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Research Article

Artificial intelligence (AI)-enabled CRM capability in healthcare: The impact on service innovation

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ABSTRACT

Although AI-enabled customer relationship management (CRM) systems have gained momentum in healthcare to enhance performance, there is a striking dearth of knowledge on how such capabilities are formed and affect service innovation. The study adopted a mixed-method approach to investigate the underlying phenomena. This research infused resource-based theory, dynamic capability theory, and theory of productivity paradox to investigate how healthcare in India acquires AI-enabled CRM capabilities and enhances service innovation. We identified the facets of AI-enabled CRM capabilities using a case study and developed a framework for AI-enabled CRM capability and service innovation. This study noticed that customer service flexibility (CSF) is a missing link in this relationship. The findings of the quantitative study employing PLS-SEM reveal the linear relationships between AI-enabled CRM capability, CSF, and service innovation. This study explains the formation of AI-enabled CRM capabilities to fill the research gap and direct innovative performance in healthcare, which is an immediate need to sustain in a volatile environment. This study provides theoretical implications to enhance the research stream and practical implications for decision-makers.

1. Introduction

In the past two decades, customer relationship management (CRM) has been recognized as an integral part of the comprehensive strategy of an organization to improve customer relationships and deliver effective services. The extant literature has described the mechanisms to implement CRM and the role of CRM capabilities in creating a competitive position for an organization (Battor & Battor, 2010; Chang et al., 2010). Further, extant literature has been filled with discussions of AI-enabled CRM capabilities (AI-CRM) across several management disciplines (Dwivedi et al., 2021; Mostafa & Kasamani, 2021). Many studies have examined how AI-CRM in the service sectors has grown and become an important facet of understanding customer idiosyncrasies (Dwivedi et al., 2021; Grover et al., 2020; Mariani et al., 2022). Businesses are developing AI-integrated CRM systems to accurately manage complex relationships and analyze customer requirements (Delloitte, 2020). In the healthcare sector, AI-enabled customer services (e.g., app-based health monitoring, chatbot driven customer services, embracing call analytics, managing high volume patient queries, utilizing patient's feedback analysis) are expected to generate capabilities for superior performance (Esmaeilzadeh, 2020). AI technologies adoption will lead to substantial automation in many aspects of clinical and administrative services, which can shift traditional healthcare facilities to more patient-centric services (He et al., 2019; Khanra et al., 2020). Prior studies highlighted the AI-enabled capabilities in healthcare for image analysis, speech recognition, precision medicine, and clinical notes (Wang et al., 2020). Therefore, healthcare organizations have recognized the importance of AI-enabled service strategies and patient relationships. For example, superior relationships with the patients as customers allows to track their changing needs and thus enable productivity and sustainability (Chatterjee et al., 2021; Kumar et al., 2021). Nevertheless, the AI-enabled CRM capability dynamics in healthcare is unclear.

Moreover, service innovation in healthcare is an important strategy that provides growth and strength to organizations (Snyder et al., 2016). Researchers posit that service innovation in healthcare is imperative due to complexity, urgency, and technological advancements (Khanra et al., 2020). AI-CRM capabilities are an antecedent to innovation as they could enhance the capabilities to understand customer requirements and preferences. Healthcare organizations with AI-CRM capabilities can

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track patient behaviors and gain insights into the changing demand patterns (Esmaeilzadeh, 2020; Mostafa & Kasamani, 2021). Researchers argue that the increased demand for smart devices and alertness to health have provided opportunities for innovation in new product lines (Khanra et al., 2020; Palanica & Fossat, 2020). Utilizing AI-enabled platforms, tools, and services for CRM systems in healthcare, organizations will be able to develop new healthcare services and modify the existing service designs (Daugherty et al., 2019). Thus, AI-CRM capabilities in healthcare will develop the capacity to innovate services.

Scholars and practitioners argue that innovativeness is an immediate need for healthier lives (Skålén et al., 2015). Healthcare organizations operating in emerging markets must have the flexibility and ability to cope with heterogeneous customer requirements. For example, the patients as customers not only demand several customizations but also value them. Moreover, the COVID-19 pandemic has raised concerns about quick adaptation and responses to several uncertainties like complexity of diseases, diagnostic requirements, changing clinical conditions, medical inventories, etc. Therefore, healthcare organizations need to develop dynamic capabilities in the form of AI-enabled CRM capabilities and their role in service innovation (Khanra et al., 2020). Previous studies have mentioned the linkages between CRM and organizational performance (Chang et al., 2010). Despite the growing importance of AI-based technologies in understanding and record customer requirements, it is unclear in the literature how it generates service flexibility (Ferreira et al., 2021). There is limited research examining whether AI-CRM capabilities strengthen customer service flexibility (CSF) mechanisms to enhance service innovation. The authors posit that AI-CRM capabilities contribute to service innovation in healthcare. Thus, the following research questions are proposed to guide this study.

(i) What are the dimensions of AI-CRM capability in healthcare?
(ii) How does AI-CRM capability affect service innovation?
(iii) Is CSF the missing link to achieve service innovation (SI) in healthcare?

The organization of this manuscript is as follows. The next section provides a review of the relevant literature and highlights the knowledge gap. Section 3 describes the research methodology. Further, the qualitative study is described and the hypothesis are developed. Section 5 presents the quantitative study and results of hypothesis testing. Thereafter, we discuss the findings and implications of this study. Finally, we point out the limitations and sketch future research directions.

2. Theoretical background

Artificial intelligence (AI) has become ubiquitous and has transformed the value creation process across businesses. AI is conceptualized as "computational agents that act intelligently to perceive, learn, memorize, reason, and problem-solve towards goal-directed behavior" (Mariani et al., 2022). Daugherty et al. (2019) argue that the adoption of AI can significantly improve business models, lower costs, and enhance productivity while simultaneously creating markets. There are heightened expectations concerning several tools and technologies of AI facilitating customer-oriented marketing and improved experiential value (Islam et al., 2019; Prentice & Nguyen, 2020). In India, AI-enabled technology is no longer an emerging technology segment. It is increasingly adopted across Chatbots-driven customer services, media delivery, e-commerce, tourism, agriculture, and healthcare, to name a few sectors. Indian businesses have been using AI for contextual understanding (e.g., insurance service providers to offer discounts for safe driving or real-time feedback), enabling them to withstand market changes (Kumar et al., 2021; Shareef et al., 2021). Recent reports indicate that fitness bands, for instance, comprise 92 % of wearable healthcare devices, while Fitbit remains a major player with more than 20 % of the market share (Ferreira et al., 2021; NAH, 2020).

In the past few years, the literature has been populated with the discussions of big data, AI, IoT in various aspects of healthcare, which varies from contextual to organizational (Alalwan et al., 2016; Cao et al., 2021; Sivathanu, 2018). There have also been multiple discussions revolving around the adoption of AI technologies, promising to lead to substantial automation in many aspects of clinical and CRM tools, which in effect, could shift traditional hospital settings to patient-oriented sites (He et al., 2019). Healthcare organizations and practitioners alike have been leveraging AI technology to drive precision medicine and insightful medical data analytics (Esmaeilzadeh, 2020; Kok et al., 2013). Researchers agree that AI is increasingly a constituent of the modern healthcare ecosystem, encompassing early detection, diagnosis, training, and decision-making (Gutierrez et al., 2019; Peiffer-Smadja et al., 2020). Several clinical inquiries in healthcare have reported that a widespread application of AI drives improvements across the care continuum—robotics surgery, clinical trials, treatment of rare diseases, drug discovery, and customer services (Esmaeilzadeh, 2020; Xu et al., 2015). AI-enabled technologies and devices have automated the treatment procedures, affected the healthcare supply chain, and offered personalized care (Grover et al., 2020; Saha & Ray, 2019). In the post-COVID-19 world, the paradigm shift in healthcare will imprint new opportunities for AI-enabled technologies and devices (Palanica & Fossat, 2020).

The theory of productivity paradox highlights several issues of technological-productivity correlations (Wamba-Taguimdje et al., 2020). Despite increasing investments in advanced technologies like AI, the decreasing rate of productivity is explained by the methodological and measurement issues. Due to limited understanding of value creation processes by AI-enabled capabilities, it is generally difficult to justify their positive relationship with performance (Mariani et al., 2022). Previous studies have accepted the potential of AI to provide better outcomes (Khanra et al., 2020; Kumar et al., 2021). Researchers argue that AI provides new methods to innovate and suggest to address the issues of AI productivity paradox to better understand the generation of new tools for patient benefits (Noorbakhsh-Sabet et al., 2019; Wamba-Taguimdje et al., 2020). To capture business values, AI capabilities create a set of organizational and artificial intelligence resources (Wamba-Taguimdje et al., 2020).

