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Cognitive engagement with AI-enabled technologies and value creation in healthcare

Pradeep Kumar[1] | Demetris Vrontis[2,3] | Fabiano Pallonetto[4]

[1]Birla Institute of Management Technology (BIMTECH), Greater Noida, India

[2]Department of Management, University of Nicosia, Nicosia, Cyprus

[3]S P Jain School of Global Management – Dubai Campus, Dubai, United Arab Emirates

[4]School of Business, Institute of Innovation, Maynooth University, Kildare, Ireland

Correspondence
Pradeep Kumar, Birla Institute of Management Technology (BIMTECH), Greater Noida, India.
Email: pradeep.kumar@bimtech.ac.in; pradeep.kumar14fpm@iimranchi.ac.in

Abstract

Despite the potential for artificial intelligence (AI)-enabled technologies in healthcare, their benefits are limited owing to the numerous challenges of cognitive engagement. This research paper explores the factors of "cognitive engagement with AI-enabled technologies" and its impact on the customers' benefits and value creation. A mixed-method study was utilized in the Indian health-care setup where AI-based technology is developing. The qualitative findings shed light on the factors of cognitive engagement with AI-enabled technologies. Grounded on the theories of customer benefit, an integrative framework of customer-perceived financial, experiential, psychological, and functional benefits, alongside perceived instrumental and terminal values, was developed. The quantitative findings of PLS-SEM explain the dynamics of the patients' cognitive engagement with AI-enabled technologies. The results enrich a more nuanced understanding of how the patient benefits of AI applications have different impacts on perceived value. The study concludes with theoretical and practical implications.

1 | INTRODUCTION

In recent years, artificial intelligence (AI)-enabled technologies and devices (e.g., heart rate tracking, sleep recording, blood pressure monitoring, exercise control, and nutrition) have gained momentum (Talukder et al., 2021). Wang et al. (2018) argue that AI-enabled technologies are relevant in developing countries where the infrastructure of health-care systems can be adjusted to meet heterogeneous needs. For instance, India's health-care ecosystem has been at the vanguard of realizing the importance of AI-enabled technologies in service operations and deliveries. The report of an international data corporation indicated that India's AI market is expected to reach $7.8 billion, growing at a CAGR of 20.2% by the end of 2025 (NAH, 2022). Some reports indicate that fitness bands, for instance, comprise 92% of wearable health-care devices, while Fitbit remains a significant player with more than 20% of the market share (Ferreira et al., 2021; NAH, 2022). The government agencies demonstrate that businesses in India will accelerate the adoption of AI-centric applications (Chatterjee et al., 2021). While many organizations have created a new product category of AI-based devices for Indian customers, increased demand for such devices and alertness for health have provided opportunities for innovation in new product lines (Khanra et al., 2020; Palanica & Fossat, 2020). These innovative devices have changed the market trends and have accelerated the patients' intrinsic motivation based on new service propositions (Lui & Lamba, 2018). Several companies such as IBM, Microsoft, and Google are now developing partnerships with private and government hospitals in India to strategize on the implementation of AI at various levels (NSSO, 2020). However, these companies cannot afford to imitate the Western hemisphere and yet expect rapid success in the Indian health-care market. Identifying the factors of cognitive engagement as a push for customers is essential to break into the Indian health-care market and attain a sustainable competitive advantage (Balakrishnan & Dwivedi, 2021; Kumar et al., 2023).

Many counties, including India, influenced by market trends of automated medical devices, have begun identifying innovative methods of managing healthcare across different age groups (Khanra et al., 2020). Notably, AI-enabled wearable devices are increasingly being adopted by Indian consumers for the enhancement of everyday health and lifestyle patterns. They have become commonplace in the market, thereby affecting their commercialization cycle and is creating business viability (Paschen et al., 2019). Moreover, value creation in healthcare remains crucial to meet the fast-changing needs of the patients in a cost-effective and efficient manner (Esmaeilzadeh, 2020). AI-enabled technologies like virtual health assistants, early diagnosis of fatal blood diseases, and automation of redundant health-care tasks allow for an understanding of the patients' conditions, and, thus, generate value-creation capabilities. They promise better care and higher returns while creating new service models for inclusive growth in healthcare. The health-care market has observed that value-creation strategies demonstrate a better relationship with patients and an improved performance (Kumar et al., 2023). Scholars argue that customer value analysis is a key theoretical and empirical issue in marketing (Almquist et al., 2016; Heinonen et al., 2013; Kumar et al., 2021). Several marketing-based theories have been used, such as means-end-chain, customer-dominant logic, and managerial dynamic cognitive capabilities (Chen et al., 2017; Heinonen et al., 2013; Zeithmal, 1988) thus far to explain the value creation processes. Some authors have shown how a strategic focus could influence customer-perceived benefits and create value (Chen et al., 2017). Moreover, AI-enabled technologies can improve a firm's understanding of customers, enable convenient delivery and offer personalized attention, and, thus, create value for them (Leslie, 2019; Siachou et al., 2021). Therefore, demystifying the customers' cognitive perspectives with value creation and capture remain crucial for company success as well as inclusive growth (Heinonen et al., 2013; Lemon & Verhoef, 2016). Nevertheless, cognitive underpinnings of AI-based service products from value creation perspectives have yet to be explored (Eggers & Kaplan, 2013).

Some studies have explored AI-enabled technology's role in rapidly influencing health-care service delivery (Chinchanachokchai et al., 2021; Lui & Lamba, 2018; Mariani et al., 2022). These studies focused on the impact of AI-enabled service delivery on organizational performance and outcomes without considering factors of adoption, perceived benefit, and value creation from a cognitive perspective of the AI-enabled technology. Extant marketing literature described several models of customer perceptions, the effects of the attributes of overall buyer-perceived values, perceived customer benefits, and experiential values (Bolton et al., 2018; Galati et al., 2021). Scholars have also shown how improving customer benefits can create value (Almquist et al., 2016; Chatterjee, Chaudhuri, & Vrontis, 2022). Specifically, "cognitive engagement" is anticipated to contribute to value formation in the context of AI-enabled technologies, thereby affecting sustainable and innovative performance in healthcare (Ferreira et al., 2021; Mariani et al., 2022). Researchers have pointed out that cognitive engagement ensures that products build customer experience (Zomerdijk & Voss, 2010). Bowden et al. (2017) argue that companies are concerned with engaging customers cognitively to facilitate personalized experiences throughout the product lifecycle. Thus, AI-enabled technologies have led to an increased competence, and the customer's lens of cognitive engagement and value creation is long-ignored. Building upon the concept of customer benefits and value creation (Jayawardena et al., 2022; Pereira et al., 2022), we aim to detail how cognitive engagement with AI-enabled technologies is constituted and its potential impact on the perceived benefit and value creation.

The objective of our study has been to identify the constituents of cognitive engagement with AI-enabled technologies by the patients and examine their impact on perceived benefit and value creation.

The following research questions primarily guided us:

1. What factors constitute the patients' "cognitive engagement with AI-enabled technologies"?
2. To what extent does cognitive engagement with AI-enabled technologies influence perceived benefits and value creation?

The remainder of the paper is structured as follows; Section 2 presents a literature review of AI-enabled technologies and their cognitive engagement in healthcare. Section 3 provides the qualitative study and synthesizes the findings. After that, we offer the methods and results of the quantitative research. Finally, we present the implications for further theory and practices, and future avenues of research are sketched.

