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LEVERAGING AI CAPABILITIES FOR BUSINESS MODEL INNOVATION: MEDIATING ROLE OF CHATBOT AFFORDANCES & MODERATING IMPACT OF BIG DATA ANALYTICS

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ABSTRACT

This study examines the impact of AI capabilities on business model innovation (BMI) via the mediating mechanism of chatbot affordances and the moderating influence of big data analytics capability based on Resource-Based View (RBV) theory. Data were gathered through a structured questionnaire from bank customers with access to chatbot services. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to assess the hypothesized relationships among AI competencies, chatbot affordances, big data analytics capability, and Business Model Innovation (BMI). Results indicate that AI capabilities increase chatbot affordances considerably, with the latter having a positive influence on Business Model Innovation (BMI). Chatbot affordances act as mediators between AI capabilities and BMI, with big data analytics capability solidifying this relationship. Organizations must emphasize creating a strong AI infrastructure, strategic planning abilities, and an innovative, proactive approach to use chatbot technologies for strategic transformation. Increased big data analytics further maximizes these advantages. This research uses RBV theory to unearthing the manner in which intangible digital competencies (AI capabilities and chatbot affordances) become innovative business outcomes, providing digital strategy actionable insights for service sectors.

Keywords: AI Competencies, Chatbot Affordances, Business Model Innovation, Big Data Analytics Capability and Digital Transformation.

1. Introduction

There is no denying that artificial intelligence (AI) is increasingly becoming part of our daily lives. Interaction with AI or AI technology is increasingly becoming a common practice in both work and leisure settings. As of 2022, nearly one-third of all businesses globally had implemented AI, an increase of four points from the preceding year. At the same time, 42% of the firms had not yet started applying AI but had begun exploring its potential (Carolus, Koch et al. 2023). AI comprises a wide range of systems, from chatbots to sophisticated humanoid robots, and is generally seen as a breakthrough technology that will affect all sectors, such as technology, medicine, and education (Luckin and Holmes 2016, Bialik, Frank et al. 2019). In healthcare, AI assists in diagnostics, treatment planning, and drug development. In education, it assists in personalizing learning experiences and increasing student engagement and assessment (Luckin and Holmes 2016, Pearson 2019). Chatbots, which are powerful AI tools, have been extensively adopted by organizations to innovate marketing strategies and improve customer service (Lin, Wang et al. 2024). It is estimated that by 2023, the value of e-commerce transactions executed through chatbots will be $112 billion (Senadheera, Yigitcanlar et al. 2024). Chatbots can provide automatic answers to frequent customer questions, even beyond regular business hours (Liu, Shao et al. 2022). They are prime examples of AI use that have been extensively employed for coping with more service requests and performing communication work once done by people. The emergence of the Internet in the mid-1990s brought about explosive growth in data creation, triggering scholarly debate about how to efficiently use "big data" to facilitate governance, business, and societal progress. Big data are complex datasets that must be converted into value through different dynamic processes, such as identification, collection, storage, and analysis (Lin and Kunnathur 2019). The growing body of BMI literature improves our understanding of the concept, but the relationship between BMI and innovation management literature tends to be neglected (Kohtamäki, Parida et al. 2019).

Interest in AI literacy has increased in recent times, particularly after 2020, as AI technologies find their way into everyday life (Miao, Schwarz et al. 2021). Current studies show that chatbots are less effective than highly capable employees in persuading sales (Jia, Luo et al. 2024). Therefore, full automation of customer service using chatbots may be dangerous and would have adverse impacts on service quality. Customers can easily generate useful big data from their Internet behavior without any specific knowledge or effort (Xie, Girshick et al. 2016). We do not foresee that all the elements of AI literacy will be strictly hierarchical. The unique features of chatbots allow us to evaluate their assistance by extending the traditional IT artifact to include both information and emotional assistance. In addition, our results provide a robust empirical basis for developing further research on human-AI interactions and collaborations (Raisch and Krakowski 2021) as well as the possibility of AI reshaping work and service automation (Faraj, Pachidi et al. 2018, Lacity, Willcocks et al. 2021). Firms that collaboratively develop innovation will put their own interests above channel profits (Ge, Hu et al. 2014). This strategy is most relevant to the healthcare and tourist sectors, as it enhances the business performance of companies. We integrate the BMI literature into current debates concerning innovation management (Biemans, Griffin et al. 2007, Biemans, Griffin et al. 2010, Antons, Kleer et al. 2016) and propose new research directions.

