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LEVERAGING AI-CRM TO ACHIEVE THE TRIPLE BOTTOM LINE: AN ANALYSIS OF ITS EFFECTS ON ECONOMIC, SOCIAL, AND ENVIRONMENTAL PERFORMANCE

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Abstract

Organizations increasingly adopt customer relationship management systems enabled by artificial intelligence (AI-CRM), yet evidence on their contribution to sustainability is concentrated on economic outcomes. This conceptual article develops a framework that explains how AI-CRM capability may influence economic, social, and environmental performance, the three pillars of the triple bottom line, and under which conditions. A narrative review of 37 sources, 14 of them published between 2021 and 2026, was combined with the resource-based view, the natural-resource-based view, dynamic capabilities, and stakeholder theory. The review shows that empirical AI-CRM research examines economic and relationship outcomes in business-to-business settings, whereas social and environmental effects must be inferred from adjacent literatures on AI ethics, regulation, and the carbon footprint of AI. Recent firm-level evidence on AI and environmental outcomes is divergent, which supports a conditional rather than a uniform view. The framework proposes that AI-CRM supports economic performance through retention, personalization, and efficiency; affects social performance through trust, service quality, and inclusion, subject to privacy and fairness risks; and has an ambiguous environmental effect because waste reduction may be offset by energy use and rebound effects. Data governance and ethics, sustainability orientation, digital capability, and top-management support are proposed as moderators. Eight propositions, each with an evidence-status assessment and a suggested test, are offered. The article presents no primary data; the propositions require empirical examination, for example through survey-based structural equation modeling and energy accounting of AI workloads.

Keywords: *AI-CRM, Artificial Intelligence, Customer Relationship Management, Sustainability Performance, Triple Bottom Line*

1. INTRODUCTION

Pressure on organizations to demonstrate sustainability performance has grown, and the triple bottom line has become a common way to frame it. Elkington (1997) proposed that firms should be assessed on three dimensions, economic prosperity, social justice, and environmental quality, often summarized as profit, people, and planet. Slaper and Hall

(2011) describe it as a framework that measures performance along economic, social, and environmental lines. Elkington (2018) himself cautioned that the concept was often reduced to a reporting exercise and failed to displace the single bottom line paradigm, a reminder that adopting the vocabulary of the triple bottom line is not the same as achieving balanced performance.

In parallel, organizations manage customer relationships with increasingly intelligent systems. Customer relationship management (CRM) is a strategic approach to creating value through relationships with customers (Payne & Frow, 2005; Buttle & Maklan, 2019), and the economics of retention have long been recognized (Reichheld & Sasser, 1990). Advances in artificial intelligence (AI), including machine learning, natural language processing, and conversational agents, now allow CRM to predict customer behavior, interpret customer language, and automate customer-facing decisions (Davenport et al., 2020; Huang & Rust, 2021). Research on AI in marketing has grown quickly and remains fragmented across disciplines (Mariani et al., 2022). In this article, AI-CRM refers to CRM systems and practices in which AI techniques are used to analyze customer data and to support or automate customer-facing decisions.

Empirical evidence on AI-CRM is still recent and concentrated on economic and relational outcomes. Chatterjee et al. (2021) examined AI-based CRM, organizational performance, and competitive advantage in the business-to-business context through institutional theory and the resource-based view. Chatterjee et al. (2022), using data from 312 respondents in 14 firms, found that an AI-embedded CRM system is positively associated with B2B relationship satisfaction and firm performance, with technology turbulence and leadership support acting as moderators. More broadly, a measured AI capability has been linked to organizational creativity and firm performance (Mikalef & Gupta, 2021). In the sources reviewed here, none of the AI-CRM studies measured social or environmental outcomes.

The sustainability implications of AI are double-edged. In an expert elicitation covering the 169 targets of the Sustainable Development Goals, Vinuesa et al. (2020) concluded that AI can enable 134 targets but may inhibit 59. On the environmental side, the carbon cost of AI spans data, experimentation, training, and inference, and includes the embodied carbon of hardware (Wu et al., 2022); a life-cycle estimate for one 176-billion-parameter language model reached about 50.5 tonnes of CO2eq (Luccioni et al., 2023). Firm-level evidence is divergent: AI adoption was associated with better green governance performance among Chinese listed firms (Arif et al., 2026; Feng et al., 2026), whereas AI capability was associated with higher ecological footprint intensity in a sample of innovation-leading economies (Balcı et al., 2025; Windarsari & Arif, 2026). On the social side, the use of customer data raises concerns about privacy (Martin & Murphy, 2017), fairness (Blodgett et al., 2020), and ethical principles for AI (Floridi et al., 2018), and

regulators have begun to respond (European Parliament & Council, 2024; Republic of Indonesia, 2022).