The resource-based theory (RBT) influences the dynamics of customer relationships (Battor & Battor, 2010; Meyer & Schwager, 2007). The RBT theorists suggests that organizations possess a set of valuable resources that are non-substitutable and inimitable (Bhardwaj, 2000). For instance, healthcare firms possess a set of medical devices and the skilled professionals as their valuable resources. The current development of AI-based tools and platforms provide an infrastructure to generate customer-related services that are adaptable (Kumar et al., 2021). Healthcare organizations mechanize their valuable resources and skills to develop customer-related capabilities (Kaleka & Morgan, 2019). A subset of these resources is utilized by the organizations to gain a competitive advantage. In effect, the relationships with the customers are dependent upon various resources of the firm that are utilized to create customer values (Gronroos & Gummerus, 2014). For instance, healthcare organizations develop and maintain relationships with their patients relying on their internal (e.g., equipment, the competence of medical employees) and external (e.g., alliance with the other hospitals, coordination with WHO or Red-Cross for specific services) (Dwivedi et al., 2021). Bhardwaj (2000) highlighted the role of technological resources and capacities, which are built upon other tangible resources of the firm. The possession of AI-based tools and capacities enable organizations to interpret heterogeneous customer preferences and maintain relationships with them (Dwivedi et al., 2021; Mostafa & Kasamani, 2021).

Moreover, researchers contend that to deal with the rapid turbulence, organizations coordinate with internal and external skills (Teece et al., 2016). Under an uncertain environment, organizations utilize specific processes to implement dynamic capabilities and enhance performance (Brozovic et al., 2016; Dai & Singh, 2020). The literature specifies dynamic capabilities as the "organizational routines" that allows to quickly reconfigure the resources and skills while dealing with environmental dynamism (Kumar et al., 2020; Mikalef et al., 2020). Dynamic capabilities are firm-specific routines that are utilized to deal with the changes and respond to market trends (Javalgi et al., 2005). Studies contend that customer-related capabilities are one of the most important marketing capabilities that are selected and built to enhance customer experience (Gronroos & Gummerus, 2014; Javalgi et al., 2005). In the past, such capabilities have been reshaped with the integration of AI-enabled technologies and applications, which strengthens the organizational capacities to improve customer-oriented services (Naumann et al., 2020). Thus, healthcare organizations recognize the importance of AI-enabled CRM capabilities to maintain superior relationships with customers, provide prompt responses to diversified customer demand, and customized services (Vorhies & Morgan, 2005).

2.1. AI-enabled CRM capability in healthcare

Recent advancements in AI have enabled this technology to be integrated with CRM tools. Organizations are adopting CRM software with AI-enabled capabilities to nurture relationships with customers (Chatterjee et al., 2021). AI-enabled CRM capability refers to the AI-based resources and processes that could focus on establishing and maintaining long-term relationships with customers (Mariani et al., 2022; Wamba-Taguimdje et al., 2020). AI-enabled CRM capabilities are firm-specific routines that are focused on customer-oriented activities and generating tremendous knowledge on customers' requirements (Chatterjee et al., 2021; Mostafa & Kasamani, 2021). Wamba-Taguimdje et al. (2020) posit that AI-enabled CRM capabilities reflect skills and accumulated knowledge of the firms to identify prospective customers and initiate a quick relationship with them to improve business performance. Thus, AI-enabled CRM capabilities are embedded in organizational processes that are focused on AI-based interactions (e.g., Chat boat driven services) to upgrade the AI-based customer-oriented activities and re-establish AI-based connections with customers. AI-enabled CRM capabilities allow data-driven business decisions using AI-based applications, such as listening and note-making tools, call analytics, AI-based calendar management (Jain et al., 2022; Mostafa & Kasamani, 2021; Pantano & Pizzi, 2020).

In healthcare, data volume has risen exponentially, which needs a powerful CRM system to interpret and analyze data in real-time. Companies are integrating AI and the Internet of Things (IoT) to address emergency health situations, remote monitoring of patients, early diagnostics, predicting women's fertility, and AI-based wearable for blind or visually impaired (Wu et al., 2016). Thus, AI-CRM is increasingly recognized as an important technique to collect accurate patient data, which helps end-to-end customer engagements (Gao et al., 2015). AI-CRM capabilities facilitate developing a customer-centric organizational system, which elevates the customer experience (Sung et al., 2021). AI-enabled capabilities accelerate content management by integrating the natural languages and thus organizing the customized e-mail, reviews, and customer reports. Further, AI-CRM capabilities reflect the enhanced skills that could identify prospective customers, manage relationships, and leverage those relationships into profit through the mechanization of AI resources and capacities (Chatterjee et al., 2021; Mostafa & Kasamani, 2021). The major activities of AI-CRM capabilities are advocated as AI-based customer interaction management, AI expertize for re-establishing relationships, and AI-infrastructure flexibility to upgrade those relationships with customers (Wamba-Taguimdje et al., 2020).

2.2. Customer service flexibility: a dynamic capability perspective

The concept of flexibility has widely been explored as an instrument to deal with environmental uncertainties (Powers & Jack, 2008). Researchers argued that service providers need several types of flexibility across the value chain to satisfy customer-needs (Gronroos & Gummerus, 2014; Shukla & Sushil, 2020). Luangsakdapich et al. (2016) conceptualized customer service flexibility (CSF) as the ability to quickly manage the resources to adapt heterogeneous customer requirements and deliver customized services. CSF allows specifying the significant changes to deal with demand uncertainties and enhance service performance (Morgan et al., 2014). Researchers argued that CSF is essential for developing customer values and achieving a competitive advantage (Shukla & Sushil, 2020). Service delivery systems are faced with dynamic customer requirements and uncertain environment. Dynamic capability of a firm is crucial for generating specific resources for adaptation and customization (Mikalef et al., 2020; Teece et al., 2016). Resources, skills, and competence of organizations enhance flexible execution while quickly responding to the changes (Brozovic et al., 2016). For instance, technological advances like AI, would develop capabilities of adaptation and deliver several customizations. Volberda (1996) suggest that there is a trade-off between flexible capabilities and efficiency. However, firms develop dynamic capabilities to balance the tradeoff between flexibilities and efficiency to achieve a competitive position (Kortmann et al., 2014). Therefore, developing and implementing CSF is a dynamic capability of the firm that is contingent upon several technological investments (e.g., AI-based tools and platforms) (Luangsakdapich et al., 2016; Prentice & Nguyen, 2020).

2.3. Service innovation: the new logic

Service innovation is referred to the reconfiguration of diverse resources involving a network of actors to create value (Lusch & Nambisan, 2015). Service innovation is a strategy to create new services and respond to the customer's heterogeneous requirements (Kindström et al., 2013). Skålén et al. (2015) demonstrate the importance of service innovation in achieving competitive advantage by the changes in service offerings and delivery models. Researchers argue that service innovation creates novel resources concerning improvements in the existing services and creating new service models (Cheng & Krumwiede, 2012; Dwivedi et al., 2017). Katzan (2015) argue that the focus of innovation has been shifted from the production of products and design of services to value creation. This change in the logic of service innovation involves the optimization of resources and developing capabilities. The new logic (Lusch & Nambisan, 2015) indicates that service innovation is a function of resources liquefaction and integration. Digital infrastructure (e.g., AI-based equipment and services) supports the constant integration of resources and enables several flexibilities to enhance service performance. Moreover, the new logic of service suggests the application of new skills and competencies through AI-based platforms (Mariani et al., 2022). This new logic of AI-based services would provide easy access to the appropriate bundle of healthcare resources and improve professionalism, and hence customer satisfaction (Haefner et al., 2021). However, there is a dearth of information on whether CSF is an antecedent to service innovations (Table 1).

3. Mixed-method design

The extant literature in various disciplines suggests a mixed-method study to strongly infer and obtain robust findings (Venkatesh et al., 2013). There is an increasing agreement that a mixed-method approach enhances the understanding of the context (Fox & James, 2020). To explicate the underlying dynamics of phenomenon under study, we employed a mixed-methods design. Hou et al. (2022) argue that mixed methods design allows incorporating multiple views to understand the phenomena. Researchers have outlined the purposes of combining qualitative and quantitative studies, such as initiation, data triangulation, expansion, and diversity (Hossain et al., 2020). The discussions around AI-CRM capabilities have recently populated in the

Table 1
Related works.

Authors	Theme of study	Major findings
(Battor & Battor, 2010; Chang et al., 2010)	CRM	Role of CRM and addressing the dark side of CRM
(Maklan & Knox, 2009)	Technology and CRM	Implementing the technology-based CRM and frameworks
(Teece et al., 2016; Zhang et al., 2003)	Resource-based theory	Firms utilize their resources and capacity to deliver services
(Brozovic et al., 2016; Day, 2000; Skålén et al., 2015)	Dynamic capabilities	Reconfiguration of internal and external resources to deal with uncertainties.
(Iivari et al., 2020; Khanra et al., 2020; Kumar et al., 2021)	Artificial intelligence in healthcare	AI has a significant role in medical analytics, accuracy of diagnosis, virtual assistance, and contact less support.
(Chatterjee et al., 2021; Dwivedi et al., 2021)	Role of AI in CRM	AI-powered CRM systems are tremendously being utilized for a range of services.
(Nair et al., 2013; Wimmer et al., 2016)	Clinical capability	Clinical skills and knowledge develop the capabilities for evidence-based medicine.
(Gronroos & Gummerus, 2014; Gronroos & Ravald, 2010)	Service capability	Firms utilize their resources for customer-oriented services
(Graffigana et al., 2015; Kumar et al., 2021; Scott & Walczak, 2009)	Engagement capability	Concerns for privacy invasion and intrinsic motivation would enhance the capability to engage with AI-based resources.
(Brozovic et al., 2016; Luangsakdapich et al., 2016; Shukla & Sushil, 2020; Volberda, 1996)	Flexibility, customer service flexibility,	Adjustment of capacity to deliver customized services and their impact on performance
(Haefner et al., 2021; Kindström et al., 2013; Lusch & Nambisan, 2015; Skålén et al., 2015)	Service innovation	Antecedents and consequences of innovation in services.

practitioners' literature (Delloitte, 2020; Wang et al., 2020). Despite the profuse development in the medical practitioner's domain, the theoretical standpoint is still unclear. To explore the constituents of AI-CRM capability and to answer three distinctive questions of the current study, either the quantitative or qualitative methods would not clarify the underlying dynamics. We employed a qualitative study to inform the findings to the next stage of the quantitative study (Fox & James, 2020).

