Cross-Context Comparison of AI-Enabled CRM: Mechanisms, Challenges and Future Directions in B2B and B2C Settings

Zibo Lin

School of Business, South China Normal University,China
E-mail: st_lzb@qq.com

Abstract Artificial intelligence is reshaping customer relationship management (CRM) in both business-to-business (B2B) and business-to-consumer (B2C) contexts, yet the two settings differ markedly in relationship structure, decision-making processes, data characteristics and customer expectations. The core argument of this review is that AI-CRM exhibits significant contextual differences between B2B and B2C, with variations in its capability dimensions, action pathways, performance outcomes, and facilitating and hindering factors. Accordingly, firms cannot directly transfer AI-CRM strategies from one context to another; instead, they should adapt strategies based on differences in relationship structures, decision-making processes and customer expectations. By integrating existing literature, this paper systematically compares the mechanisms, performance outcomes and challenges of AI-CRM across B2B and B2C scenarios. The study finds that AI-CRM in the B2B context places greater emphasis on organizational capabilities, institutional support and process integration, while the B2C context focuses more on personalized experiences, emotional interaction and consumer trust. Both contexts face common challenges such as ethics, privacy and data bias, but differ in focus and response approaches. Existing research mostly examines B2B or B2C in isolation, lacking direct comparison. Future research should strengthen cross-context theoretical construction and empirical testing. Finally, this paper outlines the future research directions derived from the review.

Keywords Artificial Intelligence; Customer Relationship Management; B2B; B2C; Cross-Context Comparison; Relationship Marketing

1. Introduction

Artificial intelligence is reshaping marketing and customer relationship management in profound ways. Davenport et al. argue that AI is not merely a technological upgrade but a paradigm shift altering how firms interact with customers, manage data and make decisions [1]. In recent years, AI-driven CRM systems have been widely adopted, and the related research base has grown accordingly; bibliometric evidence likewise indicates rising scholarly interest in this area [2]. Yet much of the existing work examines either B2B or B2C settings in isolation, and systematic comparisons between the two remain relatively uncommon. Such separation produces a fragmented picture of AI-CRM and leaves practitioners without clear theoretical guidance when they seek to apply AI-CRM across different contexts.

This review advances a central argument: AI-CRM differs substantially across B2B and B2C settings in terms of capability dimensions, action pathways, performance outcomes, and the factors that facilitate or hinder its use. Consequently, AI-CRM strategies cannot simply be transplanted from one context to the other; rather, they need to be adapted to variations in relationship structures, decision-making processes and customer expectations. This argument informs the entire review and seeks to offer scholars and practitioners a cross-context comparative framework for understanding how AI reshapes CRM across different market structures.

B2B and B2C contexts differ in fundamental ways. B2B customers are organizations, and their relationships typically involve long decision chains, complex interactions, data-intensive processes and strong demands for customization; relationship management therefore engages multiple stakeholders, supply chain collaboration and long-term contracts. B2C customers, by contrast, are individual consumers whose priorities include instant experiences, emotional interaction, personalization and trust. Such differences imply that AI-CRM capability building, mecha-

nisms and performance outcomes are likely to vary across the two contexts. AI-CRM in B2B, for instance, may depend more heavily on institutional support and organizational capabilities, whereas AI-CRM in B2C may rest more on emotional interaction and personalized services. Cross-context comparison thus carries both theoretical and practical value.

Guided by the discussion above, this review poses three research questions:

1. What capability dimensions make up AI-CRM in B2B and B2C, respectively?
2. In what ways do the pathways linking AI-CRM to performance and relationships differ between the two contexts?
3. How do facilitating and hindering factors vary between B2B and B2C?

Drawing on existing literature, this paper offers a comparative analysis centered on these questions and identifies research gaps and future directions. The remainder of the paper is organized as follows. Section 2 provides the theoretical background, defining core concepts and reviewing major theoretical frameworks. Section 3 presents the literature review, comparing empirical effects, sustainability impacts and industry applications of AI-CRM in B2B and B2C. Section 4 discusses key findings, points of consistency and contradiction, and research limitations. Section 5 concludes the paper and outlines future research directions.