The gap is therefore specific. Evidence on AI-CRM concerns the economic pillar, evidence on the environmental and social consequences of AI comes from adjacent literatures, and the two have not been integrated into one framework. As a result, managers lack guidance on how to use AI-CRM so that gains on one pillar do not come at the expense of another. Studies outside the reviewed sources may address parts of this problem; the present review does not claim to cover them.

This article therefore asks four questions. (RQ1) Through which mechanisms may AI-CRM influence economic, social, and environmental performance? (RQ2) What trade-offs and synergies arise among the three pillars? (RQ3) Which organizational conditions moderate these effects? (RQ4) What propositions follow for empirical testing? The article contributes an integrated framework, a mapping of mechanisms and trade-offs that distinguishes direct from inferred evidence, and eight propositions. It is a conceptual article and presents no primary data.

2. RESEARCH METHOD

This is a conceptual article. It does not collect or analyze primary data. Its purpose is theory building through the synthesis of existing literature, following the logic of conceptual article design described by Jaakkola (2020), and it assembles the literature through a narrative review approach (Snyder, 2019).

Jaakkola (2020) distinguishes four approaches to conceptual articles: theory synthesis, theory adaptation, typology, and model. This article combines theory synthesis, which integrates insights across separate literatures, with model development, which specifies relationships among constructs. The result is a framework and a set of propositions rather than findings about particular organizations.

Literature was selected purposively from the five streams described in the Literature Review. The inclusion criteria were: (a) peer-reviewed journal articles, major conference papers, books, or primary legal sources; (b) seminal or widely cited works in their stream, or recent studies from 2021 to 2026 that update the evidence; and (c) direct relevance to the relationship between customer-facing technology, AI, and sustainability performance. To strengthen the recency of the evidence base, targeted searches were run in October 2026 on AI-CRM, AI capability and firm performance, the environmental footprint of AI, and AI governance, and bibliographic details of the added sources were checked against publisher or repository records. No systematic database protocol (such as PRISMA) was applied, and the review does not claim to be exhaustive. Sources are in English apart from Indonesian legislation.

The framework was developed in five steps: (1) identifying AI-CRM capabilities from the CRM and AI literature; (2) identifying, for each pillar of the triple bottom line, the mechanisms through which these capabilities may have positive or negative effects; (3) identifying organizational conditions that may moderate the effects, drawing on the four theories; (4) specifying relationships among pillars; and (5) deriving propositions with their theoretical basis and a suggested design for testing them. Each mechanism and proposition was also assigned an evidence status: direct when AI-CRM studies address it, adjacent when evidence comes from AI or related technologies in other contexts, and theoretical when it rests on theory only. The framework was evaluated for conceptual clarity, internal coherence, and testability. Mechanisms and moderators are the authors' syntheses and not empirical findings.

3. RESULTS AND DISCUSSION

The synthesis yields five outputs: a profile of the evidence base, a definition of AI-CRM capability, a mapping of mechanisms and trade-offs for each pillar, an integrated framework, and eight propositions. All are conceptual outputs derived from the literature. Effects described below are possible mechanisms to be tested, not established results.

3.1 Characteristics of the Evidence Base

Table 1 profiles the 37 sources cited. 14 of them (38%) were published in 2021 or later, and these carry most of the evidence on AI-CRM, AI capability, the carbon footprint of AI, and firm-level environmental outcomes. Foundational work dominates the triple bottom line and theory streams. Three studies directly address AI-CRM or AI capability and firm performance, and all concern economic or relational outcomes (Chatterjee et al., 2021, 2022; Mikalef & Gupta, 2021). The social and environmental pillars of AI-CRM are therefore supported mainly by adjacent evidence, which shapes the evidence status assigned below.

Table 1. Profile of the cited evidence base by stream

Stream	Sources (n)	Published 2021–2026 (n)	Dominant evidence type
Triple bottom line and sustainability performance	7	2	Meta-analysis, panel studies, conceptual
CRM, AI-CRM, and AI in marketing	11	5	B2B surveys (PLS-SEM), reviews, frameworks
AI and sustainability (including Green AI)	8	5	Carbon accounting, expert elicitation, reviews
Ethics, privacy, fairness, and regulation	5	2	Ethical frameworks, critical surveys, legislation
Theory and method	6	0	Seminal theory, method guidelines
Total	37	14	

Note: Each source is counted once under its primary stream.