Previous studies have focused on isolating AI capabilities or chatbot applications without considering the mediating mechanisms that transform AI investments into strategic impacts (Diederich, Brendel et al. 2022). This research addresses these essential shortcomings by adopting the Resource-Based View (RBV) as a conceptual framework (Madhani 2021) to analyze how AI capabilities, under the mediating effect of chatbots' affordances (Lin, Wang et al. 2024) and the moderating effect of big data analytics, contribute to banks' business model innovation. In doing so, it applies the RBV model to the field of digital transformation and provides actionable insights for organizations to address the convergence of AI, big data, and innovation (Dong and Yang 2019).

RQ1. Do AI competencies positively affect Chatbot affordance?

RQ2. Does Chatbot affordance mediate between AI competencies and BMI?

RQ3. Does big data analytics capabilities moderate the relationship between AI competencies and chatbot affordance?

2. Literature Review

2.1 Resource-Based View Theory

The RBV hypothesis provides a framework for understanding how firms can gain and sustain competitive advantage through planned and optimal resource management. According to the RBV, resources that are valuable, rare, inimitable, and non-substitutable are essential to an organization's maximum performance and posterity (Barney 1991). This theoretical perspective emphasizes the significance of internal resources and capabilities in shaping a firm's competitive position in the market (Barney 1991, Holdford 2018, Madhani 2021). Artificial intelligence capability is increasingly a critical and intangible resource for business performance advancement (Lou and Wu 2021, Mikalef and Gupta 2021, Belhadi, Mani et al. 2024). AI competence can deliver business access to valuable, rare, inimitable, and irreplaceable resources (Ghasemaghaei 2021). The RBV provides an appropriate theoretical basis because knowledge of what AI-specific resources a firm has to manage is a core part of attaining a competitive advantage. Since the objective of this study is to identify key organizational resources, such as infrastructure, business spanning, and proactive stance, that enable the development of AI competencies, which subsequently facilitates Chatbots affordance and leads to business model innovation, the selection of the Resource-Based View (RBV) as the theoretical framework is justified.

2.2 Chatbots: A Review from a Technological View

The literature presents two general types of chatbots according to their underlying algorithms: rule-based and AI-powered (Cahn 2017, Adamopoulou and Moussiades 2020). A rule-based Chatbot functions by applying predefined rules to arrive at answers (Ramesh, Ravishankaran et al. 2017). On the other hand, AI-powered Chatbots utilize advanced AI techniques such as deep learning, neural networks, and natural language processing (NLP) (Thaichon and Quach 2023, Jia, Luo et al. 2024), which work well in processing and generating data necessary for customer support. Examples of AI-powered chatbots include Amazon Lex, Messenger Platform, and IBM Watson Assistant, in contrast to a rule-based chatbot that can provide only predefined answers and has no capability of generating new knowledge to improve employee performance (Ramesh, Ravishankaran et al. 2017). AI-powered Chatbots can understand the context of a conversation, so they can interact with users in a human-like and conversational manner. They greatly support employees in their work and improve human capabilities, which is a key area of our research. For example, an Amazon Lex-powered Chatbot can provide information or transactional capabilities, be embedded in websites, social media, or other applications, and can employ generative interaction patterns. This focus is on recent research on chatbots; for example, Big Data has received considerable attention from academics and practitioners in recent years (Gandomi and Haider 2015).

2.3 Chatbots in public service delivery

Chatbots are increasingly used to deliver public services (Mehr, Ash et al. 2017). They can interact with different categories of citizens in the natural language (24/7) throughout the year. Regardless of continuous chatbot training improvement, they could not respond to all questions. Unlike humans, chatbots do not possess the capability to hold long conversations, understand the flow of discussions, or show empathy during stressful situations (Syvänen and Valentini 2020). The potential of chatbots in public service delivery is constrained by the contextual nature of user questions, the variety and complexity of administrative services, differences between technical terminology and user language, and the essential need to obtain the correct answer to every question (Lommatzsch 2018). In the long term, chatbots can become "co-workers" for service representatives within customer service teams, assisting customer service agents during real-time interactions. Nonetheless, the literature lacks comprehensive research on the effective integration of chatbots with service agents to create hybrid service teams. It can be viewed from the perspective of resource-based view theory, since chatbots interact with customers and aid in minimizing the cost of support while providing services around the clock.