2. Theoretical Background

2.1 Definition of Core Concepts

AI-CRM refers to the integration of AI technologies with CRM systems for customer data management, interaction, decision-making and relationship maintenance. Ledro et al. note that AI in CRM encompasses a range of technologies such as machine learning, natural language processing and predictive analytics [3]. In recent years, scholars have further argued that AI-CRM should not be regarded merely as a technical tool, but also as an organizational and dynamic capability [4][5]. This shift from a "tool perspective" to a "capability perspective" is an important premise for understanding cross-context differences in AI-CRM. In the B2B context, AI-CRM capabilities are often embedded in organizational processes and institutional environments, emphasizing integration with supply chains, partners and internal systems; in the B2C context, AI-CRM capabilities focus more on customer interaction, personalization and emotional experience.

B2B CRM is characterized by inter-organizational relationships, multi-role decision-making, long-term contracts, high customer lifetime value and supply chain collaboration. Relationships are typically complex, involving multiple touchpoints and customized solutions. B2C CRM involves individual consumers, emphasizing mass personalization, instant interaction, emotional connection and rapid conversion. The focus is on delivering seamless experiences and building consumer trust. From a cross-context perspective, AI-CRM in B2B places more weight on organizational capabilities, institutional support and process integration; AI-CRM in B2C places more emphasis on customer experience, emotional interaction and personalized services. This difference is reflected not only in capability dimensions, but also in the choice of theoretical frameworks.

2.2 Major Theoretical Frameworks

In B2B research, commonly used theories include institutional theory, the resource-based view and dynamic capabilities theory. Institutional theory posits that organizational values, norms and expectations influence AI-CRM implementation [6]. The resource-based view emphasizes that valuable, rare, inimitable and non-substitutable data and resources form the basis of competitive advantage [7]. Dynamic capabilities theory focuses on sensing, seizing and transforming capabilities that enable firms to adapt to changing environments [8]. Together, these theories explain why AI-CRM in B2B requires institutional support, organizational capabilities and resource integration.

In B2C research, commonly used theories include the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), social presence theory, anthropomorphism theory, and expectancy violations theory. TAM and UTAUT focus on the effects of perceived usefulness, perceived ease of use and social influence on user adoption [9][10]. Social presence theory and anthropomorphism theory explain trust and interaction with chatbots [11][12]. Expectancy violations theory is used to analyze the relationship between emotional expression and customer satisfaction [13]. These theories are more oriented to individual psychology and interaction, emphasizing consumer cognition, emotion and trust.

B2B theorizing tends to operate at the organizational and institutional level, whereas B2C theorizing is more concerned with individual psychology and interaction. Such a contrast in theoretical orientation reinforces the need for cross-context comparison. Applying B2C frameworks to B2B, or the reverse, risks overlooking contextual factors that shape AI-CRM. The literature analysis that follows therefore examines capability dimensions, action pathways and outcomes separately for each context.

3. Literature Review

3.1 Theme 1: Comparison of Empirical Effects of AI-CRM in B2B and B2C

In the B2B context, AI-CRM has been linked to gains in relationship satisfaction and firm performance. Chatterjee et al. report that AI-integrated CRM systems significant-

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ly enhance both B2B relationship satisfaction and firm performance, with automated decision-making and operational efficiency emerging as key drivers of the former [6]. However, technological turbulence plays a negative moderating role: when technological change is too fast and unpredictable, the positive effect of automated decision-making and operational efficiency on B2B relationship satisfaction is weakened. Leadership support plays a positive moderating role: the stronger the leadership support, the stronger the positive effect of B2B relationship satisfaction on firm performance. Another study by Chatterjee et al., combining institutional theory and the resource-based view, finds that successful AI-CRM implementation requires multiple conditions: implementation quality, employee skills and attitudes, and technological capabilities [6]. Institutional theory explains how organizational values, expectations and norms affect the implementation of new technologies; the resource-based view explains how valuable, rare, inimitable and non-substitutable data and resources help firms unlock the potential of AI-CRM. Well-implemented AI-CRM enhances organizational performance and competitive advantage. Leadership support also plays a moderating role.

In the B2C context, AI-CRM enhances marketing ambidexterity, which in turn affects sustained profitability and competitive advantage [5]. Alnofeli et al. view AI-driven CRM as a high-order organizational capability, and find that AI-CRM capabilities consist of three dimensions: data management capability (data governance, data analysis and intelligence, data privacy), multi-channel integration capability (content consistency, process consistency), and service delivery capability (personalization, automation, meaningfulness) [5]. These capabilities positively influence marketing ambidexterity—a firm's ability to both exploit existing markets and explore new opportunities. Marketing ambidexterity further affects sustained profitability and sustained competitive advantage. Service delivery capability has the strongest explanatory power for overall AI-CRM capability, and marketing ambidexterity plays a partial mediating role.