2 | LITERATURE REVIEW

AI has affected almost all spheres of human lives. It has become an engineering means to gain market insights through adaptive learning. Mariani et al. (2022) define AI as "computational agents that act intelligently to perceive, learn, memorize, reason, and problem-solve towards goal-directed behavior." Researchers posit that AI can be utilized for various innovative marketing decisions, for instance, changes in marketing models, predictive retailing, sales processes, customer services, and behavioral changes (Kumar et al., 2023; Wang et al., 2020; Zhang et al., 2021). Substantial engagement with AI-enabled devices will accommodate the customers' intent and emotions, thereby giving businesses a sustainable competitive advantage by driving better targets and closing sales (Hollebeek et al., 2016; Mikalef et al., 2020). From the customers' perspective, the adoption of AI is no longer restricted to home appliances, but is also used for patients as health-care consumers are increasingly using several tools and devices for monitoring their health. Given the tremendous support from governments regarding technology-friendly policies, licensing for private players, and concern for privacy, the health-care market has grown significantly in the past few years (Mckinsey, 2021; NSSO, 2020; Wearn et al., 2019). Lastly, the COVID-19 pandemic has produced silver linings of AI-based applications and innovations in the health-care sector (Esmaeilzadeh, 2020; Palanica & Fossat, 2020).

2.1 | AI-enabled technologies in healthcare

The health-care industry is ripe for significant changes and provides tremendous opportunities to leverage technology in the deployment of more effective and efficient inpatient care interventions. It has witnessed the applications of AI in improved clinical productivity, offering of customizations to each patient, and its effectivity in providing a seamless patient experience like queue-less registration, AI-powered self-service portals, and automatic calls for health checkups (Esmaeilzadeh, 2020; Kumar et al., 2023). Although, it is difficult to completely replicate the contemporary health-care delivery models which depend on human reasoning, patient-clinician communication, and patient relationships, many AI-enabled technologies and devices have automated treatment procedures, affected the health-care supply chain, and have offered personalized care (Chatterjee, Chaudhuri, & Vrontis, 2022; Kumar et al., 2023). The innovative applications of AI in medical devices fall into two major categories: managing chronic diseases and medical imaging. Besides, many companies are integrating AI and the Internet of Things (IoT) to address emergency health situations, remotely monitor patients, conduct early diagnostics, and to predict the women's fertility, and are also developing AI-based wearables for the blind and visually impaired individuals (Wu et al., 2016). For instance, Philips healthcare has developed innovative solutions for continuous monitoring of patients and Medtronic has developed solutions for monitoring diabetic conditions. Talukder et al. (2021) argue that AI-enabled services are expected to revolutionize the Indian health-care market. On the other hand, intrinsic motivation and psychological engagement with such devices and technologies would influence the patient's buy button (Bircan & Sungur, 2016). Thus, AI-enabled technologies have truly empowered patients to make better and more informed decisions regarding their health. This era of inclusive growth, characterized by AI-enabled technologies, has attracted significant attention from scholars to describe the phenomena from marketing, strategic, and psychological dimensions (Mariani et al., 2022; Vrontis et al., 2022). Some authors have emphasized the implementation of responsible AI in healthcare for value creation and market performance (Kumar et al., 2021; Wang et al., 2020). Responsible AI integrates ethical and accountable use of AI-based tools to implement the strategic planning process (Wang et al., 2020). It is a tool that helps organizations improve trust and minimize privacy invasion.

2.2 | Cognitive engagement with AI-enabled technologies

An overview of "engagement"-related conceptualizations indicates several sub-forms, including "brand engagement," "customer engagement," "consumer engagement," and "customer brand engagement" (Bowden et al., 2017; Christofi et al., 2018; Heinonen, 2017). Most of the reviewed conceptualizations explain engagement from an intra-individual perspective through an organizational lens. Brodie et al. (2011) opine that the "interaction between a specific subject and object is essential for emerging relevant engagement." Scholars suggest that the dimensions of "engagement" may vary across business contexts and point out the conceptual distinctiveness from "cognitive engagement" (Hollebeek et al., 2016). Scrutiny of research in several disciplines indicates that cognitive engagement is an essential facet of "customer engagement leading to acceptance of service products and greater market value" (Bowden et al., 2017; Graffigana et al., 2015). While researchers accept that cognitive engagement as a specific form of engagement is relevant in marketing, studies underlying the dynamics of "cognitive engagement" are limited to date. Hollebeek et al. (2016) clarify the specificity of cognitive engagement as a customer's thoughts, concentration and interest levels in specific service products. Therefore, cognitive engagement as a distinct construct connotes the psychological investment and effort to learn and understand a particular product.

Furthermore, cognitive engagement arises from intrinsic motivation and interest which a customer shows toward a particular product (Dessart et al., 2015; Graffigana et al., 2015). Intrinsic motivation indicates inherent satisfaction from a specific product or service, thereby further driving consumption. For example, if a patient is interested from within toward a particular device or tool without an external reward, he is likely to engage with it. Scholars have explored the concept of cognitive engagement across contexts like education, tourism, and healthcare. They suggested that it creates an opportunity for organizations to market their products (Barello et al., 2016; Christofi et al., 2018; Schwappach, 2010). An implicit overview of cognitive engagement in extant literature has been advocated from the customer-dominant (CD) logic (Heinonen et al., 2013). The CD logic highlights the importance of customer co-creation of experiential value. Many authors emphasize that customers who are cognitively engaged with the products will buy more and will also recommend them to others (Chen et al., 2017; Pantano & Pizzi, 2020). Some studies found that cognitive engagement contributes to knowledge and skill development, which results in the profitability of the companies (Wang et al., 2020). The patient's involvement in adopting and learning new technologies fosters their self-management skills. As such, cognitive engagement remains crucial to legitimize the patient's clinical and psychological needs, thereby resulting in better professional interventions for the self-management of diseases. In this way, cognitive engagement with AI-enabled technology facilitates learning about one's health, compares treatment modalities, and shares relevant information with clinicians (Kim, 2015; Wimmer et al., 2016).

The literature on the medical application of AI-enabled technologies indicates the positive impact of such tools and devices on health-care service providers and patients (Esmaeilzadeh, 2020; Khanra et al., 2020). However, despite profuse development in the domain of health-care practitioners, academic inquiry into "cognitive engagement with AI-enabled technologies" has yet to catch up. The existing literature describes various models and frameworks to explain the customers' acceptance of new technologies and the adoption factors, such as the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). Academic research has accepted that AI is different from previous technology waves, and many customers of AI have fear and are naturally uncomfortable with such technologies (Lui & Lamba, 2018; Rahman et al., 2016). Therefore, enhancing their knowledge and skill in handling these products will lead to better utilization of the AI-enabled technologies to what they are capable of. It is helpful for companies to explore AI-driven business capabilities and

TABLE 1 Interview response and coding.