This research was carried out in the healthcare context in India, wherein AI-enabled technologies are in the developing phase (Delloitte, 2020). India is a land of opportunities in AI-enabled technologies (Khanra et al., 2020). Due to the adoption of AI-enabled technologies in several patient-oriented programs, service strategies and consumption patterns have drastically changed in the past few years (Alalwan et al., 2016; Chatterjee et al., 2021). Given this background a case study was conducted and qualitative data were collected through semi-structured interviews. Next, a set of hypotheses were developed to test the proposed model. Thus, we empirically investigate the research model by employing a mixed-method (Fig. 1) study design.

4. Study 1. Qualitative and hypothesis development

Qualitative research provides a broad and rich description of the phenomenon under study (Yin, 2008). A qualitative study draws information from multiple sources in a natural setting, including personal experience, interviews, and secondary sources (Denzin & Lincoln, 1998). An exploratory case study was conducted in the Indian healthcare context. The sample organization was India's most extensive healthcare system in terms of facilities, functional departments, and medical employees. The sample organization has the largest number of patient registrations, beds, and a range of clinical, para-clinical, and auxiliary services (MOHFW, 2020). This organization was the pioneer in advanced medical education and care in India. A major expenditure in technology adoption and AI-based diagnostic equipment has been observed during the last three years within the organization (Mckinsey, 2021).

4.1. Participants and measures

The respondents were healthcare professionals at various levels from different medical units of the sample organization. The respondents were recruited based on their experience and interest in academic research (Table 2). We approached them based on personal contacts. The snowball sampling method was used to collect data (Hou et al., 2022). Due to the adverse situations of COVID-19, it was difficult to conduct face-to-face interviews and the respondents were also reluctant. However, 18 telephonic interviews could be managed due to personal contacts and explaining the academic importance. We prepared a schedule of questions (Appendix A) to facilitate the interview process. The questions were prepared by extracting the relevant concepts from the literature. The primary inputs were taken from three healthcare professionals. We modified the questions as per their feedback. The interview consisted of questions on the overview of AI, the importance of AI, the relationships with the patients through AI-based tools and platforms, demand patterns in healthcare, the resources and capacities to tackle them, and innovative services for the patients.

4.2. Data collection

To explore the dynamics of AI-enabled CRM capability, we collected qualitative data by conducting semi-structured interviews. The interviews were conducted during July–September 2021. The duration of the interviews was from 20 to 55 min. The interviews with the healthcare professionals were recorded with their permission. The interviews were also repeated to improve reliability and clarity (Patton, 1990). To do data triangulation, we collected data from multiple sources (Creswell, 2006). Data were collected from the medical documents and records. Relevant information was also gathered from the website, medical education unit, telemedicine, and various nursing units regarding clinical procedures and treatment modalities. The data collection procedure was discontinued when the researchers were able to predict the informant's response before they expressed it, i.e., when very few fresh insights were gained (Creswell, 2006). We followed the recommendations of Denzin and Lincoln (1998) to ensure validity and trustworthiness. The rich verbatim descriptions of participants were included to support the findings. All the three researchers were engaged to reduce the bias. Meticulous record keeping of data collection process ensured that interpretations are transparent and consistent.

4.3. Data analysis and coding

The qualitative study was focused on exploring the underlying dynamics of AI-enabled CRM capabilities in healthcare. We aimed to understand the components of AI-CRM. The process of data analysis involved NVIVO 10 software and thematic analysis. Many authors recommend NVIVO for qualitative data analysis (Welsh, 2002). NVIVO helps organize the interview data (Table 3) and provides patterns to understand the meaning. The qualitative interview data was extracted into the software. We created "memos" and "nodes" generate several codes and patterns ((Fox & James, 2020). The coding process was performed by the two independent coders (one researcher and one medical professional). The coding was initiated without any pre-set code but developed and modified during the process of coding (Braun & Clarke, 2006). We followed the six-step process of coding (Appendix B) as suggested by Braun and Clarke (2006). The inter-coder reliability was examined by Kappa's score (k = 0.9113) (Fleiss, 1971).

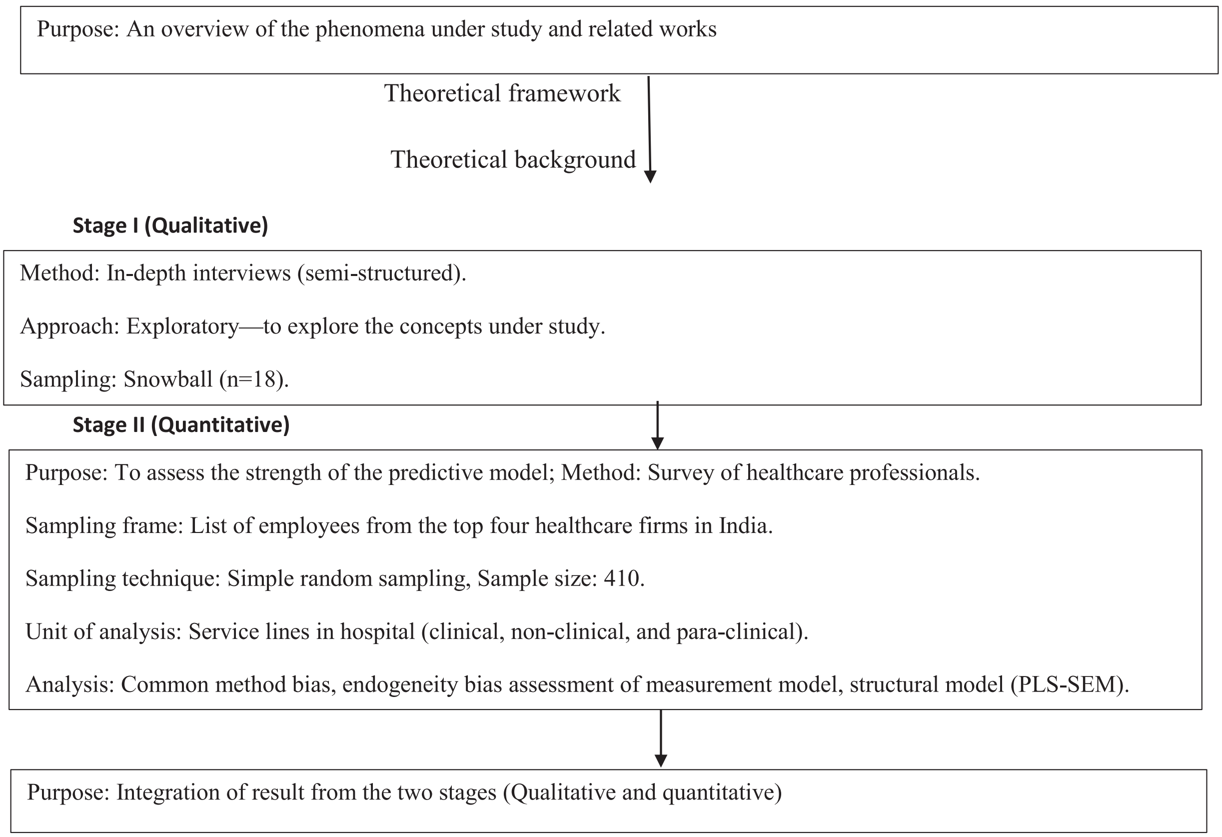

Fig. 1. Mixed-method design.

Table 2
Participants overview.

Sl. no.	Position	Experience (Yrs)	Interview (min)	Interview (n)
1.	Medical superintendent	30	32	1
2.	Medical dean	32	30	1
3.	Senior administrative officer	20	35	2
4.	Nursing superintendent	25	41	1
5.	Administrative officer	20	25	1
6.	Medical IT officer	15	35	1
7.	Research officer	10	25	2
8.	Faculty (Medicine)	22	20	2
9.	Faculty (Surgery)	25	20	2
10.	Faculty (Gynecology)	24	25	2
11.	Faculty (Radiology)	24	20	1
12.	Senior laboratory technician	15	25	1
13.	Information officer	15	28	2
14.	Senior programmer	12	34	1
15.	Telemedicine officer	12	35	1
16.	I/c Information resources	15	50	1
17.	Senior supervisor (logistics)	10	52	1
18.	Senior statistical officer	16	30	1

4.4. Convergence of findings

This section outlines the synthesis of the qualitative findings. We employed a bottom-up approach whereby the key dimension of "AI-enabled CRM capability" was identified. Based on the richness of the concepts observed for AI-CRM, we present an outline of the specific dimensions. The illustrative responses followed by thematic analysis yields further insights into the foundation of the quantitative analysis and develop several hypotheses (Fig. 2).