Zhang et al., based on expectancy violations theory, investigate whether AI chatbots expressing "caring" emotions can improve customer satisfaction [13]. The study finds that chatbots expressing care for customers can increase customer satisfaction, and the underlying mechanism is that care expression reduces customer expectancy violation. Moderating conditions include customer goal orientation (the effect is more pronounced with low process orientation or high outcome orientation), the anthropomorphic degree of the chatbot avatar (the less human-like the avatar, the weaker the negative effect of emotional expression on expectancy violation), and relationship type (expectancy violation is lower when the customer and chatbot have a "friend" relationship; the difference is not significant when they have an "assistant" relationship).

Mariani et al. conduct a systematic review of AI conversational agents (CAs) in marketing and consumer research, identifying four major research themes: consumer trust in CAs, applications of natural language processing in CA design and development, communication with CAs, and the impact of CAs on value creation and firm value [14]. They propose a "drivers—CA adoption—outcomes" framework: drivers include CA design (anthropomorphism, personalization), user characteristics (ease of use, perceived usefulness, trust and privacy, enjoyment, technology attitude), and situational environmental factors; outcomes include user-level sustained use, purchase intention, attitude, advice compliance, participation, satisfaction, as well as firm-level brand image, word-of-mouth, loyalty, and satisfaction.

In comparison, B2B places more emphasis on organizational performance, relationship quality and process efficiency, while B2C focuses more on individual experience, emotional connection and instant satisfaction. A common point is that both emphasize trust, data quality and leadership or organizational support. But the differences are also notable: AI-CRM in B2B requires institutional support and resource integration, while AI-CRM in B2C relies more on emotional interaction and personalized services. This difference directly supports the core argument of this paper, namely that AI-CRM strategies may not be directly transferable across contexts.

3.2 Application Context Check: Sustainable CRM in B2B and B2C

Rather than treating sustainability as a separate research theme, this subsection uses sustainable CRM as an application context to test whether the cross-context differences identified in RQ1–RQ3 carry over into this domain.

Capability building for sustainable AI-CRM varies by context (RQ1). In B2B, such capabilities are embedded in organizational processes, institutional arrangements and supply chain collaboration—green supplier identification, circular economy support and supplier sustainability evaluation being typical examples [3]. B2C, by contrast, places greater weight on consumer-level capabilities, including the identification of green consumers, personalized green communication and the analysis of sustainable attitudes [3].

The pathways through which AI-CRM shapes sustainability outcomes also diverge (RQ2). In B2B, influence flows mainly through network development, process optimization, reverse logistics and resource management [3]. In B2C, green consumption is more likely to be affected via recommendation systems, sustainable communication and trust-building mechanisms [3].

Both contexts encounter similar challenges around privacy, ethics, the digital divide and trust (RQ3). Yet the responses differ: B2B leans more on institutional design, compliance and cross-organizational coordination, where-

as B2C depends more on consumer trust building and transparent communication. One barrier specific to B2C is that the impersonal nature of AI may weaken consumers' willingness to engage in green consumption [3]. Broader hindering factors—ethical concerns, data bias and distrust—also surface in AI relationship marketing more generally [4].

Overall, the sustainable CRM domain mirrors the wider B2B–B2C pattern: organizational and institutional capabilities dominate in B2B, while consumer trust and personalized interaction dominate in B2C. This pattern reinforces the core argument that AI-CRM strategies cannot simply be transferred across contexts.

3.3 Theme 3: Specific Industries and Interaction Technologies: Cross-Context of B2B and B2C

In the healthcare industry, Kumar et al. study AI-CRM capabilities in the Indian healthcare sector [15]. AI-CRM capabilities are divided into three dimensions: clinical capabilities (AI diagnosis, AI treatment, data-driven clinical skills), service capabilities (AI customer service, teleconsultation, app-based medical services), and AI engagement capabilities (encouraging patients to use AI tools, platforms and services). The core finding is that AI-CRM capabilities positively influence customer service flexibility (CSF); CSF positively influences service innovation; the direct effect of AI-CRM on service innovation is not significant; CSF is the "missing link" that acts as a bridge. That is, AI-CRM itself does not directly bring about service innovation, but first enables firms to respond more flexibly to patient needs, which in turn promotes service innovation.