3.2 AI-CRM Capability and Its Links to the Three Pillars

AI-CRM capability is treated here as the organization's ability to collect and integrate customer data, derive predictions and insights from them with AI techniques, and act on those insights through automated or human-supported decisions. This follows the capability logic of Mikalef and Gupta (2021), applied to the customer-facing domain. Table 2 distinguishes five typical applications and indicates the pillars they are most likely to affect.

Table 2. Typical AI-CRM applications and their possible links to the three pillars

Application	Economic pillar	Social pillar	Environmental pillar
Predictive analytics (churn, demand, customer value)	Higher retention and customer lifetime value; targeted spending	Proactive service for at-risk customers; risk of profiling	Better demand forecasting may reduce overproduction and waste
Natural language processing and voice of the customer	Faster detection of problems; improved offers	Greater responsiveness; risk of language bias	Compute and energy use for model training and inference
Personalization and recommendation	Higher conversion and basket value	Relevance and convenience; risk of manipulation and privacy intrusion	May reduce irrelevant communication; may also stimulate additional consumption
Chatbots and service automation	Lower cost to serve; extended availability	Wider access; possible exclusion of less digital customers and effects on employees	Energy use of always-on systems
Digitized customer processes (e-statements, paperless service)	Lower processing costs	Convenience; accessibility concerns	Lower paper and physical resource use

Source: Authors' synthesis of the reviewed literature (2026).

3.3 Mechanisms for Each Pillar

a) Economic pillar

The most direct mechanisms operate through retention and value. AI-CRM can help identify at-risk customers and tailor interventions, and since retention is linked to profitability (Reichheld & Sasser, 1990) and CRM process quality is linked to performance (Reinartz et al., 2004), a positive effect on economic performance is plausible. Direct evidence exists for B2B firms, where AI-embedded CRM was positively associated with relationship satisfaction and firm performance (Chatterjee et al., 2022). This is the best-supported pillar, although the evidence is limited to the B2B context and perceptual measures.

b) Social pillar

AI-CRM can improve service quality, responsiveness, and personalization, which may strengthen customer trust and satisfaction. It can also harm social performance when data are used without adequate safeguards. Privacy intrusion (Martin & Murphy, 2017), biased treatment of customers whose language or behavior differs from the training data (Blodgett et al., 2020), and opaque automated decisions conflict with the principles of justice and explicability (Floridi et al., 2018). Regulation such as the EU Artificial Intelligence Act and Indonesia's personal data protection law raises the cost of weak governance (European Parliament & Council, 2024; Republic of Indonesia, 2022). Automation may also change employees' work and exclude customers who are less comfortable with digital channels. The net social effect therefore depends on governance, and the evidence is adjacent rather than direct.

c) Environmental pillar

Possible positive mechanisms include better demand forecasting, which can reduce overproduction and waste, more targeted communication, and the replacement of paper-based processes. Possible negative mechanisms include the energy and carbon cost of training and running AI models (Strubell et al., 2019; Schwartz et al., 2020; Wu et al., 2022; Luccioni et al., 2023). Adjacent firm-level evidence points in both directions (Feng et al., 2026; Balcı et al., 2025). In addition, we argue conceptually that a rebound effect is possible: if personalization is used mainly to stimulate additional purchases, increased consumption may offset efficiency gains. This argument is a theoretical possibility that requires empirical examination. The net environmental effect is therefore ambiguous and depends on the purposes for which AI-CRM is used and on how computational efficiency is managed.

d) Relationships among pillars

The pillars are not independent. Social performance, in the form of customer trust and perceived fairness, may mediate the long-term effect of AI-CRM on economic performance, consistent with the positive association between social and financial

performance reported by Orlitzky et al. (2003). Conversely, economic objectives such as maximizing conversion may conflict with environmental objectives when they promote consumption.

Table 3. Mechanisms, risks, moderators, and evidence status by pillar

Pillar	Enabling mechanisms	Risks and trade-offs	Key moderators	Evidence status
Economic	Retention, customer lifetime value, conversion, cost to serve	Over-reliance on short-term conversion; investment cost	Digital capability; top-management support	Direct (B2B AI-CRM; AI capability)
Social	Trust, service quality, responsiveness, inclusion	Privacy intrusion, algorithmic bias, opacity, employee and exclusion effects	Data governance and ethics; regulation	Adjacent (ethics, privacy, regulation)
Environmental	Demand forecasting, targeted communication, paperless processes	Energy and carbon cost of AI; rebound effect from consumption-driving personalization	Sustainability orientation; Green AI practices	Adjacent and divergent; rebound is theoretical

Source: Authors' synthesis of the reviewed literature (2026).