4.4.1. Clinical capability and AI-CRM

Healthcare organizations essentially need to develop excellent clinical practices and treatment modalities to serve the patients. The clinical skills and diagnostic capacity attracts new patients and maintain relationships with them (McKinney et al., 2021). AI in healthcare is widely used for clinical decision support and increases the ability to better predict patients' clinical conditions. It remains crucial to maintain a relationship with the patients by marinating high-quality clinical capabilities and knowledge of treatment modalities. Many authors argue that clinical capability is the outcome of complex clinical processes that require training and knowledge codification (Zafar & Rehman, 2017). Clinical capability is referred to as diagnostic capacity and treatment skills, which is enabled by the various forms of AI (Nair et al., 2013; Peiffer-Smadja et al., 2020). AI-enabled technologies would improve the clinical skills and competence of healthcare professionals (Wang et al., 2020). For instance, the AI-enabled technologies that focuses on best practices and indicates how well clinicians diagnose and treat patients' health issues (e.g., machine learning in precision medicine). AI-enabled diagnostics, medical data analytics, and disease predictions are crucial for long term relationships with patients. As a result of increased clinical capabilities, the patients are assured of better care and early recovery. The clinical processes (treatment modalities, diagnostic accuracy) are valued by the patients and improve the relationships. Contrary to this, lack of clinical information and clinical capacity would reduce the trust in the hospital systems (Tiainen et al., 2021; Wimmer et al., 2016). From the RBT perspective, AI-based resources as a rare and non-imitable resource would improve the skills of medical employees. They are equipped with AI resources to demonstrate a significant contribution in building trust and superior relationships with the patients (Teece et al., 2016).

Table 3
Interview response and codes.

Interview response	Second-order codes	First-order codes
"Our skills and competence are increased by AI technology- both in diagnostics, and treatments. AI-based diagnostic not only reduces the risk of infection but also enhance the diagnostic capacity by accurate detection. This certainly helps to maintain relationships with the patients. In the long run, we can quickly assess the clinical data and contact them for the necessary actions". "We have experienced and learnt new skills which are based on AI technologies. In fact, during COVID, we were monitoring patients remotely. The process of registration to discharge – was mostly automated and contactless. Our competence increased and we are now closer to the patients.	AI-driven diagnostics, AI tools for treatments, increased clinical accuracy.	**Clinical capability**
"AI-based Chatbots are gaining popularity for patient services. From generic to AI-specific many angles are changed. We can quickly understand the patient requirements and accordingly serve them better. For example, we provide tele-consultations and app-based medical services". "I would say the service environment has changed. What I have seen in my 15 years of the medical sector is that modern technology is tremendous. We advise warbles, we track heart rates, and we monitor blood pressures through AI. The automated post-discharge complaint registration and follow-ups are the new arenas of service to the patients.	Quick and effective services, understanding of patient's requirements, AI-driven services	**Service capability**
"AI-enabled technologies are being used for a range of clinical and other services. Organizational processes are focusing to increase awareness and attract the patients toward such tools and devices. Community programs are redesigned and integrated with AI-related information and advantages". "Patient's engagement with modern devices is important. We recommend, say wearable ECG, to cardiology patients to monitor the heart rate. It needs attention and acceptance to these tools. If we cannot engage them or develop trust with these, it will not work".	The ability to engage with AI-based health services, the specific processes to motivate and increase awareness to use the devices and tools, the capacity to engage, to ensure privacy concerns.	**AI-engagement capability**

4.4.2. *Service capability (SC) and AI-CRM*

Services represent a wide range of intangible product offerings that are valued by customers (Gronroos & Gummerus, 2014). Gronroos and Ravald (2010) reconceptualized service as the application of competence through processes and performance. Researchers posit that service is inherently relational and customer-oriented (Skålén et al., 2015). The changing landscape of the healthcare delivery environment, which is characterized by AI-enabled tools and platforms is capable of sustained relationships with the patients (Wang et al., 2020; Yu et al., 2021). Accordingly, AI-enabled service capability involves the application of AI resources for providing benefits to the patients (Esmaeilzadeh, 2020; Gursoy et al., 2019). For instance, chatbot driven support, tele-consultation, app-based medical services, health alert, tracking through wearable devices, etc. Thus, we argue that service capability in the healthcare context is the application of AI-based capacity for efficiently providing patient services. AI-based resources, tools, and platforms provide a modular structure for the interaction of healthcare service providers and patients (Mikalef et al., 2020; Wang et al., 2020). During COVID-19, contactless services and many other dimensions of services have emerged with the AI-enabled platforms that prescribe the protocols of service exchange. AI-enabled platforms in healthcare (e.g., PathAI app for individualized care, Buoy health for symptom checking) provide an interface to facilitate various healthcare activities like a second opinion, early diagnosis, tracking of symptoms and general screening, post-discharge support to the patients, re-admittance, and quick access of medical records (Delloitte, 2020). AI has the power to increase primary care services through virtual nursing assistance and administrative workflow assistance (Noorbakhsh-Sabet et al., 2019). It is argued that AI increases the service capability in healthcare and enhance AI-enabled relationships.

4.4.3. *AI-engagement capability (AI-Eng) and AI-CRM*

AI-engagement capability reflects the processes and abilities to enhance patients' engagement with AI-related service products and consumption (Kumar et al., 2021; Wu et al., 2016). Engagement is essential for acceptance of service products and greater customer value (Bowden et al., 2017; Graffigana et al., 2015). AI-engagement capability refers to the organizational processes and embedded routines that would trigger intrinsic motivation and interest of patients towards AI-based tools, devices, and platforms (Graffigana et al., 2015; Kumar et al., 2021). As an organizational perspective, it reflects the capacity to enhance patient's interest and motivation toward the AI-based health interventions (Graffigana et al., 2015). Therefore, harnessing the potential of AI-based services and interactions, organizations need to develop the capabilities to overcome patient's skepticism and ensure privacy invasion. To reduce the AI-based functional barriers, organizations need to focus on specific processes that engage the patients with AI-enabled services and platforms (Shareef et al., 2021). We argue that the organizational capability to engage with AI tools and platforms in healthcare is crucial to legitimate the patient's health needs and obtain better relationships with them. The patient's involvement in adopting and learning new technologies fosters their self-management skills. Scott and Walczak (2009) stated that organizations are essentially concerned with engaging customers to facilitate personalized experiences and long-term relationships. In healthcare, engagement is crucial to obtain better outcomes and enhance patient relationships. It allows them to understand their health conditions, compares treatment modalities, and shares relevant information with clinicians (Wimmer et al., 2016). Moreover, patient accurate data is essential for CRM practices in healthcare to strongly support the customization of services to fit the patient's requirements, for instance early and accurate diagnosis would improve organizational ability to sustain relationships (Mehta & Pandit, 2018; Palanica & Fossat, 2020).

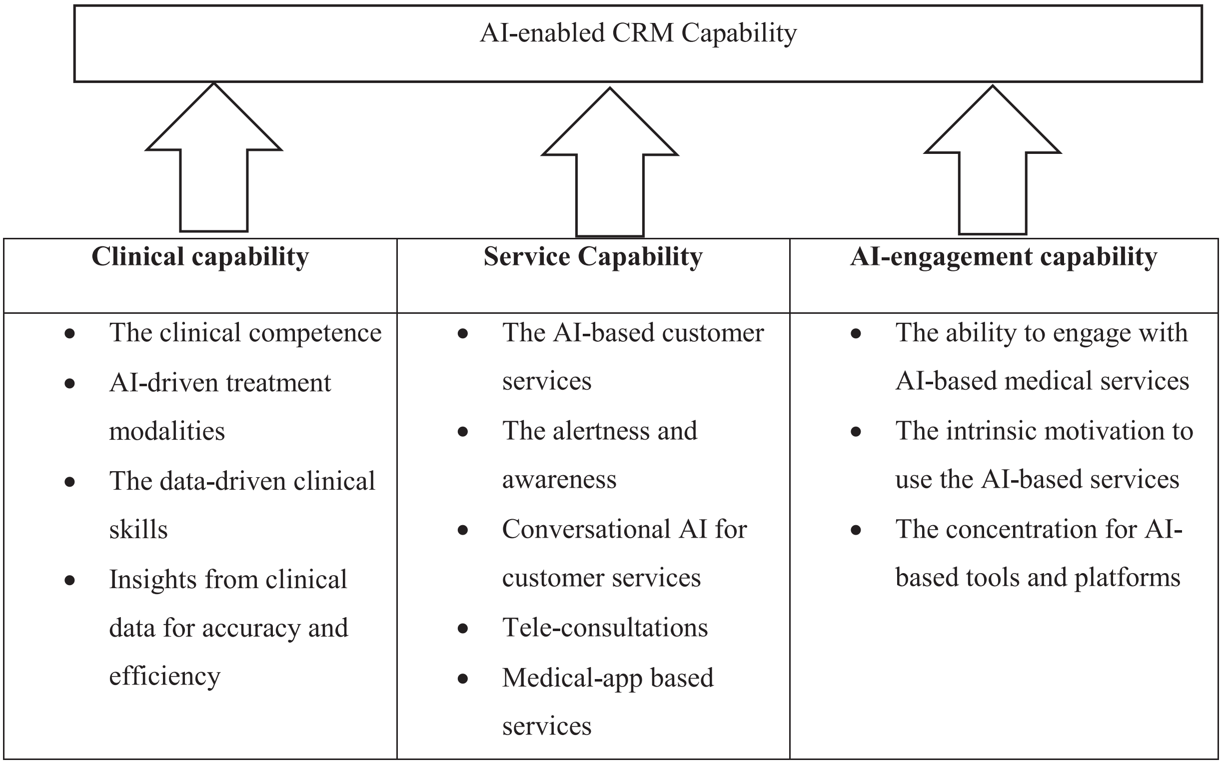

Fig. 2. Convergence of qualitative findings.