This study is used here as evidence from a mixed B2B–B2C context rather than as pure B2C evidence. Healthcare involves both consumer-facing relationships (patients as individual service users) and organizational relationships (hospitals, insurers, suppliers and regulatory bodies). Kumar et al.'s capability dimensions reflect this duality: clinical and service capabilities operate at the patient interaction level, while the development of these capabilities depends on organizational processes, institutional support and cross-organizational coordination [15]. The finding that AI-CRM affects service innovation only indirectly, through customer service flexibility, is therefore relevant to both contexts. It shows that AI-CRM capability building in healthcare cannot be reduced to either B2C personalization or B2B process integration alone. This mixed character makes the study useful for the cross-context comparison: it suggests that the B2B–B2C boundary is not always sharp, and that some AI-CRM capabilities span both relationship types. It also reinforces the core argument that AI-CRM strategies must be adapted to the specific relationship structure, rather than transferred wholesale from one context to another.

In terms of conversational agents, the reviewed B2C literature extensively examines chatbots and voice assistants and their effects on trust, emotion and satisfaction [13][14]. In contrast, the reviewed B2B literature places relatively greater emphasis on their use for partner selection, virtual assistance and automated decision-making [6], rather than on emotional expression and anthropomorphism. This difference reflects the emphasis of the reviewed studies, not a direct measure of actual adoption frequency.

Mariani et al. find that conversational agent (CA) design (anthropomorphism, personalization) is an important driver of adoption, and user characteristics (ease of use, perceived usefulness, trust and privacy, enjoyment, technology attitude) also affect adoption [14]. Outcomes include sustained use, purchase intention, attitude, advice compliance, participation and satisfaction. At the firm level, CAs affect brand image, word-of-mouth, loyalty and satisfaction. Zhang et al. further find that care expression by chatbots improves satisfaction, but the effect depends on customer goal orientation, anthropomorphic degree of the avatar and relationship type [13].

Within the reviewed literature, therefore, CAs in B2C are examined more in terms of anthropomorphism, emotional expression and instant interaction, while CAs in B2B are examined more in terms of task efficiency, decision support and system integration. This contrast indicates that even for the same AI technology, design goals, mechanisms and performance outcomes differ across contexts. Therefore, firms cannot directly transfer successful chatbot strategies from B2C to B2B, and vice versa.

4. Discussion and Synthesis

4.1 Key Findings and Trends

Rather than cataloguing individual studies, this section organizes the literature around a single comparative framework—capability foundations, action mechanisms, outcome variables, and boundary conditions and risks—and uses that framework to compare B2B and B2C research on AI-CRM. Broad agreement exists that B2B leans toward organizations and institutions while B2C leans toward individuals and interactions. Even so, direct comparisons within a single study remain uncommon, and many of the differences noted here are inferred rather than established through head-to-head empirical testing.

Capability foundations differ in emphasis. B2B research stresses organizational capabilities, institutional support, and resource integration. Chatterjee et al. report that implementation quality, employee skills and attitudes, and technological capabilities jointly shape AI-CRM effectiveness, with organizational values, norms and expectations also influencing technology adoption [6]. Ledro et al., writing on sustainable CRM, observe that AI applications in B2B are embedded in supply chain collaboration, green supplier evaluation, and inter-organizational coordination [3]. Roy et al. treat AI relationship marketing as both an

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organizational capability and a dynamic capability [4]. B2C research, by contrast, gives more weight to data management, multi-channel integration, service delivery, personalization, and trust. Alnofeli et al. propose three dimensions of AI-CRM capability—data management, multi-channel integration, and service delivery—with service delivery explaining the largest share of overall capability [5]. Mariani et al. show that anthropomorphic and personalized design of conversational agents (CAs), together with user characteristics such as ease of use, perceived usefulness, and trust and privacy, affect adoption [14]. Zhang et al. focus on chatbots' emotional expression [13]. The contrast between B2B's organizational-institutional orientation and B2C's emphasis on individual perception and interaction therefore rests on multiple studies and appears relatively robust.

