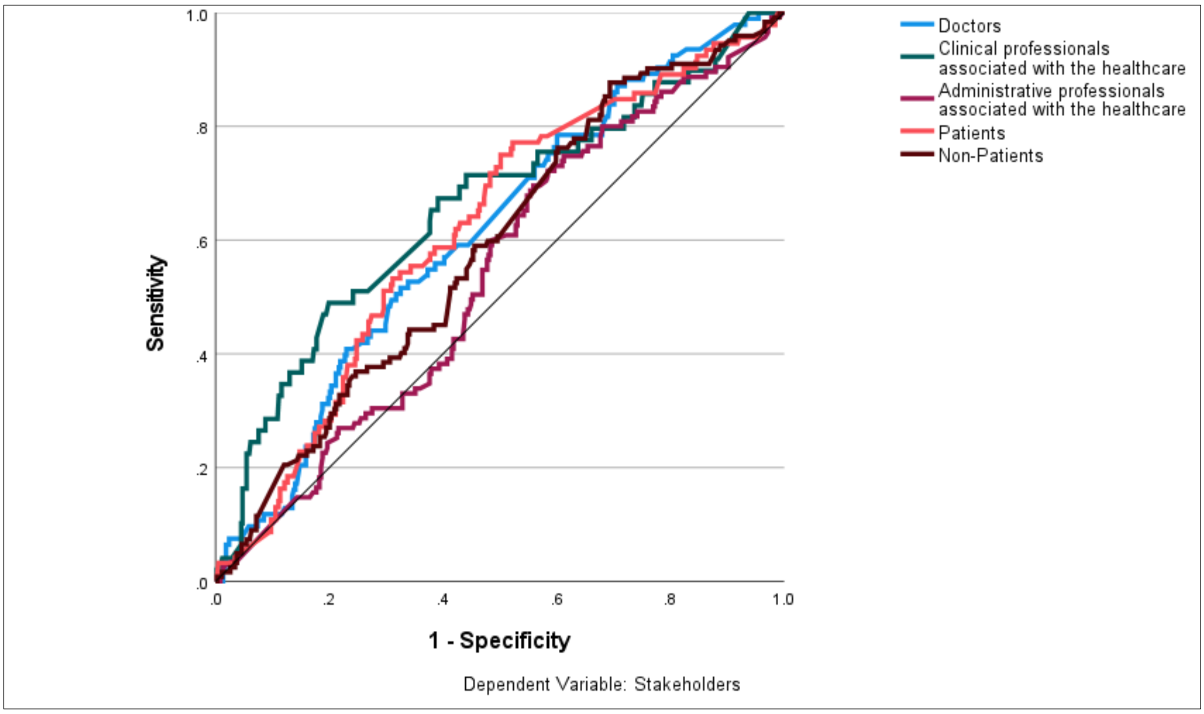

Figure 4: Sensitivity Chart

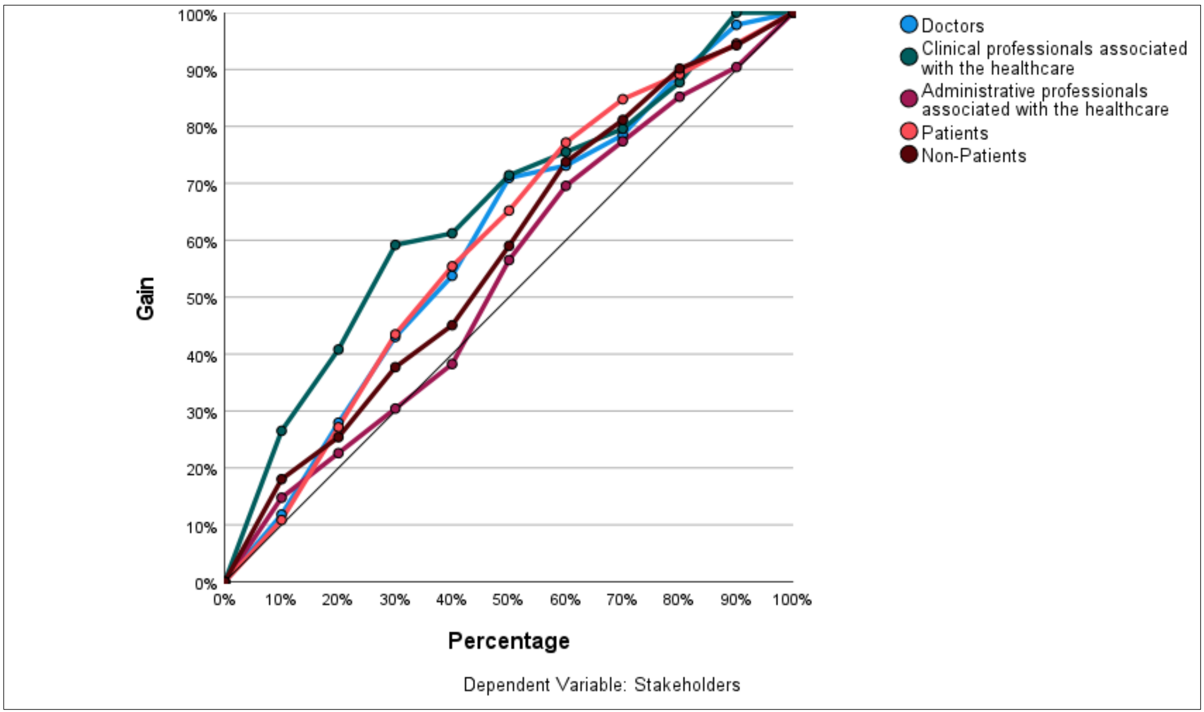