4.5. Hypothesis formulation

4.5.1. AI-CRM and customer service flexibility (CSF)

In literature, it is widely accepted that technological capabilities enable flexible execution across the value chain (Javalgi et al., 2005; Shukla & Sushil, 2020). AI-CRM capabilities would allow to understand patient's requirements and support a rapid adjustment in resources (Dwivedi et al., 2021). Healthcare organizations that possess AI-CRM capabilities are adaptive to the changing environments and can quickly respond to the various needs of the patients (Peiffer-Smadja et al., 2020; Wetering, 2018) AI-CRM capability generates a patient-centric system to initiate information sharing, overcome several issues and complaints, and thus, resolve them quickly (Esmaeilzadeh, 2020; Tiainen et al., 2021). For instance, AI-based tools and devices help understand and analyze complex medical conditions. Thus, service providers can understand the emotions of the patients and are more closely associated with them. AI-CRM capability would allow reconfiguring the resources (e.g., utilization of equipment, ordering and tracking medical inventories, or improvement of medical employee's skills) and delivering the customized services to the patients. During the current pandemic, healthcare organizations have tremendously developed AI-enabled CRM capabilities to merge the clinical and social data to mitigate risk (Mckinsey, 2021; Park et al., 2021). The strength of AI-CRM capabilities nurtures the overall service capacity and make the healthcare system robust. Clinical management and treatment plan become patient-oriented and personalized. Moreover, AI-enabled CRM capability would provide an appropriate mechanism to understand the heterogeneous requirements of the patients and provide opportunities to recover them when something wrong has happened in the process of care. Thus, AI-enabled CRM capabilities would allow them to respond to them as flexibly as possible.

H1. AI-CRM positively influences customer service flexibility (CSF).

4.5.2. Customer service flexibility (CSF) and service innovation (SI)

CSF is an important strategy that links organizational activities with patient-related services. The mechanisms of CSF improve adaptability and offers new services to satisfy the patients (Luangsakdapich et al., 2016) Combining the functional characteristics of services, CSF attempts to improve service processes and new service proposals to provide an enhanced experience of care (Ponsignon et al., 2015). For instance, responsiveness toward the patients would allow the service providers to generate the capabilities of adaptation. CSF strategy in healthcare reduces demand variability by managing the increased volume of patients and improving the service process (Powers & Jack, 2008). Additionally, the capabilities of CSF deliver several convenient services and appropriately modify the existing services. The possession of customer-oriented flexibilities would enhance the ability to execute various tasks with improved responsiveness and performance (Luangsakdapich et al., 2016). By executing CSF, healthcare organizations attempt to adjust the infrastructure including the medical employee's training and relocation, the design of diagnostic equipment, quality of inventory management, and several external relationships to increase the range and quality of services. Such flexible capabilities give room to generate new services and working methods by the mechanization of several medical resources (Skålén et al., 2015). Moreover, customer service flexibilities would provide accurate and intensive medical information to design and develop new services. CSF as a dynamic capability allows enhancing the overall reputation and image of the healthcare organizations. It allows focusing on competitiveness and service performance through several changes in the provision of services (Brozovic et al., 2016). CSF strategy would force healthcare organizations to identify new clinical methods and tools to satisfy their patients (Nair et al., 2013). We argue that CSF plays a significant role in developing the capability of adaptation and is likely to promote healthcare organizations to achieve service innovation. Thus, we propose the following hypothesis (Fig. 3).

H2. customer service flexibility (CSF) has a positive and significant impact on SI.

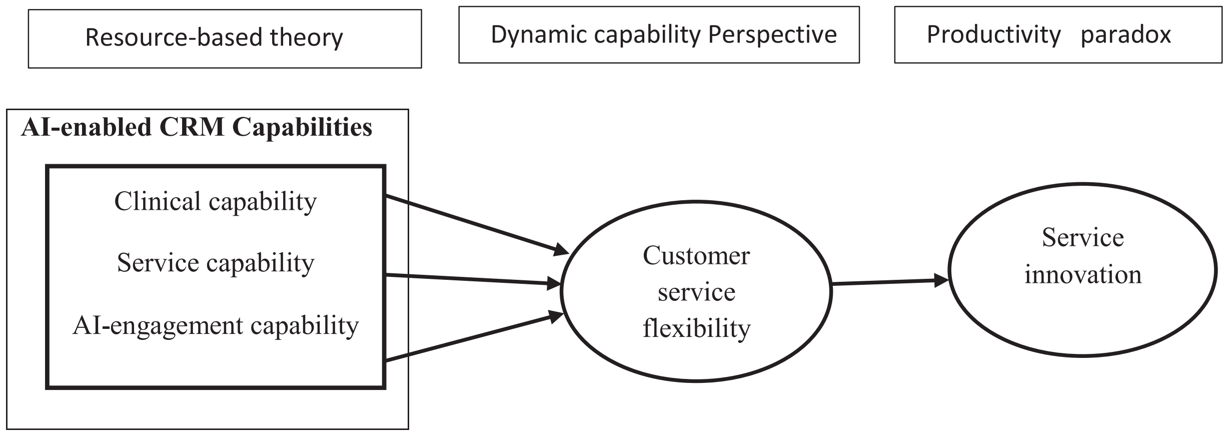

Fig. 3. Research framework.

5. Study II: quantitative

We infused the relevant literature with the findings of the qualitative study. The conceptual framework was developed to guide the second stage of the study. The quantitative assessment of the explanatory model was intended to confirm the qualitative research findings. A structural equation model was specified to analyze the multiple relationships developed during the qualitative phase. The model was subjected to statistical analysis to ensure reliability and validate the conceptualized model. We developed the survey instrument for the quantitative study and reached the respondents through personal visits and e-mails.

5.1. Quantitative data collection

The survey instrument consists of five constructs. The measurement scale (Appendix A) was adapted from the relevant literature. Five items of the measurement scale (one item in each construct) were developed by qualitative interviews (Fox & James, 2020). Furthermore, the survey instrument was subjected to first level purification. We modified language of the survey make simpler and capture phenomena under study. The survey instrument was shown to three medical professionals and two professors, who works in the same domain. We incorporated their suggestion and modified the items of the scale to finalize the survey. We collected 60 responses from the respondents and pre-tested the measurement scale for validity and reliability. The pre-tested instruments were further utilized for data collection. The final survey instrument consisted of 17 measurement items of five constructs. The second-order construct (AI-CRM) was not included in the scale which is examined by its three underlying dimensions as clinical capability, service capability, and AI-engagement capability. The following table (Table 4) outlines the study constructs, measurement parameters, and literature support.

Table 4
Operationalization of the constructs under study.

Construct	Type	Operational definition	No. of Measurement parameters and literature support
Service Innovation (SI)	Dependent variable	The capability to improve and reposition the existing services	Four (Haefner et al., 2021; Lusch & Nambisan, 2015)
Customer service flexibility (CSF)	Mediated variable	The capability of adaptation to provide customized services	Four (Brozovic et al., 2016; Luangsakdapich et al., 2016)
AI-enabled CRM capability	Higher-order construct	AI-based capacity and resources to maintain long term relationships with the patients	Measured as a second-order construct
Clinical capability (CLC)	variable	The capability to provide AI-based clinical services	Three (Nair et al., 2013; Zafar & Rehman, 2017)
Service capability (SC)	variable	The capability to provide AI-based services in a responsive manner	Three (Gronroos & Gummerus, 2014; Pantano & Pizzi, 2020)
AI-engagement capability (AI-Eng)	variable	The capability to engage patients with AI-based services	Three (Chen et al., 2017; Kumar et al., 2021)

The sampling frame for the data collection was the list of healthcare organizations in India accredited with National Accreditation Board of Hospital and Healthcare Providers which consists of 910 hospitals (MOHFW, 2020). Respondents from the top four major healthcare organizations were selected randomly and requested to participate in the survey. One researcher of this study has a prior background and access to the healthcare sector, which was helpful in the data collection process. We followed simple random sampling from the list of hospital employees. Participants were selected from the database of the hospital employees. The random selection of participants from various medical units and other operational groups (e.g., medical IT, advanced diagnostic labs, medical research lab) facilitated the PLS-SEM analysis. The academic importance was explained to the respondents. We also included some filter questions to understand the interest and knowledge of the participants toward the phenomenon under study (e.g., what do you understand by Artificial intelligence? what are the usage of AI in your hospital setting? do you think that AI-based tools strengthen the relationships with patients?). Some respondents were unclear in the response and the authors dropped twenty such responses from the final study. The AI-CRM system was in practice in the corresponding organizations, although not matured (e.g., AI-based automatic reminders, voice assistance in telemedicine, Chatbot driven services, contactless registration, and document delivery) (Appendix D). Additionally, participants requested some clarity of customer service flexibility and service innovation. Besides, we provided an explanation of the measurement items and all the five constructs of the study. The survey was completed in three months duration (June 2021–August 2021). The questionnaire was prepared with a proper description of the purpose of the study and a brief explanation of the constructs. Out of 470 final surveys, we received 430 completed surveys and only 410 (86.31 % response rate) were used for the study, which is greater than ten times of total constructs. Thus, the sample size was adequate for the study (Hair et al., 2016). The respondents were suggested to mark their response (perception) based on the Likert-scale on the corresponding parameters (1 = strongly disagree to 5 = strongly agree) (Table 5).