The mechanisms through which AI-CRM operates also diverge. In B2B, effects on performance tend to be indirect, working through organizational processes and relationship quality. Chatterjee et al. find that automated decision-making and operational efficiency drive B2B relationship satisfaction, with technological turbulence weakening this effect and leadership support strengthening the link between relationship satisfaction and firm performance [6]. Kumar et al. show in a healthcare setting that AI-CRM capability does not directly produce service innovation; it first enhances customer service flexibility (CSF), which then promotes service innovation [15]. B2B pathways thus appear generally indirect, mediated by organizational processes or relationship quality. In B2C, AI-CRM influences outcomes more directly through personalized experiences, emotional interaction, and trust mechanisms. Alnofeli et al. find that AI-CRM capability affects sustained profitability and competitive advantage through marketing ambidexterity, which serves as a partial mediator [5]. Zhang et al. report that chatbot care expression reduces customer expectancy violation and improves satisfaction, though the effect is moderated by customer goal orientation, the anthropomorphic degree of the chatbot avatar, and relationship type [13]. Mariani et al. note that conversational agents shape adoption through design features and user characteristics, which in turn affect sustained use, purchase intention, attitude, advice compliance, participation, and satisfaction [14]. Direct comparisons of B2B and B2C mechanisms within a single study remain rare, so the differences identified here should be treated as preliminary rather than fully validated.

Outcome variables show a similar split. B2B research focuses more on relationship satisfaction, firm performance, competitive advantage, service innovation, and supply chain sustainability. Chatterjee et al. examine B2B relationship satisfaction, firm performance, organizational performance and competitive advantage [6]; Kumar et al. investigate service innovation [15]; Ledro et al. examine supply chain sustainability and the circular economy [3]; and Roy et al. address long-term outcomes of relationship marketing [4]. B2C research focuses more on customer satisfaction, sustained profitability, competitive advantage, purchase intention, loyalty, and sustained use. Alnofeli et al. examine sustained profitability and sustained competitive advantage [5]; Zhang et al. focus on customer satisfaction [13]; and Mariani et al. summarize outcomes at the individual level (sustained use, purchase intention, attitude, advice compliance, participation, satisfaction) and the firm level (brand image, word-of-mouth, loyalty, satisfaction) [14]. The contrast between B2B's organizational-level performance and relationship quality and B2C's individual-level experience and satisfaction is supported by multiple studies. Yet outcome variables are operationalized inconsistently across studies, so direct comparisons require caution.

Boundary conditions and risks reinforce the contrast. B2B research focuses on technological turbulence, leadership support, implementation quality, employee skills and attitudes, human oversight, and AI literacy. Chatterjee et al. find technological turbulence to have a negative moderating effect and leadership support a positive one [6]. Chatterjee et al. stress that implementation quality, employee skills and attitudes, and technological capabilities are conditions for successful implementation [6]. Roy et al. identify human oversight and AI literacy as facilitators, and AI noise, ethical concerns, data quality and bias, friction, and distrust as barriers [4]. B2C research pays more attention to customer goal orientation, degree of anthropomorphism, relationship type, trust and privacy, algorithmic fairness, and the risk of emotional manipulation. Zhang et al. find that customer goal orientation, the anthropomorphic degree of the avatar, and relationship type moderate the effect of emotional expression [13]. Mariani et al. note that trust and privacy, enjoyment, and technology attitude affect adoption [14]. Ledro et al. point out that AI's impersonal nature may reduce willingness for green consumption [3]. Ethics, privacy, and data bias appear in both contexts, but B2B is more concerned with compliance, supply chain ethics, and multi-stakeholder interests, while B2C is more concerned with consumer trust, algorithmic transparency, and emotional manipulation risk. This difference is supported by multiple studies, yet context-specific ethical governance frameworks remain largely conceptual and untested empirically.

The strength of evidence varies. Several judgments appear relatively robust because multiple studies support them: B2B capability foundations lean toward organizations and institutions, while B2C ones lean toward individual perception and interaction; B2B outcome variables lean toward organizational performance and relationship quality, while B2C ones lean toward individual experience and satisfaction; and trust, data quality, and organizational or leadership support matter in both contexts. Other issues remain preliminary and insufficiently evidenced, including

direct comparison of B2B and B2C action mechanisms, the mediating role of marketing ambidexterity in B2C, context-specific ethical governance frameworks, and the boundary between B2B and B2C in mixed settings such as healthcare. The cross-context framework proposed here therefore both integrates existing evidence and sets a future research agenda: only by comparing B2B and B2C within a single study can scholars determine which differences are robust and which remain provisional.

4.2 Research Limitations

4.2.1 Limitations of Existing Literature

Current research is largely fragmented: B2B and B2C are mostly studied in isolation, and direct comparisons between the two contexts remain scarce. The number of B2B studies is smaller than that of B2C studies, and empirical research on AI-CRM in the B2B setting is particularly insufficient. B2C studies predominantly employ experimental methods, which limits their external validity, whereas B2B studies mostly rely on questionnaires and cross-sectional designs, making it difficult to establish causal relationships. Cross-cultural and cross-industry comparisons are likewise lacking, and insufficient attention has been paid to failure cases, employee resistance, and organizational change.