Sample quotes	Coding
[...] *When I look at these advanced technology, it is a tool to be used in achieving a healthy society. It will also upgrade the quality of care as per many western counties. These devices and platforms give a feeling of being modern. The platforms are best suited to a segment of people, mostly urban elite.* "[...] we can internalize the modern developments in healthcare which are the aspects of 'western-care' and much relevant in our country. It is very important to understand and adopt the symbolic trappings modern societies."	*Medical modernization* [% agreement 72.61]
"[...] Of-course, it meets our cultural needs. It reduces many barriers within societal groups and attempts to provide high quality of care regardless of cultural barriers." "[...] regardless of language barriers, AI applications and devices for our health attempts to interact for high level of satisfaction. These platforms engage the community without considering the race or ethnicity. Proficiency of English or local languages. The aim is high quality care for all."	*Cultural competence* [% agreement 71.63]
[...] *AI-based devices are making the lives easier. It could shift our mood, perspectives, and behavior. AI applications are a major tool for emotional connectedness. As a platform to connect not only with 'hospitals and physicians' but also inspire, educate, and enable the practices that are meaningful to us. For example, the 'Chatbots' provide a platform wherein we can fully express our expectations and complaints.* [...] *It shapes our 'mental state' and we feel that we can cope with immense stress, these devices enhance trust and ensure to reduce the complexities. Thus it's a concern with quality-life, positive feeling, and autonomy.*	*Emotional well-being* [% agreement 68.31]
[...] *I feel; it is designed for "me". I am using "Fitbit" for last one year. I can monitor my health all the time by Fitbit. Last year, I used "Move ECG". The convenience and adjustments as per my schedule are the best part. Physical visits are reduced and it can be used irrespective of the location.* [...] *we find these technologies with several flexibilities. I must say, it can bring hospital to home. The range of multiple use, the convenience in use, and most importantly- personalized as per the individual requirements.*	*Functional flexibility* [% agreement 77.67]

marketing implications through the lens of cognitive engagement (Wearn et al., 2019). Many authors argue that engagement with AI applications is affected by various sociological, psychological, and epistemological factors (Kok et al., 2013; Warwick, 2013). Research in health psychology (Graffigana et al., 2015) indicates that various motivational factors are responsible for cognitive engagement with AI-enabled technologies.

3 | QUALITATIVE STUDY AND FINDINGS

This study utilized a mixed-method approach to obtain robust findings and incorporated multiple views to explore the study phenomena (Venkatesh et al., 2013). First, a qualitative research method (Creswell, 2006) was adopted to provide a detailed description of the phenomenon and to inform the findings of the next stage of the study. Bluhm et al. (2011) suggest that a qualitative study aims to describe the phenomena via interpretations and draws information from multiple sources in a natural setting. To explore and understand the psychological antecedents of "cognitive engagement with AI enabled-technologies", we utilized an interpretive approach. This approach focuses on interpreting the concepts (Harrison & Reilly, 2011). The users of AI-enabled tools and platforms who consented to the academic study were selected as respondents. Relying upon the suggestions of Plakoyiannaki and Budhwar (2021), we selected the respondents in real-time and from a contextually relevant setting (a total of 52 participants, 22 female users and 30 males, aged between 21 and 55 years were chosen).

The data collection procedure involved semi-structured interviews conducted during April–June 2022. The duration of the interviews was around 35–55 min. The interviews were also repeated to improve reliability and clarity and to counter-balance the weakness of a single response (Creswell, 2006; Patton, 1990). They were recorded to improve the accuracy of data collection as it made the interviewer more attentive toward the interviewee (Patton, 1990). The data collection procedure was discontinued when the researchers could predict the informant's response. The data analysis was done utilizing the NVIVO 10 software (Welsh, 2002). We transcribed the various reactions and fed them into the software package.

Further, a thematic analysis was employed to interpret the facets of cognitive engagement. Following the recommendations of Aronson (1995), significant patterns were identified and collated into initial themes. Two independent coders performed the coding process. They initiated the process without any pre-set code but developed and modified it during the coding process (Braun & Clarke, 2006). The recommendation of Fleiss (1971) was utilized to ascertain the inter-coder reliability level. Fleiss's kappa ($k = 0.91$) was obtained with the extent to which the observed agreement value exceeded the expected value. Finally, we calculated the percentage of agreements based on themes between the coders (Table 1). We considered a minimum threshold of 50%, as recommended by the Boyatzis (1998) formula.

3.1 | Convergence of findings

This section outlines the synthesis of the qualitative findings. We employed a bottom-up approach, whereby, the key dimension of "cognitive engagement with AI-enabled technologies" was identified (Table 2). Based on the richness of the concepts observed for cognitive engagement with AI-enabled technologies, we present an outline of the specific dimensions (Figure 1).

TABLE 2 First-order factors of cognitive engagement with AI-enabled technologies.

First-order factors	Operational definitions
Medical modernization (Daugherty et al., 2019)	Medical modernization is conceptualized as an inherent process of changing the mode of achieving a healthy population from traditional to modern, rational, and scientific ones.
Cultural competence (Barello et al., 2016).	Cultural competence refers to the ability of service providers to deliver effective healthcare that meets the social, cultural, and linguistic needs of patients
Emotional well being (Pantano & Priporas, 2016).	Emotional well-being refers to the practices of stress management, good feelings, and life satisfaction that affect emotions
Functional flexibility (Brozovic et al., 2016).	Functional flexibility refers to the number of tasks and features offered by a service product that improve customer experience

3.2 | Hypothesis formulation

3.2.1 | "Cognitive engagement with AI-enabled technologies" and patient benefits

AI-enabled devices are widely used in the process of patient care. Researchers posit that "cognitive engagement with AI-enabled technology" has several positive outcomes. AI-enabled technologies are viewed as a practical resource that could facilitate the care process for patients. Therefore, patients perceive several benefits from engagement with AI-based devices (Khanna et al., 2012). Recent studies have emphasized that "cognitive engagement with AI-enabled technologies" has a series of benefits, including functional, financial, experiential, symbolic, emotional, and psychological benefits (Rahman et al., 2016; Swar et al., 2017). Many authors (Parry, 2001) have outlined the categories of perceived benefits as functional, experiential, financial, and psychosocial. The patients utilize AI applications and devices to perform the necessary tasks, for emotional connectedness, and for their self-image and intelligence. Thus, it is hypothesized as.

> **H1.** "Cognitive engagement with AI-enabled technologies" has a positive and significant impact on "financial benefit" (H1a), "experiential benefit" (H1b), "psychological benefit" (H1c), and "functional benefit" (H1d).

3.2.2 | Patient benefit and value creation

Value creation is an essential element of a service provider's competitive strategy (Gronroos & Gummerus, 2014; Heinonen et al., 2013). Chen et al. (2017) have explored "cognitive engagement" with service products as a unit of analysis for value creation. We argue that patient benefits as a function of "cognitive engagement with AI-enabled technologies," tools, and platforms are important to explore. The patients' "cognitive engagement with AI-enabled technologies" corresponds to a series of benefits due to a "cost reduction" and various offerings, thereby creating value. The AI applications allow one to conveniently interact with the products. The AI-based tools and platforms create the instrumental value (e.g., reduced hospitalization, queue-less registration) and terminal value (e.g., service design, nostalgia) (Almquist et al., 2016). Scholars (Magids et al., 2015) found that such technologies provide emotional-connection-driven opportunities. Such connections with AI applications create a sense of "freedom" and "belongingness." They influence the patient's behavior and create "terminal value." Thus, "cognitive engagement with AI-enabled technologies" provides a series of benefits that could be perceived as offering more terminal value.