Table 5
Sample characteristics (N = 410).

Participants	Frequency	Percentage
Male	215	52.43
Female	195	47.56
Position		
Doctor	128	31.21
Nurse	82	20.00
Para-medical staff	23	5.60
Medical IT staff	45	10.97
Hospital Manager	12	2.92
Others	120	29.26
Qualification		
Post graduate	235	57.31
Graduate	142	34.63
Others	33	8.04
Working Experience		
< 3 yrs.	105	25.60
3–5 yrs.	90	21.95
5–10 yrs.	79	19.26
10–15 yrs.	55	13.41
> 15 yrs.	81	19.75

5.2. Results

We focused on the prediction of multiple paths and the effects between different variables of the current study. Prior research indicated that PLS-SEM is suitable for "exploratory and predictive modeling" (Hair et al., 2016). PLS-SEM provides variance based flexible modeling structure (Hair et al., 2019). PLS-SEM takes care of the missing data and non-normal distribution of data. Many authors have clarified that PLS-SEM can be utilized for both formative and reflective models (Janssen et al., 2018; Sarstedt et al., 2020). We utilized the latest version (v.3 2.6) of Smart PLS for quantitative assessment of the predictive model (Ringle et al., 2017). We analyzed the quantitative data set that was gathered to explain the model.

5.2.1. Common method bias and non-response errors

According to Craighead et al. (2011), the concerns of common method bias should not be ignored in empirical studies based on perceptual measures. To address the issues of CMV, this study has followed the suggestions of prior studies (Podsakoff et al., 2003). We assured the respondents regarding the confidentiality of the information provided by them for academic purposes. Next, we also conducted Harman's single factor test. We found only 21.03 % of the variance was accounted for the first factor. In view of the limitations of the Harman's single factor test, we utilized common method approach and included a factor in PLS model whose parameters include all the other construct's items. The results indicate that the ratio of substantive variance to method variance is 47:1. Further, the marker variable approach as recommended by Malhotra et al. (2006) indicate less than 0.04 difference between the CMV-adjusted and correlations of the study's constructs (Table 6). The construct green human resource management (GHRM) was used as a marker variable (theoretically distinct) which was a part of the other study under the same project. Based on these findings we argue that method is not a concern in this study. We also analyzed the non-response bias of the collected data. The extrapolation technique was employed to accommodate the late response to non-response. The two-wave survey was conducted from June 2021 to August 2021. The filled-in survey data was split into two groups n = 215 after the first wave and n = 195 after the second wave. We employed two-sample *t-tests* and found that the results from the two wave survey data was not significantly different.

Table 6
Common method variance analysis: marker variable correlation table.

	Correlation without marker variable	Correlation with marker variable	Marker variable: GHRM (Chan et al., 2016)
CLC-AI CRM	0.161	0.124	1. We set a green goal for every employee in the organization.
SC- AI CRM	0.577	0.558	2. Our employees are trained with green training to promote green values
AI-Eng.-AI CRM	0.566	0.543	3. We provide green training to an employee to develop the skills required for green management
AI CRM - CSF	0.451	0.421	
CSF- SI	0.526	0.511	4. We align workplace green behavior in performance appraisals.

5.2.2. Assessment of endogeneity bias

Researchers (Hult et al., 2018) argue that endogeneity is a significant concern in PLS-SEM based on predictive models and suggests reporting the endogeneity bias. We examined the "non-linear bivariate causality direction ratio" (NLBCDR). The results reveal that value of NLBDCR was 0. 875 (i.e. greater than the acceptable threshold of 0.7). Additionally, the values for each path in the hypothesized model indicate a weak support [CLC→AI-CRM (0.911); SC→AI-CRM (0.891); AI-Eng→AI-CRM (0.977); AI-CRM→CSF (0.901); CSF→SI (1.001)] for reversed hypothesized direction of causality. Hence, the authors posit that endogeneity bias is not present in this research.

5.3. Higher-order model (AI-CRM) specification

The quantitative data analysis was performed to achieve the objectives of the study. The analysis was first aimed to understand the higher-order modeling of AI-CRM capability. We utilized the two stage approach suggested by Sarstedt et al. (2019) to estimate and validate the higher order sub-constructs. In doing so, we first explored the multidimensionality of the AI-CRM construct with its three underlying sub-dimensions. The first order constructs for AI-CRM are clinical capability (CLC), service capability (SC), and service innovation (SI). The convergent validity of the three constructs were established by two methods: (i) construct reliability (CR) values and (ii) average variance extracted (AVE) [CLC (CR = 0.789, AVE = 0.559), SC (CR = 0.779, AVE = 0.591), AI-Eng (CR = 0.776, AVE = 0.537)]. The construct level VIF values (CLC = 1.008; SC = 1.256; AI-Eng = 1.254) indicate that multicollinearity does not exist between the constructs. Further, the HTMT values were below the threshold of 0.85 indicating the discriminant validity of the four constructs were established. Next, the structural analysis was performed for the second-order reflective construct AI-CRM by utilizing a "repeated item indicator approach" (Hair et al., 2016; Sarstedt et al., 2019). We found that all the ten items were significantly loaded on the second-order reflective construct (AI-CRM). We found that the average variance explained by AI-CRM was low (0.269). As per the suggestions of Hair et al. (2019) the low variance of higher order construct (HOC) signifies the resistance to converge into a single factor (AI-CRM). Thus, the findings validate the conceptualization of HOC. Furthermore, the three paths [CLC→AI-CRM (β = .842, t = 17.653, p = 0.000), SC→AI-CRM (β = .0.834, t = 17.490, p = 0.000), AI-Eng→AI-CRM (β = .261, t = 2.145, p = 0.032)] were significant with AI-CRM. Thus, the data supports the conceptualization of the AI-CRM as a "second-order reflective construct" and it is measured by its three dimensions as CLC, SC, and AI-Eng (Fig. 4).

5.4. Model testing

The study next intended to test the hypothesized model. We utilized path modeling and estimates by utilizing PLS-SEM. The two constructs CSF and SI were introduced in the earlier model (higher-order model of AI-CRM) and examined. Relying on the suggestion of Baron and Kenny (1986), we first examined the significance of direct path AI-CRM→SI

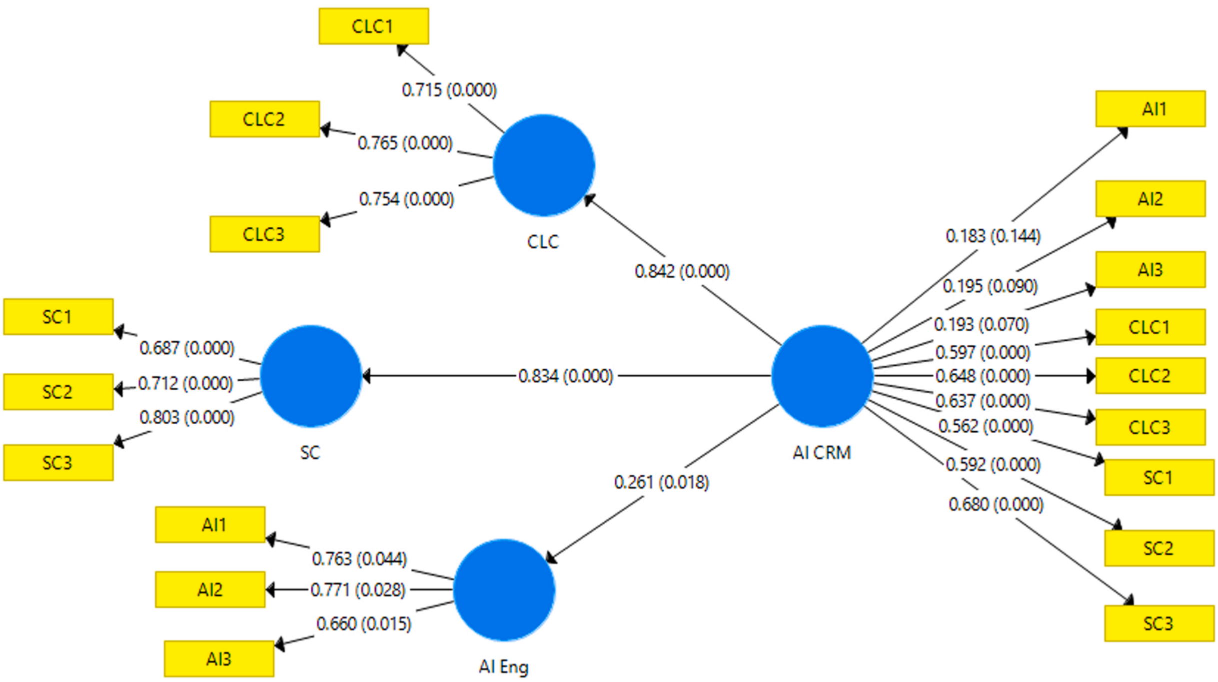

Fig. 4. AI-CRM: second order factor validation (β and p- values).

without introducing the CSF variable in the model. The results of bootstrapping procedure reveal that the path is not significant ($\beta = .019$, $t = 1.129$, $p = 0.046$). Thus, we argue that CSF does not affect the model as a mediation mechanism and we did not examine the mediation effects of CSF between AI-CRM and SI variables. We next introduced the CSF variable and examined the hypotheses of the proposed model of the study.