2.4 Chatbot Marketing Efforts

The rise in AI technology is significant today. Customer experiences can be revolutionized by social media bots through a shift from product- or service-focused interactions to interactions with an effective computer-based decision-making system (Klaus and Zaichkowsky 2020). Earlier studies categorized chatbots according to a number of parameters, including their physical presence, interaction design, response mechanisms, conversation types, and roles. Embodied conversational agents have a physical shape (such as a body or face) and engage in real-time conversations, whereas disembodied conversational agents interact only through text-based messaging in conversational format. The second feature, information, identifies the key marketing role of chatbots, which is to make available information about the product, service, or brand to customers. Empirical evidence suggests that consumers find it favorable to receive information from digital AI platforms compared to other Internet sites (Abbott, Abbott et al. 2019). Customization is the extent to which AI-based Chatbots can provide personalized care to meet customer requirements (Godey, Manthiou et al. 2016).

2.5 AI Competence and Chatbot

Organizations that are strong in AI competencies usually involve business, operational, and marketing professionals to work with analytics experts, thus converting solitary working practices into a cohesive interdisciplinary effort to improve organizational success (Fountaine, McCarthy et al. 2019). AI ability is the key factor influencing how students interact with and utilize chatbots for learning. It makes such chatbots interactive learning companions, enhancing students' motivation and interest (Han 2020). AI ability is the ability to solve problems using AI, including knowledge representation, data learning, machine learning, deep learning, and AI ethics (Ahn and Oh 2024). By having greater proficiency in AI, users are able to better detect and utilize the capabilities provided by ChatGPT, thereby encouraging its use and resulting in more efficient interactions (Hidayat-ur-Rehman and Ibrahim 2023). As stated by (Kitcharoen, Howimanporn et al. 2024), AI competence plays an essential role in addressing practical problems involving cognitive, behavioral, and emotional aspects. The educational effectiveness of chatbot technology increases as students possess greater AI capacities because it enables them to use and interact better with the capabilities of chatbots, leading to increased digital capacity and user satisfaction (Moral-Sánchez, Rey et al. 2023). Greater AI capacities enhance the capacity of users to identify and utilize the capabilities of chatbots, thus amplifying human–chatbot interaction success. Therefore, we propose the following hypothesis:

H1: There is a positive relationship between AI competencies and Chatbot affordances.

2.6 Chatbot Affordance and Business Model Innovation

Chatbot affordances positively influenced BMI. Factors such as anytime-anyplace connectivity, information association, visibility, and interactivity directly and positively influence chatbots' affordances. When AI-based systems consider different marketing solution strategies, marketers can use their knowledge to make decisions supported by AI-driven analysis (Fountaine, McCarthy et al. 2019). Smart technologies are tools that help bridge the gap between frontline workers and customers to create value (Marinova, de Ruyter et al. 2017). Interacting with a chatbot enhances users' positive perceptions of its capabilities, which in turn increases their engagement with the organization and creates novel alterations to the business model. As long as consumers feel that the company has adequate infrastructure, technical support, and resources, this further reinforces AI Competence development, which in turn increases the perceived ability of chatbot technologies (Rodríguez-Espíndola, Chowdhury et al. 2022). The concept of affordance is gaining increased attention in organizational research and is increasingly being used to examine the ways in which AI-driven technology, such as chatbots, impacts organizational interactions and enables new interaction patterns leading to business model innovation (Majchrzak, Faraj et al. 2013). The concept of "affordance" provides a strong theoretical apparatus for examining the dynamics between users and chatbot technologies in organizations as well as providing a more precise vocabulary for systematic accounts of how AI capability supports particular innovative practices (Fayard and Weeks 2014).

H2: There is a positive relationship between Chatbot Affordance and Business Model Innovation.

2.7 AI Competencies and Business Model Innovation

Empirical research and theoretical developments suggest that customer satisfaction is the forerunner of loyalty (Schirmer, Ringle et al. 2018). If customers are satisfied, they tend to establish an emotional connection with the brand and seek repeat service encounters (Fraering and Minor 2013). Above all, marketing information management can be defined as an organization's ability to collect and process relevant information about different stakeholders to develop effective marketing strategies(Cavazos-Arroyo and Puente-Diaz 2019). When Chatbots personalize their services in accordance with the requirements of customers, personalized experiences amplify the customers' relationship with the chatbots and create feelings of ownership. Through the use of AI-based marketing information management software, organizations can enhance decision making, thus enhancing productivity and overall performance. The innovative application of chatbots impacts customer service performance through the mediating roles of internal and external agility (Teece, Peteraf et al. 2016). The creative use of chatbots plays a central role in this mediated relationship by forming dynamic capabilities, in addition to their standard application (Teece, Peteraf et al. 2016).