Thus, the following hypotheses are developed:

> **H2a–H2d.** Perceived benefits (financial, experiential, psychological, functional) significantly affect instrumental value.

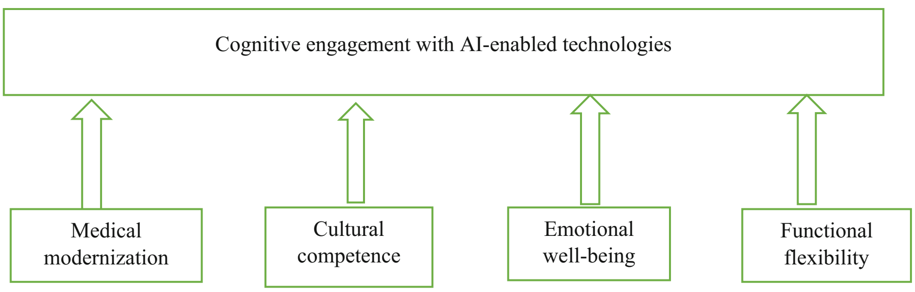
> **H3a–H3d.** Perceived benefits (financial, experiential, psychological, functional) significantly affect terminal value.

Thus, the following research framework (Figure 2) is proposed:

4 | QUANTITATIVE DATA COLLECTION AND ANALYSIS

A quantitative study was conducted using a survey of health-care customers (patients). The survey instrument (Table 3) was developed from

FIGURE 1 The constituents of "Cognitive engagement with AI-enabled technologies."



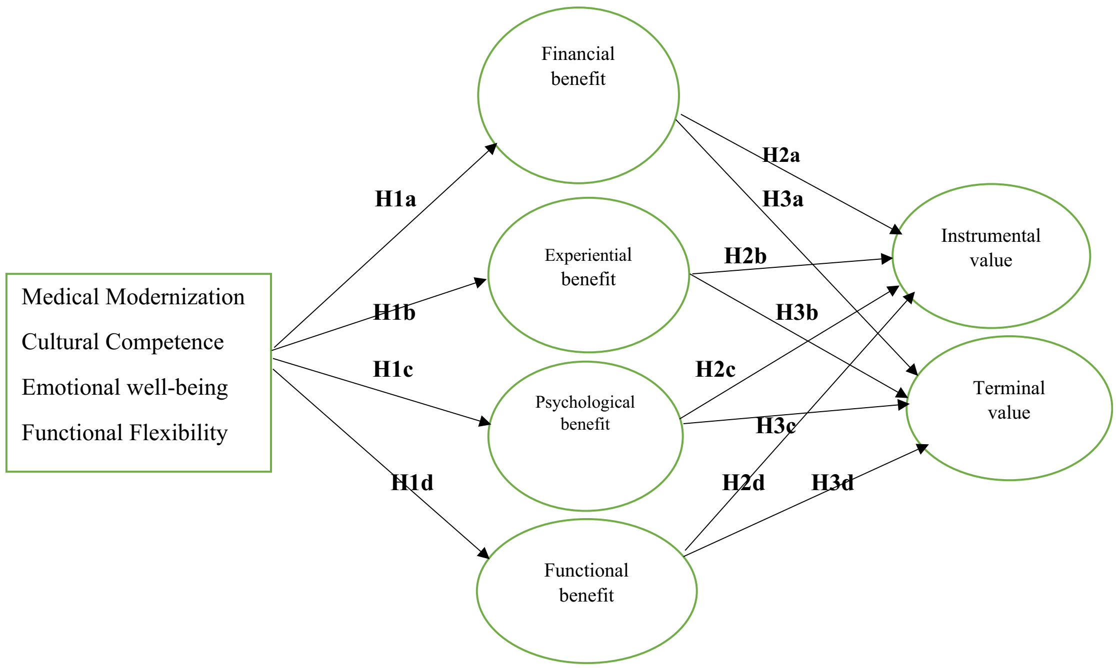


FIGURE 2 Summary of hypothesis and proposed model.

the extant literature. Besides, a few items were taken from the output of interviews. We first examined the content validity of the questionnaire with the help of seven professors and five medical professionals. The potential respondents for the study were approached through personal contacts, and emails were sent asking them to participate in the survey. The survey instrument was pre-tested with 60 responses. Six items of the scale (MM4, EMW1, FFX1, FNB1, FNB2, and FUB2) were dropped due to improper loadings. The final survey was conducted with the pre-tested instruments, and 330 participants (58% male) in India joined the study. The five-point Likert scale (1 = strongly disagree to 5 = strongly agree) was used in the survey.

5 | RESULTS

This study utilized structural equation modeling (SEM) with partial least squares (PLS-SEM) to test the hypothesized model (Figure 2) (Hair et al., 2016). Smart PLS (v.3 2.6) software was used to conduct the PLS analysis (Ringle et al., 2022). We first assessed the outer model and examined the internal consistency (composite reliability, CR), convergent validity, and discriminant validity. We found that Cronbach's (1951) alpha was significant ($\alpha > 0.70$). The CR values were above the recommended values of 0.7 (Table 4). The average variance-extracted (AVE) values were also above the recommended value of 0.5 (Hair et al., 2016). The discriminant validity was established by two methods (Table 5). Firstly, the square root of AVE was greater than its highest correlation with any other construct (Fornell & Larcker, 1981). Second, the outer loadings of each construct were greater than their cross-loadings with other constructs (Hair et al., 2016).

5.1 | Common method bias

Researchers suggest addressing the issues of common method bias in the studies based on surveys or perceptions (Craighead et al., 2011). The authors informed the respondents about the academic nature of the study and assured them that information would be confidential (Podsakoff et al., 2003). Further, Harman's single-factor test accounted for 23.07% of the variance for the first factor. Next, we conducted the variable marker approach suggested by Malhotra et al. (2006) which indicated a difference of less than 0.03 between CMV-adjusted and the construct's correlations. The marker variable (customer experience) was used, which was theoretically distinct from the current model. The marker variable (CEx) was part of another project by the authors which is not reported in the current paper. Based on the above findings, it is clear that method bias is not a concern in the present study.

5.2 | Second-order factor validation

In this study, CogAI is conceptualized as a higher-order factor with the four sub-dimensions as "Medical modernization" (MMD), "Cultural competence" (CLC), "Emotional well-being" (EWB), and "Functional flexibility" (FFX). Relying on the suggestions of Sarstedt et al. (2019), the authors adopted the repeated item indicator approach to assess the second order factor. Firstly, the convergent validity and discriminant validity of all the first-order factors were established. The construct level VIF values for each construct indicate that multicollinearity does not exist. The results indicate that medical modernization

TABLE 3 Survey instrument.