5.4.1. The measurement model

The proposed model of the current study consists of the reflective constructs. The data analysis utilizing Smart PLS involves measurement model assessment as a first step. To test the predictive model, we first tested the internal consistency reliability of the constructs. First, the outer loadings for all the measurement items were estimated. The results of the PLS algorithm indicate that all the constructs and the item loadings to the corresponding constructs were significant (greater than 0.7). Second, we observed that the inter-item correlations were above the suggested value (Cronbach's alpha > 0.7). Third, given the limitation of Chronbach (1951) alpha (all the indicators load equally on the construct), we examine the composite reliability (CR) values of all the constructs by utilizing the outer model analysis, which was greater than 0.7 (Table 7). The model analysis further involved the assessment of discriminant validity and convergent validity of the study constructs (Hair et al., 2019). The convergent validity of each construct was examined by average valiance extracted (AVE). The results of the first run of the PLS algorithm reveal that AVE values were greater than acceptable values of 0.5 for each construct. We adopted two different methods to establish the discriminant validity of the constructs. First, we checked whether the square root of the average variance extracted was greater than the highest correlation (Table 8) of each construct (Fornell

Table 7
Results of the measurement model.

	M (SD)	Construct reliability	Average variance extracted	VIF	Outer loadings	t-statistics
1. **Clinical capability (CLC)**		**0.789**	**0.555**			
CLC 1	3.51 (0.91)			1.172	0.713	18.223
CLC2	3.21 (1.03)			1.223	0.765	26.051
CLC3	3.32 (1.05)			1.21	0.756	27.170
2. **Service capability (SC)**		**0.779**	**0.541**			
SC1	3.80 (0.98)			1.151	0.691	16.083
SC2	3.80 (0.99)			1.164	0.709	16.334
SC3	3.43 (1.08)			1.254	0.802	33.671
3. **AI-engagement capability (AI-Eng)**		**0.777**	**0.515**			
AI1	3.51 (1.01)			1.314	0.769	2.303
AI2	3.24 (1.09)			1.304	0.776	2.577
AI3	3.08 (1.12)			1.07	0.649	2.520
4. **Customer service flexibility (CSF)**		**0.822**	**0.537**			
CSF1	3.89(0.77)			1.508	0.814	40.642
CSF2	3.77(0.86)			1.291	0.714	19.167
CSF3	3.67(0.90)			1.408	0.729	20.633
CSF4	3.43(0.97)			1.293	0.669	14.906
5. **Service innovation (SI)**		**0.824**	**0.540**			
SI1	3.47 (0.88)			1.329	0.728	20.005
SI2	3.40 (0.90)			1.439	0.734	18.604
SI3	3.69 (1.00)			1.303	0.707	17.622
SI4	3.67 (0.95)			1.471	0.770	27.720

Table 8
Discriminant validity.

	AI-Eng	CLC	CSF	SC	SI
AI-Eng	0.734				
CLC	0.072	0.745			
CSF	0.091	0.343	0.733		
SC	0.079	0.449	0.419	0.736	
SI	0.044	0.332	0.526	0.274	0.735

* AI-enabled CRM capability (AI-CRM) is a higher order factor, hence not considered in correlation analysis.
** Diagonal elements are square root of average variance explained (AVE).

& Larcker, 1981). Next, the cross-loading values of the constructs were less than the values of the outer loadings. Thus, the outer model of the study was validated.

5.4.2. *Structural model assessment*

The next step of analysis involves the assessment of the structural model or inner model. The structural model was examined for collinearity issues. Hair et al. (2019) suggest that the path coefficient may be biased due to the collinearity among the predictor variables. We checked the construct level VIF values which were lower than 3.3. The VIF value for CSF was 1.321. The construct level VIF values for AI-CRM with CLC, SC, AI-Eng are greater than 1 (1.008, 1.256, and 1.254 respectively) which indicates the moderate level of correlation between these first order constructs (Hair et al., 2019). The inner model explains 43.07 % variance in AI-CRM, 51.20 % in CSF, and 67.32 % in SI. The standardized path co-efficient is determined by the bootstrapping process (Hair et al., 2016). We utilized the re-sample technique (5000 re-sample) of bootstrapping by utilizing smart PLS. It specifies whether the path co-efficient is significant or not. The path co-efficient for all the hypothesized paths of the proposed model [CLC→AI-CRM ($\beta = 0.566$, $t = 17.887$, $p = 0.000$), SC→AI-CRM ($\beta = 0.577$, $t = 17.806$, $p = 0.000$), AI-Eng→AI-CRM ($\beta = 0.161$, $t = 2.169$,$p = 0.023$), AI-CRM→CSF($\beta = .0.834$,$t = 11.041$,$p = 0.000$), CSF-SI($\beta = .0526$, $t = 14.042$, $p = 0.000$] are significant. Thus, hypotheses (H1, H2) are accepted. Moreover, the predictive relevance of the endogenous latent variables is assessed by the sample reuse technique (blindfolding) with omissions distance $D = 7$. The results of PLS-predict exhibits predictive relevance as the Q^2 (construct cross-validated redundancy) values for the endogenous constructs [AI-CRM = 1.000, CSF = 0.195, SI = 0.108] are positive. Further, we performed the PLS predict test to establish the out-of-sample predictive power of the model, which indicates the ability to predict future observations. We relied on the suggestions of Hair et al. (2019) to run the PLS predict with the number of holds ($k = 10$) and number of repetitions ($r = 10$). The PLS SEM error histogram of indicator variables appeared symmetrical. Hence, we compared the PLS SEM_RSME with LM_RSME for each predictor variables which indicate that only 03 indicators (out of 17 indicators) have higher LM_RSME values (Table 9). Therefore, the out-of-sample predictive power for the proposed model is moderate to high (Hair et al., 2019). Finally, the PLS results reveal a model fit with the SRMR values of 0.87, which is less than the maximum recommended value of 0.10 (Fig. 5).

6. Discussion of findings

This study has explored the dimensions of AI-enabled CRM capability in healthcare. The respondents clarified clinical skills and competence as a primary requirement for a patient (customer) related services and relationships. Therefore, the AI technologies that improve such clinical capacity would converge with AI-enabled CRM systems. Modern AI-based platforms enhance clinical understanding and knowledge (Wimmer et al., 2016). As a specific form of skills and competence, such clinical capability would facilitate maintaining patient relationships. Furthermore, the respondents indicated the changing landscape of the service environment due to AI technologies. Prior research

Table 9
Results of PLS_Predict (RSME).

Indicators	LM_RSME	PLS_RSME
AI2	0.076	0.081
CLC3	0.801	0.816
SC1	0.789	0.812
AI3	***0.117***	0.101
SC3	0.112	0.103
AI1	0.041	0.032
CLC1	0.793	0.742
CLC2	0.811	0.795
SC2	0.882	0.787
CSF4	0.921	0.938
CSF2	0.811	0.801
CSF3	***0.891***	0.883
CSF1	0.701	0.709
SI4	0.936	0.928
SI2	0.857	0.860
SI1	***0.881***	0.867
SI3	0.973	0.980

conceptualized "service" as an application of specialized resources to benefit actors involved in the service ecosystem (Lusch & Nambisan, 2015). Accordingly, possession of the service capability based on AI technologies in healthcare is an essential facet of CRM capability. Most importantly, medical professionals agree to "engagement" with AI-based tools. They opined that the capability to engage patients with AI-based tools remains crucial in healthcare. Thus, the "AI-engagement capability" is essential to attract customers toward AI-enabled technologies.

Furthermore, the quantitative study findings are new to understanding the effects of AI-enabled capabilities on customer service flexibility and, in turn, service innovation in healthcare. Previous research on AI and CRM has been limited to marketing-based performance (Battor & Battor, 2010; Grover et al., 2020). This study identified the critical constituents of AI-CRM capabilities and examined its benefits for innovative services in healthcare organizations. The study's findings suggest that the direct effects of AI-CRM and SI were insignificant. Therefore, the mediation mechanism of the CSF construct was examined, and the results demonstrate a sequential linkage between AI-CRM, CSF, and SI. The findings explain that AI-CRM capabilities contribute to organizations' flexible capabilities to realize customers' needs, provide a customized response to customers, and recover them quickly (Brozovic et al., 2016; Powers & Jack, 2008). We also found that, contrary to the other studies (Haefner et al., 2021), AI-enabled capabilities are linked indirectly with innovation-based activities through the adaptable and flexible mechanisms of the firm. Previous studies have explored the direct relationships between CRM capabilities and innovative performance. For example, in a study of UK-based companies, Battor and Battor (2010) found that developing a firm's CRM capabilities have a direct and significant relationship with innovative performance. However, this study reveals that AI-enabled CRM capabilities in healthcare affect innovative performance through firm-specific flexible capabilities, which was a missing link. We established that AI-enabled CRM capabilities in healthcare develop specific capabilities and resources to accelerate adaptability and customer-oriented flexibilities, affecting service innovations.