H3: Chatbot affordances mediate the relationship between AI Competencies and Business Model Innovation.

2.8 Big Data Analytics Capability

Feedback and ratings offered through chatbots directly influence customers' brand choices in the hospitality industry (Kore, Kuchanwar et al.). Customers are also presented with current trends and personalized information by chatbots, handling complaints, and aiding in solving issues (Chung, Sugimoto et al. 2018). Chatbots satisfy customer experience needs by interacting with customers in real time (Chiang, Korinek et al. 2020). Abolishing chatbot services may prove to be cumbersome for customers because they would compel them to exert additional time and effort to obtain other services, thus incurring higher switching costs. Better marketing planning allows an organization to proficiently integrate its diverse resources and create marketing approaches for success. Failure to take timely action will cause an organization to fail to succeed in the current uncertain market. The ability of Big Data Analytics to enrich the possible connection between AI capabilities and business model innovation, speed up required iterations, energize activity, facilitate more connections, and ultimately help bring ideas into reality, resulting in innovation (Kissi 2024). Dong and Yang (2019) emphasized that collaboration in an organization can foster innovation (Dong and Yang 2019). However, the Big Data Analytics capability of an organization does not always guarantee enhanced business model innovation because AI capabilities may require more collaboration to be most impactful (Limbu, Jayachandran et al. 2014). Big Data Analytics capability can reinforce the linkage between AI capabilities and business model innovation by providing insights, automating processes, and inducing a data-oriented approach towards innovative practices.

H4 Big Data Analytics capabilities moderate between AI Competencies and Chatbot Affordance.

3. Methodology

To test these hypotheses, we used a questionnaire-based technique. This technique provides generalizability of findings, is easy to replicate, and permits the analysis of several constructs (Pinsonneault and Kraemer 1993).

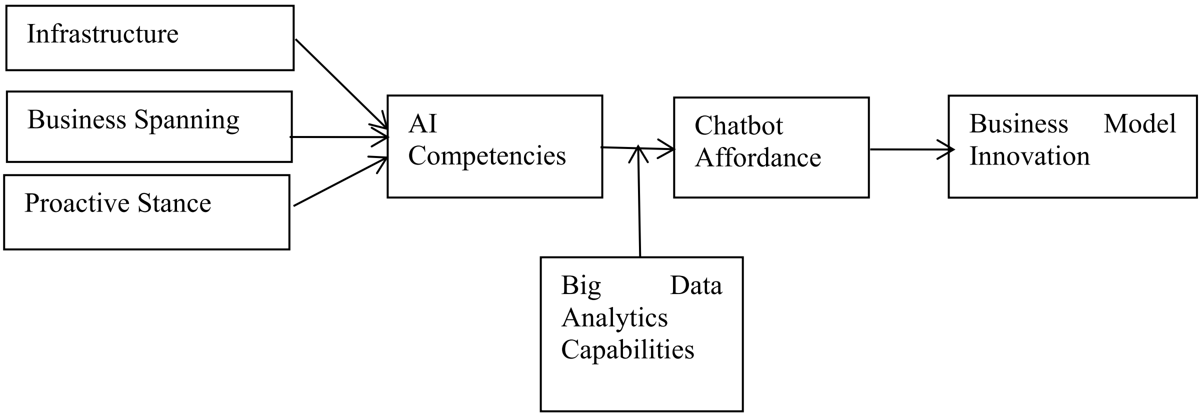
3.1 Measures

The seven constructs that form the research framework are described in Figure 1: infrastructure, business spanning, proactive stance, AI competencies, chatbot affordances, Big Data Analytics capacity, and business model innovation. AI Competence (AIC) refers to a latent construct with three dimensions: infrastructure, business spanning, and proactive stance. It refers to a company's ability to integrate AI technologies, competencies, knowledge, and other complementary resources, thus creating a competitive edge. These latent construct dimensions are congruent with the existing IT competence literature (Lu and Ramamurthy 2011), and the respective measures are customized and validated for AI-specific processes and infrastructure. The Business Spanning (BUSP) driver captures the capability of management to use AI to drive business objectives from ideas through implementation. By contrast, a Proactive Stance (PROS) focuses on enthusiasm for investigating creative applications of new and evolving AI techniques, with a constant search for ways to improve. AI Competence encompasses three unique items (Mikalef, Islam et al. 2023). In contrast, chatbot affordances have four items (Wang, Zafar et al. 2022). Moreover, Big Data Analytics capacity has six items, and Business Model Innovation has four items.