Measurement items
Medical modernization (*MMD*) (Daugherty et al., 2019), $\alpha = 0.851$
Embracing AI helps in societal changes (MM1)
We use AI application to become modern (MM2)
The AI applications indicate a scientific movement of the society (MM3)
AI applications vary useful in health-related developments (MM4) (interview output)
AI applications are used like western counties (MM5)
Cultural competence (*CLC*) (Mariani et al., 2022), $\alpha = 0.813$
AI applications support the cultural values (CLC1)
AI application reduces the cultural barriers (CLC2)
AI applications support cultural differences (CLC3)
AI applications take care of language and communication issues (CLC4)
Emotional well-being (*EMW*) (Magids et al., 2015), $\alpha = 0.819$
AI applications feel good (EMW1)
AI applications provides life satisfaction (EMW2)
AI applications affects healthy behavior (EMW3)
AI application strives to reach our goals (EMW4) (interview output)
Functional flexibility (*FNX*) (Brozovic et al., 2016), $\alpha = 0.813$
AI applications provide a range of services (FFX1)
AI applications can be modified as per changing requirements (FFX2)
AI applications can be used at a convenient location (FFX3)
The features offered of AI applications can be adjusted to fit the needs (FFX4)
Financial benefit (*FNB*) (Chen et al., 2017), $\alpha = 0.871$
AI applications are cost-saving (FNB1)
AI applications can be used at multiple locations without extra costs (FNB2)
The features of AI save our money (FNB3) (interview output)
AI applications provide support service through without additional expenses (FNB4)
AI applications reduces operational cost (FNB5)
Experiential benefit (*EXB*) (Chen et al., 2017), $\alpha = 0.818$
AI applications offer very attractive features (EXB1)
AI applications provide very good experience (EXB2)
AI applications allows to create personalized contents (EXB3)
AI applications facilitate a quality communication with medical professionals (EXB4)
AI offers self-explanation of medical problems (EXB4)
Psychological Benefit (*PYB*) (Chen et al., 2017), $\alpha = 0.815$
AI applications provide medical opinion as per the usage behavior. (PYB1)
AI applications are very appealing (PYB2)
AI applications can keep up with trends (PYB3)
AI applications can expand the social circle.(PYB4)
Functional benefit (*FUB*) (Chen et al., 2017), $\alpha = 0.873$

(Continues)

TABLE 3 (Continued)

AI applications offer an easy to use interface (FUB1)
AI applications provide classified contents (FUB2)
AI applications provide categorized features. (FUB3) (interview output)
AI applications provide a constant health monitoring (FUB4)
Instrumental value (*INV*) (Almquist et al., 2016), $\alpha = 0.891$
AI applications increase our abilities (INV1)
AI applications increase the imagination power (INV2)
AI applications can inspire our curiosity (INV3)
AI applications can increase our knowledge (INV4)
Terminal value (*TNV*) (Almquist et al., 2016), $\alpha = 0.794$
AI applications helps feel relaxed and happy (TNV1)
AI applications enhances our confidence.(TNV2)
AI applications improve our healthier feelings (YNV3)
AI applications mature view of life. (TNV4)

($\beta = 0.494$, $t = 7.983$, and $p = .000$), cultural competence ($\beta = 0.858$, $t = 52.33$, and $p = 0.000$), emotional well-being ($\beta = 0.780$, $t = 29.36$, and $p = .000$), and functional flexibility ($\beta = 0.788$, $t = 28.068$, and $p = .000$) have a positive association with the CogAI. Moreover, when loaded with a repeated indicator approach (Figure 3), they resist convergence into a single factor because they are multi-dimensional constructs. The low AVE for "CogAI" (0.291) confirms its multi-dimensionality. The results of PLS predict indicate that only three items have low values of RSME_PLS as compared to RSME_LM values. Thus, the results confirm the second-order conceptualization of CogAI (Sarstedt et al., 2019).

5.3 | Hypothesis testing

We used the bootstrapping procedure to test the hypothesized model (Figure 1). The resampling procedure indicates that the loadings were significant. We assessed the multicollinearity of each predictor set. The VIF values (Table 2) show a lower value than 3.5, as recommended by Hair et al. (2016). The structural model explains the 53.2% variance in "instrumental value" and the 47.52% variance in "terminal value." The blindfolding procedure demonstrates positive Q^2 values for INV ($Q^2 = 0.096$) and TNV ($Q^2 = 0.139$) indicating that the predictive relevance is satisfactory. The authors relied on the recommendations of Henseler et al. (2014) to show the standardized root-mean-square residuals (SRMR) as an index for model validation. The SRMR values (0.07) were less than the threshold of .10 (Hair et al., 2016). Besides, the results (Figure 4) indicate all the hypotheses of the study are supported (Table 6) except H2a (FNB → INV) ($\beta = 0.031$, $t = 0.536$, and $p = .7425$), H3a (FNB → TNV) ($\beta = 0.031$, $t = .536$, and $p = .589$), and H3b (EXB → TNV) ($\beta = 0.115$, $t = 1.931$, and $p = .054$).

TABLE 4 Reliability and validity indices.

	VIF	Outer loadings	T-values	Construct reliability	AVE
Medical modernization (MMD)				0.791	0.586
MM 1	1.358	0.743	17.499		
MM2	1.264	0.766	20.653		
MM3	1.214	0.675	13.546		
MM4 (Dropped)					
MM5	1.242	0.641	10.912		
Cultural competence (CLC)				0.831	0.593
CLC1	1.197	0.750	23.782		
CLC2	1.184	0.742	26.929		
CLC3	1.132	0.712	24.388		
CLC4	1.128	0.734	26.322		
Emotional well-being (EMW)				0.812	0.589
EMW1 (Drooped)	1.42				
EMW2	1.384	0.707	21.049		
EMW3	1.282	0.743	21.531		
EMW4	1.362	0.761	26.711		
Functional flexibility (FNX)				0.822	0.581
FFX1 (Dropped)					
FFX2	1.221	0.734	23.923		
FFX3	1.126	0.744	23.826		
FFX4	1.137	0.737	23.683		
Financial benefit (FNB)				0.835	0.566
FNB1 (Dropped)					
FNB2 (Dropped)					
FNB3	1.126	0.640	9.174		
FNB4	1.158	0.792	16.635		
FNB5	2.446	0.765	13.571		
Experiential benefit (EXB)				0.798	0.582
EXB1	1.144	0.787	26.908		
EXB2	1.101	0.690	13.532		
EXB3	2.646	0.616	10.037		
EXB4	1.137	0.751	21.122		
Psychological benefit (PYB)					0.584
PYB1	1.42	0.686	14.028	0.811	
PYB2	1.384	0.740	20.744		
PYB3	1.282	0.706	17.302		
PYB4	1.362	0.734	19.887		
Functional benefit (FUB)				0.812	0.546
FUB1	1.101	0.726	15.366		
FUB2 (Dropped)					
FUB3	2.441	0.828	33.003		
FUB4	1.107	0.678	12.615		
Instrumental value (INV)				0.798	0.597
INV1	1.42	0.729	18.063		
INV2	1.384	0.740	19.290		
INV3	1.282	0.712	17.385		

TABLE 4 (Continued)

	VIF	Outer loadings	T-values	Construct reliability	AVE
INV4	1.362	0.758	23.021		
Terminal value (INV)				0.801	0.579
TNV1	1.52	0.706	15.514		
TNV2	1.381	0.740	18.540		
TNV3	1.271	0.702	16.007		
TNV4	1.334	0.751	22.854		

TABLE 5 Discriminant validity.