Figure 5: Gain Chart

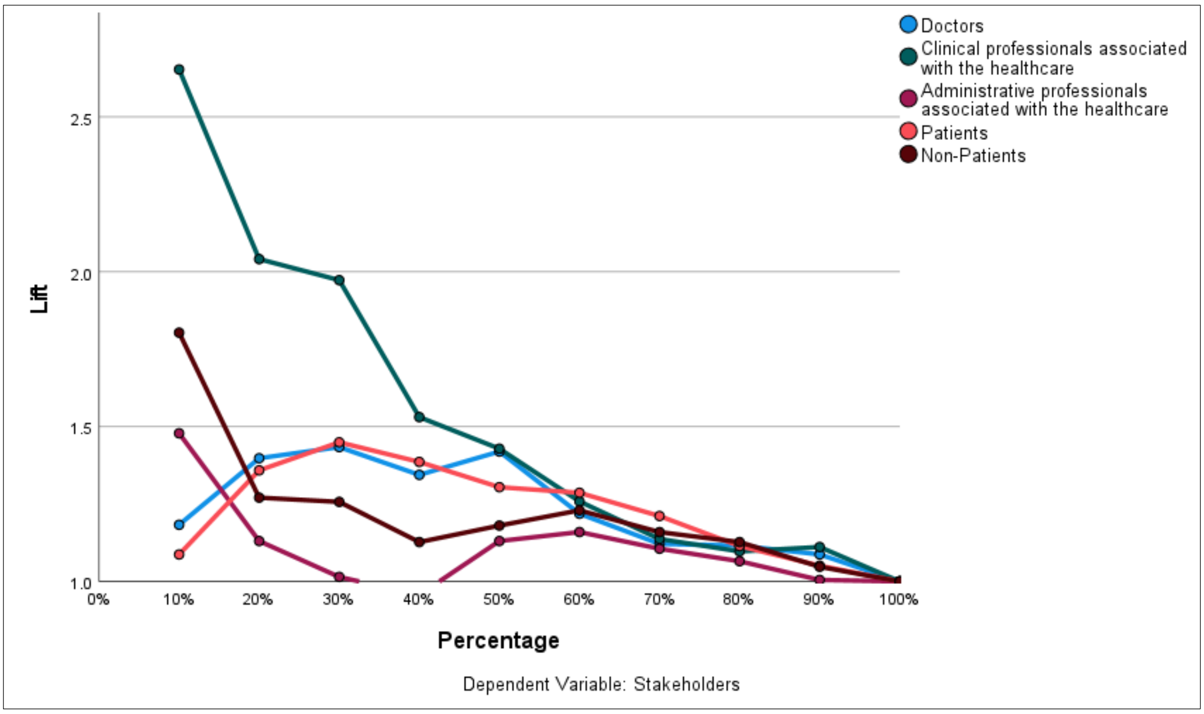

Figure 6: Lift Chart