3.2 Population and Sampling

Banks that utilize chatbots in customer interactions provide a perfect context for testing the suggested model. The data used in this research were collected by conducting an online questionnaire survey with minor adjustments to the wording of the items. We used Google Forms, a free tool provided by Google, to create questionnaires. Banking sector customers were targeted in this study. The initial questionnaire link was distributed via an online survey, on other popular forums, and WhatsApp groups. Users who had availed chatbots services once or more were asked to provide feedback on a list of research questions.

Figure 1: Research Framework



According to (Straub, Boudreau et al. 2004), survey-based research is an important technique in exploratory study environments and the initial phases of theory building. In this research, we used previously published and existing constructs, as well as survey items that were adapted to fit the context of our research. This step enabled us to establish the face and content validity of the constructs and, more importantly, ensure that respondents were clear about what the questions meant. Following the pre-testing of the first round, we contacted the respondents to hear their comments and refine any unclear questions. Qualifying questions were also given to ensure that the organizations were actually putting into practice AI applications and that the respondents possessed the requisite knowledge to provide informed responses. In total, 305 responses were received. After filtering, 281 patients were included in the final analysis.

Table 1 Demographic Profile

Demographics	Category	Frequency	Percentage
Gender	*Male*	225	80.07
	Female	56	19.93
Age (Years)	*18-30*	4	1.43
	31-35	134	47.68
	36-40	140	49.82
	Over 45	3	1.07
Education	*Undergraduate degree*	82	29.19
	Postgraduate degree	199	70.82

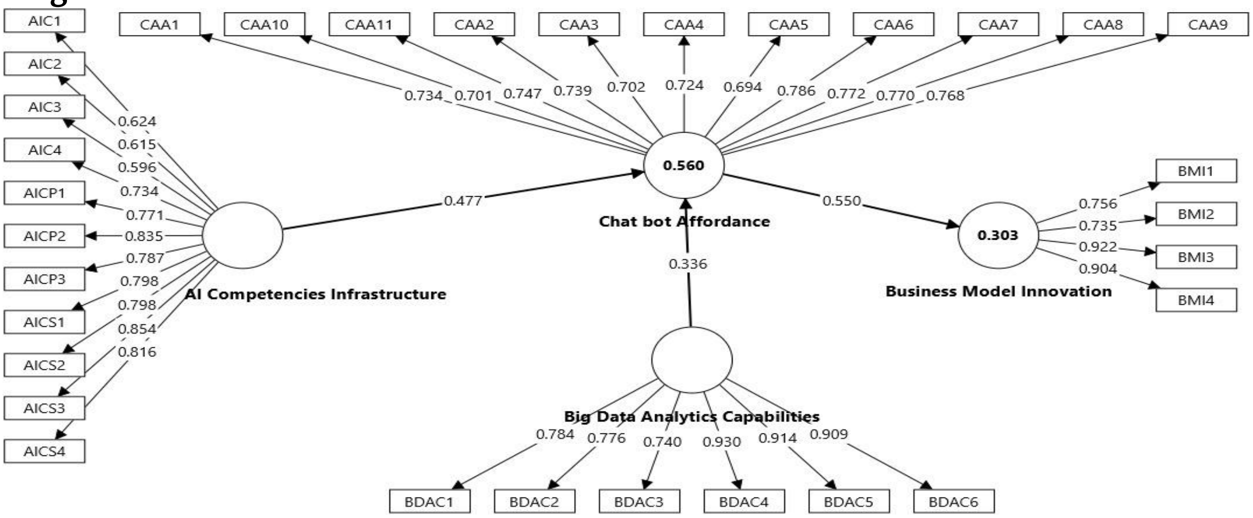
4. Results

In order to evaluate the reliability and validity of our conceptual research model, we followed a partial least squares-based structural equation modeling (PLS-SEM) framework. We used SmartPLS 4 software for the analysis (Ringle, Da Silva et al. 2015). PLS was appropriate for our research model because it enables the direct estimation of component scores, which is useful for model constructs that are measured formatively. Therefore, we use PLS-SEM to test the research model using formative measurement constructs. Based on the context of our analysis, PLS-SEM is a suitable methodology because it allows the investigation of relationships between dependent, independent, and mediating variables (Hair, Sarstedt et al. 2012). This method enables indirect and total effect identification and permits a joint analysis of relationships between multi-item constructs while reducing total model error (Astrachan, Patel et al. 2014). Content validity was ensured throughout the questionnaire development process by correlating the measurement items with literature. Moreover, given that our research model involves exploratory theory building as opposed to confirmation, we think the most appropriate one would be PLS-SEM.