	Cog AI	EXB	FNB	FUB	INV	PYB	TNV
Cog AI	0.524						
EXB	0.222	0.714					
FNB	0.205	0.562	0.732				
FUB	0.19	0.519	0.412	0.746			
INV	0.181	0.44	0.304	0.438	0.735		
PYB	0.194	0.521	0.366	0.499	0.465	0.717	
TNV	0.154	0.373	0.277	0.429	0.883	0.409	0.725

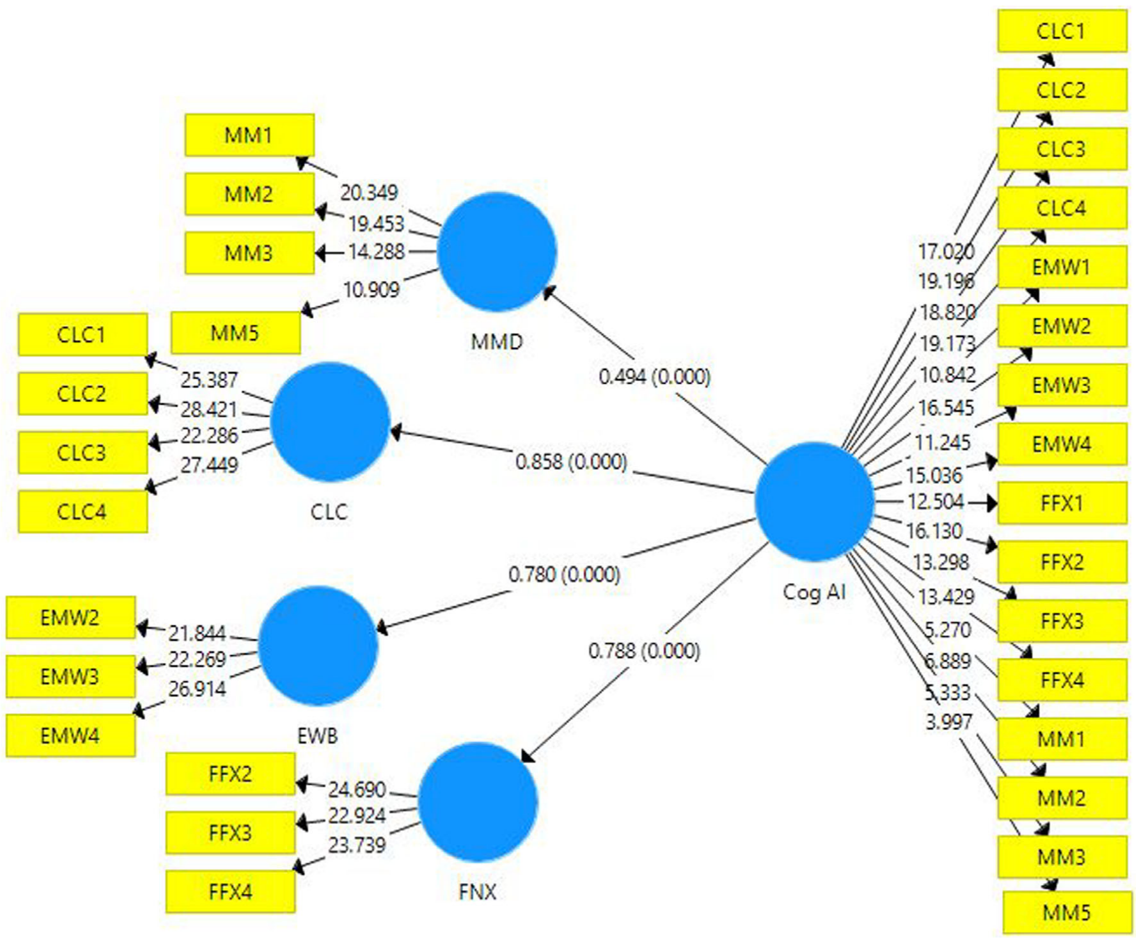


FIGURE 3 Second-order factor validation.

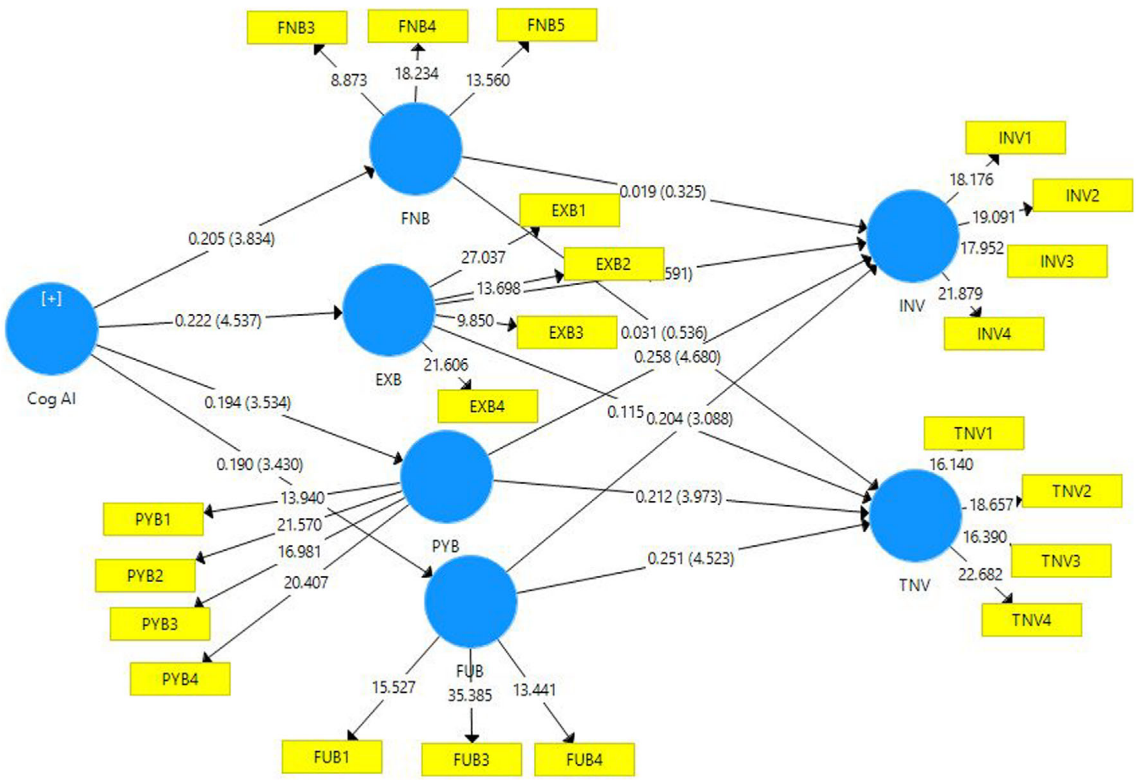


FIGURE 4 Bootstrapping (*p*-values and *t*-values).

TABLE 6 Path coefficients.