6.1. *Theoretical contributions*

This study contributes to theory in multiple ways. First, it responds to the recent call of researchers to explain the constituents of AI-enabled CRM capability in healthcare (Chatterjee et al., 2021; Gursoy et al., 2019; Mariani et al., 2022). It is a first step to assess the role of AI-enabled capabilities on performance of healthcare firms in terms of flexibility and innovation, which are limited to date. Second, this study has conceptualized and provided empirical validation of AI-CRM as a capability in a healthcare firm. Thus we extend the previous research on

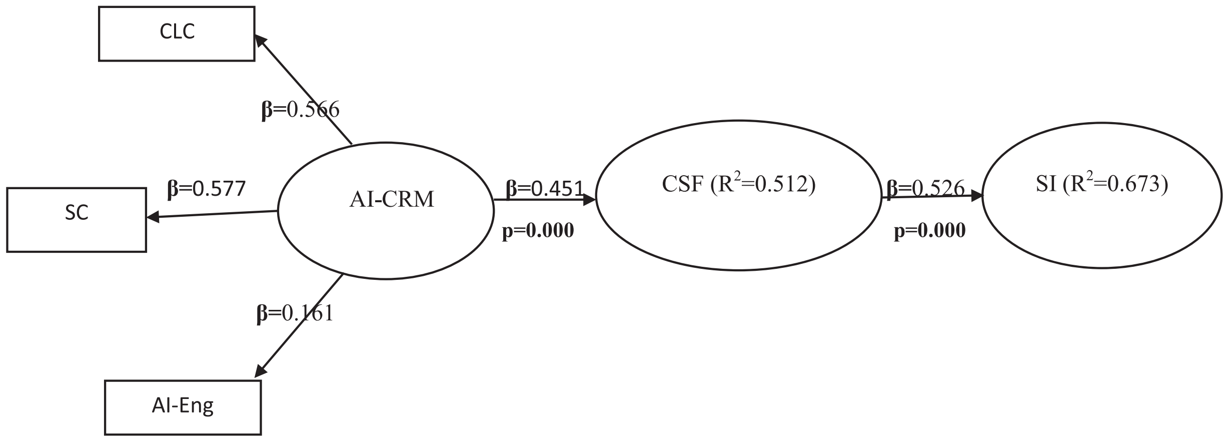

Fig. 5. Bootstrapping results *(path-coefficient and p- values)*.

AI and CRM by developing the integrated knowledge on AI-based customer relationships and their performance (Grover et al., 2020; Wang et al., 2020). From the capability perspective (Teece et al., 2016; Wamba-Taguimdje et al., 2020), this study argues that AI-CRM is a multidimensional second order construct, which is formed by three specific capabilities as clinical capability, service capability, and AI-engagement capability. We identified the three facets of AI-CRM capability and examined its benefits for innovative services in healthcare organizations. Thus, the findings advance the knowledge on AI-CRM and its connections with adaptability and performance. Third, findings indicate that AI-enabled capabilities are indirectly linked with innovation-based activities through the adaptable and flexible mechanisms of the firm. Findings contribute to the dynamic capability (Brozovic et al., 2016; Shukla & Sushil, 2020; Volberda, 1996) in the guise of customer service flexibility (CSF) is generated by such customer relationship capabilities, which causes improvements and changes in the current services and models.

Fourth, this study contributes to RBT, dynamic capabilities, and theory of productivity paradox (Agrawal et al., 2019; Day, 2000; Teece et al., 2016; Wamba-Taguimdje et al., 2020). This study identified and empirically validated the firm level specific resources and capacities in the current AI-based environment that accumulates to develop AI-enabled CRM capabilities. We argue that AI-CRM capabilities in healthcare make them patient-oriented, facilitate cross-functional coordination, and enhance competitive position of a healthcare firm. Hence, AI-CRM generates market-oriented activities (Brozovic et al., 2016), which in turn, enables flexible service deliveries. This study shows how healthcare organizations develop AI-CRM capabilities to influence flexible execution of services specify that AI-enabled service logics are aligned with service innovation (Daugherty et al., 2019; Lusch & Nambisan, 2015). Finally, this study contributes to the research on business values of AI (Mariani et al., 2022; Wamba-Taguimdje et al., 2020) by clarifying the importance of AI-enabled capabilities and their impact on realizing value creating strategies though service flexibility and innovation. We investigates contemporary assets, for instance, dynamic-process driven capabilities (Grover et al., 2020; Kortmann et al., 2014), and obtained the influence of these capabilities on overall performance of the businesses. For instance, customer related adaptation techniques and several improvements in the current model of deliveries.

6.2. Practical implications

This study offers multiple practical implications. First, this study has established that AI-enabled CRM capability in healthcare is unique and provides a competitive position to organizations. This finding will guide service providers and technology vendors with various measures to ensure patients use AI-enabled devices and platforms. Second, AI-based organizational capacities that provide efficient medical treatment remain crucial for initiating and maintaining relationships with the patient. The healthcare sector requires a candid configuration of clinical resources and patient-related services (Nair et al., 2013). In this study, the AI-CRM capabilities emerge as a different organizational routine that establishes and maintains customer relationships. For instance, AI-based genome factors, histopathological slides, and drug administration would enhance clinical capability and AI-enabled CRM capabilities. This study suggests developing AI-driven prescriptions, image analysis, speech recognition, and understanding variant classification. We recommend that clinicians, pathologists, radiologists, and healthcare managers focus on AI-enabled techniques (e.g., applying deep learning in clinical genomics) to improve clinical capability. Third, we recommend a service-oriented culture in healthcare based on AI-driven tools and platforms. However, developing a service-oriented culture and maintaining healthy patient relationships remains challenging. This study recommends implementing AI-based tools, wearable devices, and platforms to create a different healthcare service ecosystem. For example, patient health monitoring, heart rate tracking, and health alertness through AI-enabled devices should. Fourth, this study established that AI engagement capability remains crucial for establishing and maintaining a long-term relationship with healthcare customers. The dark side of AI (e.g., privacy invasion) needs to be addressed to maintain the relationship with the patients (Kumar et al., 2021). Engagement with AI is a different form, requiring a cognitive standpoint. Thus, findings guide healthcare managers to understand the dynamics of engagement with AI-based treatment and services. We recommend carefully exploring AI engagement as an ability of healthcare practitioners and managers. Understanding the importance of patient engagement with AI-based interventions in medical care, service providers must utilize internal and external resources to increase their abilities in community medicine. The community medicine programs must include awareness and training programs to utilize AI-based tools and devices. For example, lack of awareness and privacy invasion are essential factors for the underutilization of "KhushiBaby," a device to track immunization data (MOHFW, 2020). This finding suggests developing such capabilities by integrating such training and awareness with community healthcare programs. Medical professionals (doctors, nurses, and para-medical staff) must be able to explain the benefits of AI and ensure trust when using such tools. This study's findings guide healthcare practitioners to redesign bedside engagement (by understanding AI-based clinical procedures and diagnosis) and improve access to health information.

Finally, healthcare managers and practitioners concerned with effective and efficient relationship management must understand the technicalities of AI and should take an early lead in developing AI-CRM capabilities. Patients suffering from HIV/AIDS, cancer, hemophilia, or cardiac diseases require multiple visits and interactions with the hospital system. The applications of medical analytics, image processing, wearable devices, and various services through AI-based tools and platforms would develop a superior capability and facilitate remaining completive. Therefore, healthcare practitioners and policymakers need to focus on three AI-CRM capability dimensions to attain customer service flexibility and, in turn, increased service innovation. These initiatives subsequently improve physical and mental health, customer satisfaction, loyalty, and experience.

6.3. Limitations and future directions of research

This study has certain limitations. First, the data collection was limited to Indian healthcare professionals. Notably, they were part of a process that used AI-enabled technology, albeit in its developing phase. The proposed conceptual framework may be examined by collecting data from another context. Second, this study established three dimensions of AI-enabled CRM capability in healthcare. However, other dimensions may emerge which should be explored. Third, engagement with AI-enabled technologies are explored. However, many other psychological variables may affect this relationship. We urge to explore the effects from "cognitive capability" perspectives. Fourth, prior research indicates that flexibility does not accumulate, and there could be other types of flexibility to cope with environmental dynamism. This study has conceptualized the sequential relationship of customer service flexibility and examined it as an antecedent of service innovation. Additional research may be conducted with regard to the other types of service providers' flexibility.

7. Conclusion

This study presents an overview of AI-enabled CRM capability in healthcare vis-à-vis their impacts on customer service flexibility and service innovation. We employed multiple theoretical lenses infused with semi-structured interviews and proposed and tested the conceptual framework. The results confirmed the proposed dimensionality of AI-CRM, which affects customer service flexibility and innovation. Healthcare delivery systems that rely on AI-enabled CRM capabilities are more likely to increase the adaptability towards the dynamic conditions of the market and exhibit a flexible system. Consequently, the healthcare delivery system increases the customer experience quality, attains superior performance, and becomes sustainable.

CRediT authorship contribution statement

Pradeep Kumar: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Sujeet Kumar Sharma:** Conceptualization, Methodology, Validation, Formal analysis, Writing – review & editing, Visualization. **Vincent Dutot:** Supervision, Validation, Formal analysis, Writing – review & editing.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ijinfomgt.2022.102598.

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