4.1 Model Estimation

PLS-SEM was used as the main analysis method because it has been widely accepted as a strong non-parametric, variance-based method that can be applied to simple and complex research models alike (Hair Jr, Hult et al. 2021). This method is particularly suited to scenarios with challenges, such as non-normal distribution of the data, low sample sizes, and missing values, and provides better estimation compared to standard ordinary least squares regression (Becker, Cheah et al. 2022). PLS-SEM was employed to evaluate the measurement and structural aspects of the model. The research design comprises five reflective constructs: infrastructure, business spanning, proactive stance, AI competence, chatbot affordance, Big Data Analytics capabilities, and business model innovation. The measurement model is shown in Figure 2. All indicator loadings were above the recommended cut-off of 0.50 (Becker, Cheah et al. 2022), confirming acceptable individual item reliability. Additionally, the composite reliability (CR) for all constructs was greater than 0.70, as suggested by (Hair Jr, Hult et al. 2021), which attests to internal consistency reliability.

Figure 2. Measurement Model



(Becker, Cheah et al. 2022) report that all loadings in Table 2 are greater than 0.50, affirming that the reliability of individual items is satisfactory. Furthermore, composite reliability (CR) was considered better than Cronbach's alpha. (Hair Jr, Hult et al. 2021) state that both CR and alpha coefficients must be greater than 0.70. Table 2 shows that these requirements were satisfied. Convergent validity was tested by the average variance extracted (AVE), which must be more than 0.50, as recommended by (Hair, Risher et al. 2019). There were no problems with AVE reported in Table 2.

Table 2. Convergent Validity

Constructs	Items	Factor loading	AVE	CR	R2	α	Full collinearity
AI Competencies	AIC1	0.624	0.567	0.920	0.288	0.934	1.904
	AIC2	0.615					
	AIC3	0.596					
	AIC4	0.734					
	AICP1	0.771					
	AICP2	0.835					
	AICP3	0.787					
	AICS1	0.798					
	AICS2	0.798					
	AICS3	0.854					
	AICS4	0.816					