More specifically, Roy et al. draw their sample from India, and their conclusions may not be directly generalizable to other countries [4]. Alnofeli et al. cover only the Australian banking sector, with limited generalizability [5]. Kumar et al. are limited to the Indian healthcare industry, which also constrains generalizability [15]. The B2B study by Chatterjee et al. has a limited sample [6]. The literature review by Mariani et al. cuts off in May 2022 and includes few cross-cultural and cross-regional comparative studies [14]. Ledro et al. rely on a single database, include 94 articles, focus primarily on environmental sustainability, give insufficient attention to social sustainability, and over-represent B2C relative to B2B in their sample [3]. Zhang et al. employ an experimental method in a tourism context, which limits external validity [13]. Taken together, these limitations indicate that the extant literature is insufficient to fully address cross-context comparative questions, and more targeted research is needed in the future.

4.2.2 Limitations of This Review

The present review is built on the existing literature and therefore inherits the limitations of the studies it synthesizes. Its database coverage, search period, screening criteria, article count, and potential selection bias are all constrained by the source reviews and empirical studies on which it draws. For example, Mariani et al. cover literature through May 2022 [14]; Ledro et al. rely on a single database and cover literature through May 2025 [3]; Alnofeli et al. draw on a scoping review of 64 articles [5]; Roy et al. are based on 67 interviews in India [4]; Kumar et al. are limited to Indian healthcare [15]; and Alnofeli et al. are limited to the Australian banking sector [5]. These constraints may lead to the omission of relevant studies from other databases, languages, regions, or industries, and may introduce selection bias. Accordingly, the cross-context comparisons offered in this review should be interpreted with caution, and future research should conduct more targeted and systematic searches.

5. Conclusion

This review integrates existing literature to conduct a cross-context comparison of AI-CRM in B2B and B2C settings. The core argument is that AI-CRM presents significant contextual differences between B2B and B2C, with variations in its capability dimensions, action pathways, performance outcomes, and facilitating and hindering factors. Accordingly, firms cannot directly migrate AI-CRM strategies from one context to another, but should adapt them based on differences in relationship structures, decision-making processes and customer expectations.

The study finds that although AI-CRM generally improves performance and relationships, there are significant differences in its mechanisms, outcomes and challenges. In B2B, AI-CRM places greater emphasis on organizational capabilities, institutional support, process integration, long-term relationships and supply chain collaboration. In B2C, AI-CRM emphasizes personalization, emotional interaction, instant experience, consumer trust and algorithmic fairness. Both contexts face common challenges such as ethics, privacy and data bias, but differ in focus and response approaches.

Future research can be pursued along the following four directions.

First, conduct direct cross-context comparisons. Existing studies predominantly examine B2B and B2C separately, lacking direct comparisons within a single framework, and empirical research on B2B is particularly insufficient. Future research should directly compare the capability dimensions, action pathways, and performance outcomes of AI-CRM across the two contexts within a single investigation, and strengthen research on capability building, implementation barriers, and performance mechanisms in the B2B setting.

Second, adopt longitudinal and causal research designs. Existing B2C studies mostly employ experimental methods with limited external validity, whereas B2B studies mostly rely on questionnaires with cross-sectional designs that make it difficult to establish causal relationships. Future research should adopt longitudinal designs to track the dynamic effects of AI-CRM on relationships and performance, and strengthen causal identification.

Third, pay attention to employees and organizational change. The extant literature gives insufficient attention to failure cases, employee resistance, and organizational change. Future research should examine the role of em-

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ployee adaptability, organizational culture, employee resistance, and organizational change in both B2B and B2C, and should attend to facilitating factors such as human oversight and AI literacy, as well as hindering factors such as resistance and distrust.

Fourth, strengthen cross-cultural and cross-industry validation. Existing research lacks cross-cultural and cross-industry comparisons, and samples are concentrated in single countries or industries—for example, India, the Australian banking sector, and Indian healthcare. Future research should conduct cross-cultural and cross-industry comparisons to test the generalizability of the cross-context conclusions regarding AI-CRM. Through these efforts, the theoretical system of AI-CRM can be further enriched, and more context-specific guidance can be provided for practice.

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