3.4 The Conceptual Framework

Figure 1 integrates the elements. AI-CRM capability, made up of data and predictive analytics, natural language processing and customer insight, and automation and personalization, may influence economic, social, and environmental performance. Four organizational conditions moderate these effects: data governance and ethics, sustainability orientation, digital capability, and top-management support. Their roles follow from the theories reviewed. From the resource-based view and dynamic capabilities, digital capability and managerial support determine whether AI-CRM resources are converted into performance, a pattern consistent with the moderating role of leadership support reported by Chatterjee et al. (2022). From the natural-resource-based view, sustainability orientation determines whether capabilities are directed at environmental improvement. From stakeholder theory, data governance and ethics determine whether customers' expectations are respected.

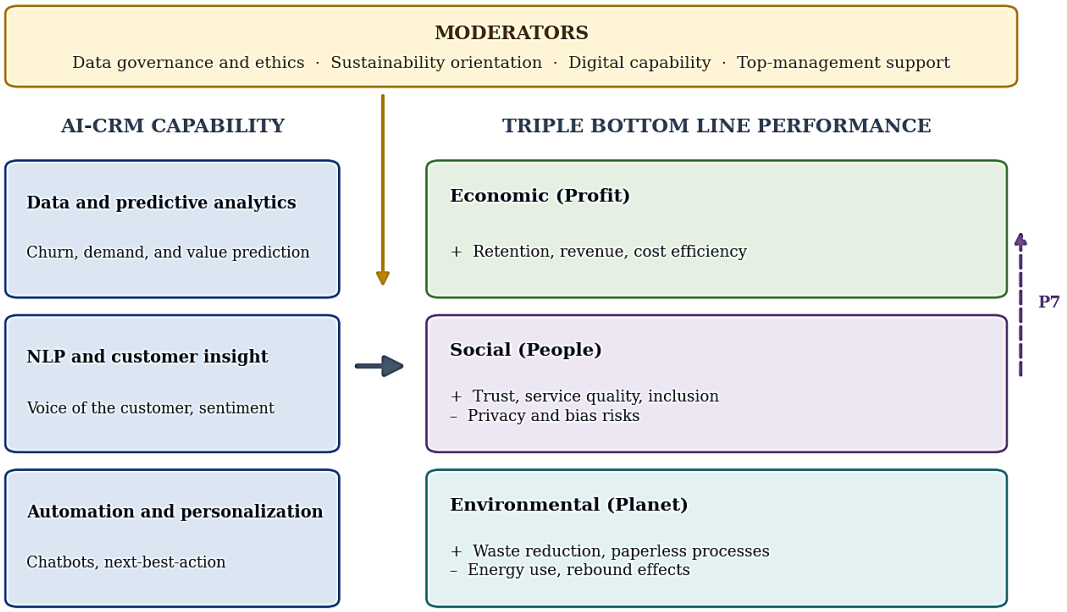


Figure 1. Conceptual Framework of AI-CRM and Triple Bottom Line Performance

3.5 Propositions

Table 4 states eight propositions with their theoretical basis, the current evidence status, and a suggested way to test each. They are theoretical expectations, not results.

Table 4. Research propositions derived from the framework

Code	Proposition	Basis	Evidence status	Suggested design or measure
P1	AI-CRM capability is positively associated with economic performance (retention, revenue, cost efficiency).	Reichheld & Sasser (1990); Reinartz et al. (2004); Barney (1991); Chatterjee et al. (2022); Mikalef & Gupta (2021)	Direct, B2B	Survey and archival performance data; structural equation modeling

Code	Proposition	Basis	Evidence status	Suggested design or measure
P2	The relationship between AI-CRM capability and social performance is positive when data governance and ethics practices are strong, and weak or negative when they are weak.	Floridi et al. (2018); Martin & Murphy (2017); Freeman (1984); European Parliament & Council (2024)	Adjacent	Survey with governance index; moderated regression
P3	The relationship between AI-CRM capability and environmental performance is conditional: positive when AI-CRM is used for waste-reducing purposes, and not positive otherwise.	Hart (1995); Vinuesa et al. (2020); Feng et al. (2026); Balcı et al. (2025)	Adjacent, divergent	Use-case coding; environmental indicators; multi-group analysis
P4	The computational and energy intensity of AI-CRM weakens its positive effect on environmental performance, and Green AI practices reduce this weakening.	Strubell et al. (2019); Schwartz et al. (2020); Wu et al. (2022); Luccioni et al. (2023)	Adjacent (AI computing)	Energy and carbon accounting of AI workloads; case studies
P5	Sustainability orientation strengthens the relationship between AI-CRM capability and environmental and social performance.	Hart (1995); Eccles et al. (2014)	Theoretical	Survey with validated orientation scale; moderation analysis