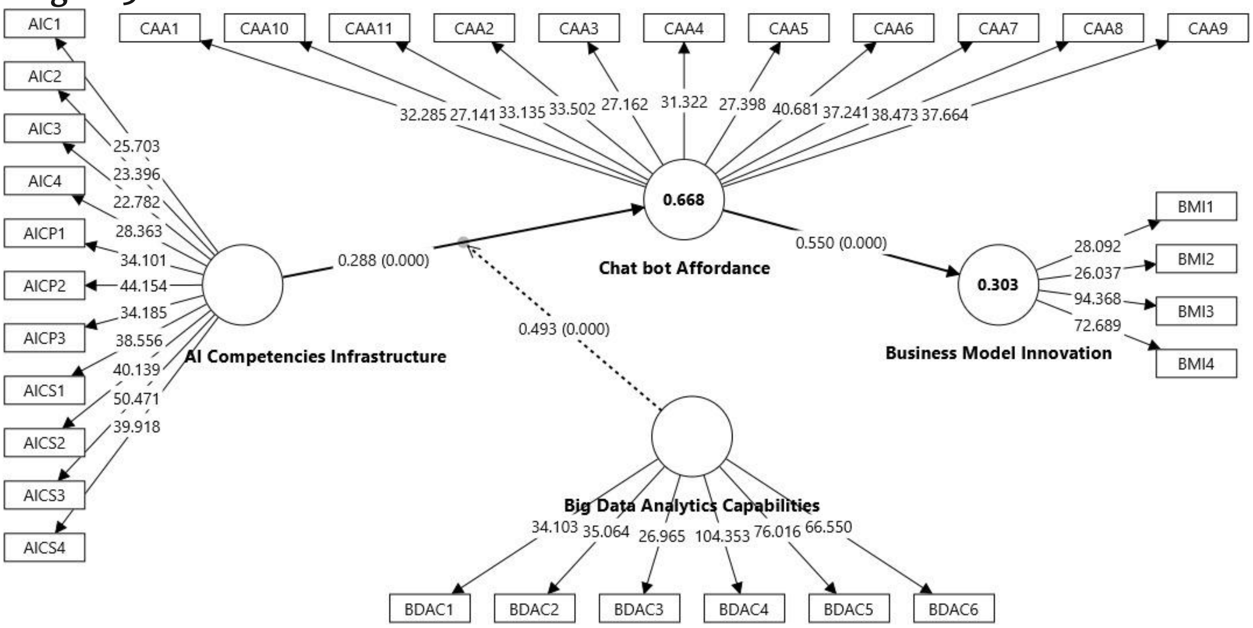
Chatbot affordance	CAA1	0.734	0.548	0.918	0.550	0.930	1.000
	CAA2	0.739					
	CAA3	0.702					
	CAA4	0.724					
	CAA5	0.694					
	CAA6	0.786					
	CAA7	0.772					
	CAA8	0.770					
	CAA9	0.768					
	CAA10	0.701					
	CAA11	0.747					
Big Data Analytics Capabilities	BDAC1	0.784	0.715	0.919	0.493	0.937	1.904
	BDAC2	0.776					
	BDAC3	0.740					
	BDAC4	0.930					
	BDAC5	0.914					
	BDAC6	0.909					
Business Model Innovation	BMI1	0.756	0.695	0.863		0.900	
	BMI2	0.735					
	BMI3	0.922					
	BMI4	0.904					

HTMT would be more suitable when there are minimal differences in loadings. (Henseler, Ringle et al. 2015) recommended that the HTMT ratio be best maintained at 0.85 for conceptually dissimilar variables, while 0.90 is recommended for conceptually similar variables. The empirical evidence provided in Table 3 shows that the requirements set to prove discriminant validity are met. According to the data presented in Table 3, all HTMT values were less than 0.85.

Table 3. Heterotrait-Monotrait Ratio (HTMT)

	AIC	BDAC	BMI	CA
AI Competencies				
Big Data Analytics Capabilities	0.735			
Business Model Innovation	0.569	0.587		
Chatbot Affordance	0.750	0.720	0.622	

Figure 3. Structural Model



AI Competence positively influenced Chatbot Affordance (β = 0.288, t = 4.706), supporting H1. AI Competence has a significantly positive impact on Business Model Innovation (β = 0.485, t = 7.945), supporting H2. Chatbot Affordance was positively related to Business Model Innovation (β = 0.493, t = 9.358), supporting H3. Big Data Analytics capabilities positively influence Business Model Innovation (β = 0.550, t = 12.057), supporting H4. In addition, mediation tests showed that Chatbot Affordance significantly mediates the effect of AI Competencies on Business Model Innovation, affirming H4. Similarly, Big Data Analytics capabilities moderate the strength of the effect of AI Competencies on Business Model Innovation, and the effect is stronger when BDAC is high. These results collectively confirm that BDAC facilitates the translation of AI capabilities into innovative business models.

Table 4. Hypotheses Testing

Hypotheses	Paths	β-values	t-values	p-values	Remarks
H1	AIC→CA	0.288	4.706	0.000	Yes
H2	CA→BMI	0.552	12.057	0.000	Yes
H3	BDAC→CA	0.486	7.945	0.000	Yes
H4	BDACxAIC→CA	0.494	9.358	0.000	Yes