Paths	Path-coefficients	S.D.	*T*- statistics	*P*-values	Hypothesis testing
Cog AI → FNB (H1a)	0.205	0.053	3.834	.000	*Accepted*
Cog AI → EXB (H1b)	0.222	0.049	4.537	.000	*Accepted*
Cog AI → PYB (H1c)	0.194	0.055	3.534	.000	*Accepted*
Cog AI → FUB (H1d)	0.190	0.055	3.43	.001	*Accepted*
FNB → INV (H2a)	0.019	0.059	0.325	.745	*Not-accepted*
EXB → INV (H2b)	0.189	0.073	2.591	.01	*Accepted*
PYB → INV(H2c)	0.258	0.055	4.68	.000	*Accepted*
FUB → INV (H2d)	0.204	0.066	3.088	.002	*Accepted*
FNB → TNV (H3a)	0.031	0.058	0.536	.592	*Not-accepted*
EXB → TNV (H3b)	0.115	0.06	1.931	.054	*Not-accepted*
PYB → TNV (H3c)	0.212	0.053	3.973	.000	*Accepted*
FUB → TNV (H3d)	0.251	0.055	4.523	.000	*Accepted*

6 | DISCUSSION OF FINDINGS

Advanced technologies like AI have tremendous potential in patient-related outcomes and seek psychological engagement with them as active agents to adopt and utilize (Kumar et al., 2023). The respondents ($n = 52$) indicated that their attention and understanding of AI is increasingly based on various healthcare-related priorities. They stated how different forms of AI-based tools and devices (e.g., "Fitbit Luxe" for heart-rate tracking, "Accusure" for blood-pressure monitoring, and chatbots for hospital check-in and assistance) are being utilized that reduce the challenges while seeking care. The results provide insights into the factors of "cognitive engagement with AI technologies" (Chatterjee, Chaudhuri, & Vrontis, 2022; Kumar et al., 2021).

The four factors are divulged into some exciting aspects of the cognitive engagement process under study. For instance, exploratory interviews indicate that patients as customers are inclined toward modern AI-based tools and are becoming competent while adopting them. The learning and engagement process with such technologies suggests a shift in behavior from a traditional to rational mindset about health concerns (Pereira et al., 2022). The "cultural competence" theme offers going beyond cultural and racial boundaries. In addition, the third dimension "emotional well-being," is connected to the belief that such devices may improve their lifestyle and satisfaction. The qualitative study findings suggest that the level of awareness is increasing on the applications of AI in healthcare. Finally, engagement and learning with AI technologies is associated with the perception of flexibility that such devices offer to patients (Jayawardena et al., 2022; Kumar et al., 2021). Participants reported enthusiasm about the abilities of AI-based tools and the flexibility associated with such devices. However, the interviews indicated the patient's apprehension about using AI-based tools and technologies in healthcare. Our results suggest that patients have multiple safety, security, and privacy invasion concerns. These findings are aligned with the recent call of researchers (Wang et al., 2018) to explore the ethical and responsible implementation of AI in healthcare.

The survey responses ($N = 330$) of the patients were utilized to assess the strength of the predicted model. The results indicate "cognitive engagement with AI-enabled technologies" as a second-order reflective construct which is the first step toward explaining the mechanisms from a psychological standpoint. The factor "CogAI" resisted converging into a single factor when employing a repeated indicator approach (Hair et al., 2016). Moreover, the low-AVE values for CogAI ($AVE = 0.28$) indicate the multi-dimensionality of the factor, which is formed by its four underlying factors. Thus, the data support the formation of "cognitive engagement with AI" as a higher-order factor.

Further, the findings also reveal that the patients' cognitive engagement with AI-enabled technologies is positively associated with their perceived financial, experiential, psychosocial, and functional benefits (Chen et al., 2017). It was found that the perceived financial benefit does not impact instrumental and terminal values. Many studies argue that value-based health-care delivery focuses on health outcomes rather than the cost (Davenport & Kalakota, 2019; Lui & Lamba, 2018). Aligned with these studies, we found that the perceived financial benefit is unimportant for value formation in healthcare. This finding indicates that compared to the other service business sectors, health-care customers do not perceive value from cost savings as healthcare is a serious concern. Besides, perceived experiential benefit affects only instrumental value and not terminal value. The pleasure experienced while using AI-based tools creates value for patients. The health-care literature is increasingly focused on exploring the convenient delivery of medical care (Tuzovic & Kuppelwieser, 2016). Our findings also indicate that the patient's experiential benefit is positively associated with instrumental values by a reduction in the overall waiting time and a hassle-free hospitalization. The results further suggest that perceived psychological benefit has a more significant influence on instrumental value than terminal value. Besides, the impact on terminal value is more significant than instrumental value due to the functional benefit.

6.1 | Theoretical implications

The findings of this study have several implications for theory purposes. Firstly, this study responds to the recent call of researchers (Chatterjee, Chaudhuri, & Vrontis, 2022; Gursoy et al., 2019; Mostafa & Kasamani, 2021) to explore the formation of "cognitive engagement with AI-enabled technologies" and explain how psychological, social, and cultural factors could affect marketing performance. We provide a more precise conceptualization of "cognitive engagement" (Hollebeek et al., 2016; Prentice & Nguyen, 2020) in the marketing literature to fill this theoretical gap. These studies have suggested that cognitive engagement is a specific form of engagement that arises from intrinsic motivation and interest in a particular product or service. Despite the advocacy of psychological underpinnings of the micro-foundations of value creation by service products, insights into cognitive engagement as a specific form are limited to date (Chen et al., 2017; Huang & Chang, 2012; Swar et al., 2017). The findings clarify that medical modernization, functional flexibility, psychological well-being, and cultural competence are the four constituents of "cognitive engagement with AI-enabled technologies," which is empirically established as a higher-order factor.

Secondly, there is an increasing agreement on the point that cognitive engagement is a vital resource and skill in the effort toward involvement with healthcare-related processes, tools, and technologies (Barello et al., 2016). It is crucial to establish a mental connection with what is being learned and utilized in the caregiving process. Therefore, marketers must understand the self-fostering mechanisms and psychological aspects that facilitate such engagements with AI-enabled technologies. The perceived benefits and values (Chen et al., 2017; Zeithmal, 1988) are the outcomes of cognitive efforts invested in learning, adapting, and utilizing AI-based tools (Graffigana et al., 2015). The study's findings clarify the notion of mental connection with AI technologies in a health-care process and precisely explain how the patients, as consumers, are inclined toward such modern tools, and, thus, affect market performance.

Thirdly, the current studies' findings also go beyond the customer-dominant logic of value formation (Heinonen et al., 2013) by exploring the dynamics of cognitive engagement with "service products," in general or "AI applications," in particular to their perceived value. This study pushes back the existing frontiers of knowledge regarding technology acceptance (Rahman et al., 2016; Venkatesh et al., 2003). The findings reveal that many other factors, which are essential from a marketing perspective, are responsible for engagement with modern AI applications. Our study provides the theoretical constructs of the four factors of "cognitive engagement with AI-enabled technologies" while simultaneously extending these theories toward technology acceptance and perceived usefulness. These findings provide an extended perspective of newer technologies, like AI, acceptance, and usefulness through the multi-dimensional construct of "cognitive engagement with AI-enabled technologies" in healthcare.

Fourthly, this study's results align with prior research that accept the role of cognitive engagement with different forms of service deliveries and their positive outcomes (Barello et al., 2016; Graffigana et al., 2015). The findings reveal that the "cognitive engagement with AI-enabled technologies" in health-care affects value creation. The results are also consistent with prior studies (Brozovic et al., 2016; Gronroos & Gummerus, 2014) that indicate linkages between service flexibility and value creation. By explaining the mechanisms of "cognitive engagement with AI-enabled technologies," this study demonstrates their effects on value creation through customization and convenience.