Code	Proposition	Basis	Evidence status	Suggested design or measure
P6	Digital capability and top-management support strengthen the translation of AI-CRM capability into performance on all three pillars.	Teece et al. (1997); Barney (1991); Chatterjee et al. (2022)	Direct for economic pillar; theoretical otherwise	Survey; moderation analysis
P7	Social performance (customer trust and perceived fairness) mediates the long-term relationship between AI-CRM capability and economic performance.	Orlitzky et al. (2003); Eccles et al. (2014)	Theoretical	Longitudinal survey; mediation analysis
P8	AI-CRM use that mainly drives additional consumption through intensive personalization reduces net environmental performance, unless personalization is designed to promote sustainable options.	Conceptual argument (rebound effect); Vinuesa et al. (2020); van Wynsberghe (2021)	Theoretical	Field experiment; consumption and footprint data

Source: Authors' synthesis of the reviewed literature (2026).

3.6 Discussion

The framework makes three contributions. First, it moves the discussion of AI-CRM beyond economic outcomes by showing that its effects on the social and environmental pillars involve both enabling mechanisms and risks, and by separating direct from adjacent evidence. Second, it joins the resource-based view, the natural-resource-based view, dynamic capabilities, and stakeholder theory into a single explanation of when AI-CRM capability turns into balanced performance. Third, it identifies the environmental pillar as the most uncertain. Recent firm-level studies disagree on whether AI improves or worsens environmental outcomes (Feng et al., 2026; Balcı et al., 2025; Sudirman et al., 2026), and life-cycle estimates show that the footprint of AI itself is not negligible (Luccioni et al.,

2023; Riu et al., 2026). This is a reminder to treat the environmental cost of AI as part of the evaluation of AI-CRM, consistent with the call to address the sustainability of AI and not only AI for sustainability (van Wynsberghe, 2021).

If the propositions are supported, several implications follow. For managers, AI-CRM investments should be accompanied by data governance, fairness checks, and human oversight, and the environmental cost of AI workloads should be measured and managed. Performance indicators should include trust and fairness measures and environmental indicators next to retention and revenue, in line with the substantive reading of the triple bottom line advocated by Elkington (2018). For regulators and industry bodies, the findings point to the importance of enforcing personal data protection rules (Republic of Indonesia, 2022), of learning from risk-based approaches such as the EU Artificial Intelligence Act (European Parliament & Council, 2024), and of encouraging transparency about the computational footprint of AI systems.

These implications must be read with caution. The framework is untested, and the mechanisms are drawn from literature that is largely not about AI-CRM specifically. Sector, firm size, and national context may change the relative strength of the pillars; for example, the environmental effects of AI differed across ownership, financing, and certification conditions in one recent study (Arif & Windarsari, 2026; Feng et al., 2026). Some propositions, especially P8, rest on theoretical arguments for which direct evidence is still needed.

3.7 Agenda for Empirical Research

Three research designs are suggested. First, a survey of managers in firms that use AI-CRM, with scales for AI-CRM capability, moderators, and perceived performance on each pillar, analyzed with structural equation modeling, would test P1, P2, P5, P6, and P7. Measurement of AI-CRM capability can build on existing AI capability instruments (Mikalef & Gupta, 2021). Second, multi-case or archival studies combining use-case analysis with energy and carbon accounting of AI workloads would test P3 and P4, drawing on carbon-accounting methods developed for AI systems (Luccioni et al., 2023; Wu et al., 2022). Third, field experiments that vary the design of personalization, for example promoting sustainable options, would test P8. Common-method bias in perceptual surveys should be addressed with objective indicators where possible, and studies in Indonesia and other emerging markets would test the generalizability of findings drawn largely from other contexts.

4. CONCLUSION

This article develops a conceptual framework that explains how AI-CRM may influence economic, social, and environmental performance. It suggests that AI-CRM supports economic performance through retention, personalization, and efficiency; that its social effects depend on data governance and ethics; and that its environmental effect is ambiguous because waste reduction may be offset by energy use and rebound effects. Data governance and ethics, sustainability orientation, digital capability, and top-management support are proposed as moderators, and eight propositions are offered for testing, each with an assessment of the current evidence.

The article has limitations. It is conceptual and presents no primary data. The narrative review used purposive selection and is not exhaustive, and its English-language orientation leaves other literature uncovered. Mechanisms and moderators are the authors' syntheses and need empirical validation. Future research should test the propositions across sectors and countries, including Indonesia, and should measure the environmental footprint of AI-CRM directly.

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