5. Conclusion & Implications

5.1. Conclusion

Rooted in RBV theory, this research empirically confirms the impact of AI competencies-consisting of infrastructure, business spanning, and proactive orientation on chatbots' affordances. Furthermore, this study examined the impact of Chatbots on BMI. Our findings strongly support the hypothesis that AI competencies boost Chatbots' affordances (H1), which further positively affects BMI (H2). Furthermore, Chatbots' affordances significantly mediate the relationship between AI competencies and BMI (H3), suggesting that AI's impact of AI on strategic innovation is realized through the technological affordances perceived by users. These findings are consistent with the notion that AI-enabled tools such as chatbots offer valuable resources beyond automation to serve as enablers of innovation. The value of big data analytics capability as a moderator (H4) reflects the prominence of data-driven decision-making as a key facilitator for companies aiming to derive value from AI usage. AI ability is the ability to solve problems using AI, including knowledge representation, data learning, machine learning, deep learning, and AI ethics (Ahn and Oh 2024). By having greater proficiency in AI, users are able to better detect and utilize the capabilities provided by ChatGPT, thereby encouraging its use and resulting in more efficient interactions (Hidayat-ur-Rehman and Ibrahim 2023). Smart technologies are tools that help bridge the gap between frontline workers and customers to create value (Marinova, de Ruyter et al. 2017). As long as consumers feel that the company has adequate infrastructure, technical support, and resources, this further reinforces AI Competence development, which in turn increases the perceived ability of chatbot technologies (Rodríguez-Espíndola, Chowdhury et al. 2022), (H2). The innovative application of chatbots impacts customer service performance through the mediating roles of internal and external agility (Teece, Peteraf et al. 2016). The creative use of chatbots plays a central role in this mediated relationship by forming dynamic capabilities, in addition to their standard application (Teece, Peteraf et al. 2016). The ability of Big Data Analytics to enrich the possible connection between AI capabilities and business model innovation, speed up required iterations, energize activity, facilitate more connections, and ultimately help bring ideas into reality, resulting in innovation (Kissi 2024). Another researcher underscored that collaboration in an organization can foster innovation (Dong and Yang 2019), (H4).

These findings highlight the subtle interplay between the technical infrastructure and user-driven capabilities. This is in tandem with the wider literature on digital transformation, where the uptake of technology is not sufficient if it is not coupled with strong capabilities to leverage its potential strategically. Chatbot affordances, such as interactivity, visibility, information association, and anytime-anyplace connectivity, are therefore the bridge through which AI capabilities are realized in concrete innovation.

5.2. Theoretical and Societal Implications

This study expands the Resource-Based View (RBV) by situating AI capabilities and Chatbots' affordances as value-generating strategic resources. In the RBV, a persistent competitive advantage is the result of distinctive, valuable, and imitable resources. In this research, AI infrastructure, business spanning capabilities, and proactive stance are conceptualized as intangible resources that facilitate Chatbots' affordances—visibility, interactivity, and information association. These affordances are not only viewed as technological attributes but also as business model innovation (BMI) mediators, highlighting that the strategic value of AI is in its use within context and utility, as perceived by stakeholders. Big data analytics capability is also proposed as a moderating factor enhancing AI resource value, consistent with a dynamic RBV viewpoint. Generally, this study points out that digital transformation is contingent on resource ownership and successful activation through user activity and data use.

From a social point of view, the successful use of AI-based chatbot technologies can boost service access, efficiency, and customization in various sectors such as banking, healthcare, and public services. By automating tasks and facilitating 24/7 engagement, chatbots help improve customer satisfaction and minimize operational loads. In addition, building AI literacy and capability at the organizational level promotes digital inclusion and enables firms to embrace change responsibly in response to changing consumer habits and innovation.

5.3. Managerial Implications

This study presents several managerial suggestions for organizations seeking to use AI in strategic innovation. First, managers must be aware that AI capabilities—strong infrastructure, business spanning strategy (strategic integration), and positive attitudes toward emerging technologies—serve as starting skills for firms to stay competitive. Through these skills, organizations are empowered to exploit Chatbots affordances, such as interactivity, visibility, and real-time connectedness, to heighten customer interactions and operating responsiveness. Second, managers need to consider Chatbots not just as support tools but as strategic assets that facilitate the interaction between AI capabilities and business model innovation (BMI). Investments should thus be geared towards creating chatbots with high-end user experience design and personalization capabilities to derive maximum value from them. Finally, the moderating role of big data analysis capability emphasizes the need to develop robust data analytics functions within an organization. Companies that combine AI and chatbot capabilities with data insights are best able to innovate business models in the face of evolving market demand.

5.3 Limitations and Future Recommendations

This study used a cross-sectional survey design, which restricts the capacity to infer causality between AI competencies, chatbots' affordances, big data analysis capability, and business model innovation. Future research should consider longitudinal studies to observe the dynamic development of these relationships over time. The study also concentrated on customers from the banks of Punjab, which could restrict the generalizability of the results. Increasing the sample size to cover different industries and organizational settings may offer more generalizable insights. Further research could also investigate other moderators, including organizational culture and top management support, and the impact of other AI tools, apart from chatbots, on business innovation.

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