Finally, when considering the contribution to the consumer theories on perceived benefits (Chen et al., 2017), perceived values (Gronroos & Gummerus, 2014), and the logics of CD (Heinonen et al., 2013), this study is unique as it describes the paths of engagement through the consumer's psychological standpoint. The findings have a novel contribution and have implications for health-care organizations to engage patients, as consumers, with modern AI-based devices. In contrast to previous studies (Brodie et al., 2011; Graffigana et al., 2015; Pereira et al., 2022), our study provides a comprehensive analysis of research pertaining to customer engagement from a cognitive perspective and examines the effect on several benefits.

6.2 | Practical implications

The results of the current study provide insights into the psychological mechanisms of cognitive engagement. They guide health-care managers in developing value propositions (Chen et al., 2017; Gronroos & Gummerus, 2014). For instance, the study's findings clarify the factors of "cognitive engagement with AI-enabled technologies". The results outline the cognitive engagement factors that enact behaviors related to the adoption and utilization of such tools. This will guide service providers and technology vendors on various measures to ensure the patients' abilities in using several devices and platforms. The results may feature the cognitive constraints that generate difficulties in using AI-based technologies.

The rigorous model developed in this research allows health-care organizations to create appropriate combinations of patient benefits. Thus, health-care organizations would become patient-centric (Barello et al., 2016) by focusing on technology-driven marketing capabilities. All of the findings suggest the cognitive elaboration of the health-care experience, for which engagement with AI can be an essential strategy. In this way, a holistic and systematic understanding of the cognitive variables of engagement with AI tools can be reached, which may help tailor AI interventions to be tuned with the inclusive growth of the market (Kaleka & Morgan, 2019). The results would guide developing ethical health-care leaders with a mindset of sustainability and inclusive growth.

The results of hypothesis testing explained the role of medical modernization, cultural competence, emotional well-being, and functional flexibility as factors of "cognitive engagement with AI-enabled technologies". The findings guide marketers to selectively deploy such practices to create value and improve market performance. The factors of "cognitive engagement with AI-enabled technologies" are likely to accelerate the growth of healthcare in emerging market countries like India through handheld and wearable devices. The government bodies in India like the "NITI Aayog" would be directly benefitted in a strategic manner for their recent projects on primary care. The innovative solutions like "XraySetu" to aid medical professionals in India's cities and villages would take the lead by understanding the aspects of cognitive engagement. The results of this study guide how the providers may focus and promote AI-based tools to create awareness and modernization, which in turn alert patients about their varying health conditions. The findings would help healthcare entrepreneurs to design their AI-based businesses by understanding the cognitive factors. The preventive and social medicine departments can redesign their community programs and include training on AI-based tools and devices for health benefits. Likewise, virtual health assistants can be utilized to support remote patients and can create value through scheduling visits, ease of access, and convenient care. Functional flexibility of AI-based chatbots (e.g., Wysa) can be promoted to help patients build mental health and reduce anxiety. Furthermore, the proposed model in this study facilitates scrutinizing health-care practices and offers value propositions through a wide array of AI-based innovative technologies.

Therefore, the study will guide how synergy can be achieved among the patient's experience of care (e.g., queue less OPD registration, functional flexibility, the feeling of modernization, early detection of blood diseases, hassle-free procedures, accurate diagnostics, health alertness, claiming of settlements, etc.) and the dimensions of "cognitive engagement with AI technologies". By considering their role in improving benefits and perceived value (Graffigana et al., 2015; Lui & Lamba, 2018), the findings have several implications for the health-care ecosystem. We recommend that medical insurers develop innovative settlements claim by understanding the cognitive aspects of AI-based devices. The diagnostic equipment and handheld devices can be better utilized by having clarity on the psychological standpoints. On the other hand, pharmaceutical companies may explore these factors for drug discovery with reduced costs, specifically for anxiety or cardiovascular treatments. Based on the findings of this study, we suggest implementing transparent and responsible AI (Wang et al., 2018) to mitigate the risk of privacy invasion which is a global concern. Accordingly, the quality of health-care experience and the patients' cognitive engagement with AI-based technologies should be the guiding principle in designing and developing evidence-based health-care devices, and thus inclusive growth of the society.

6.3 | Conclusions, limitations, and future research

The scope of the current study was confined to exploring the constituents of cognitive engagement with AI-enabled technologies and their effects on the patients' benefits and values. In doing so, firstly, we collected data from the consumer of AI-enabled technologies and tools in India. The findings were reported based on the data from Indian health-care consumers. Future studies may collect data from other emerging countries' healthcare to test the framework's generalizability. We aimed to address the recent call of researchers to demystify cognitive engagement with newer technologies like AI. While justifying the study in the Indian context and we considered the patient's cognitive standpoint. However, managerial cognitive capabilities are missed, which may sketch interesting implications in future studies. We further utilized SEM to gauge their effects on several benefits and, in turn, instrumental and terminal values. The study has taken into consideration the different psychological and social aspects. Despite this, the role of many other contextual variables remains unexplored and generates the future avenues of research. The psychology literature indicates that cognitive engagement is also a function of the brand values of the service products. A longitudinal study in this context should strengthen the theorizing. Thus we envisage the possibilities of exploring the underlying mechanisms and unearthing their marketing implications.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Pradeep Kumar https://orcid.org/0000-0002-5327-9119

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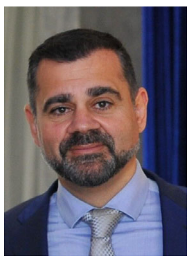
AUTHOR BIOGRAPHIES

Dr. Pradeep Kumar, PhD is a faculty in the Marketing area and Program -coordinator, Doctoral Program, Centre for Research Studies (FPM/EFPM), BIMTECH, Greater Noida, India. He has more than 08 years of experience (Pre-PhD) in Government sector as faculty (Non-medical) and administrative/technical (Medical IT) positions. He has more than 4 years of working experience (Post-PhD) as Marketing faculty and Senior Marketing Consultant. His research interests include AI, Service Science, Healthcare and Flexibility. He serves as a reviewer in various Journals and received Outstanding Reviewer Award from *Journal of Asia Business Studies* for two consecutive years (2021–2022). He has published several papers in A*/A (ABDC) Categories of Journals.



Prof. Demetris Vrontis is the Vice Rector for Faculty and Research and a Professor of Strategic Management at the University of Nicosia. He is the President of the EuroMed Academy of Business and the Managing Director of Gnosis Mediterranean Institute for Management Science. He is the Editor in Chief of the *EuroMed Journal of Business*, an Associate Editor of the International Marketing Review, an Associate Editor of the *Journal of Business Research* and a Consulting Editor of the *Journal of International Management*. He has published widely in over 350 refereed journal articles, coauthored over 50 books, and he has presented papers at conferences around the globe. He is a certified Chartered Marketer and a Chartered Business Consultant.

Prof. Fabiano Pallonetto is the Professor at the School of Business, Hamilton Institute, Maynooth University, Ireland. He has a wide experience in the energy, IT and transport sectors working as an entrepreneur, data scientist and researcher across different industries and disciplines. His academic background in Computer Science and Engineering and industry experience in energy, sustainable mobility, data analytics, control algorithms, and optimization makes him a pivotal asset for research based and commercial data centric projects. Prof. Fabiano aims at bridging academic research to industrial needs applying his multidisciplinary industry and entrepreneurship experience to build solutions and solve technical challenges for the deployment and integration of the smart grid and its associated carbon footprint reduction and promoting sustainable development goals.