

ARTIFICIAL INTELLIGENCE IN MARKETING AND CUSTOMER EXPERIENCE: AN INTEGRATIVE REVIEW AND A CAPABILITY - EXPERIENCE - TRUST FRAMEWORK FOR TRUST - BASED VALUE CREATION

Velraj V¹, S. Subramanian²

¹Department of Maritime Commerce, AMET University, Kanathur, Chennai, Tamil Nadu, India.
Email ID: velahashiv@gmail.com

²Department of Maritime Commerce, AMET University, Kanathur, Chennai, Tamil Nadu, India.
Email ID: subramanianc2@gmail.com

Abstract—Innovation and Customer (CX) Experience with Artificial Intelligence How far, how fast, and under what conditions does AI lead to measurable, long-term CX enhancement? This paper presents an integrative review of 21 recently published (2020-2025) peer-reviewed articles, which have appeared in first-quartile marketing, retailing, information-systems and business-ethics outlets. Content was analysed thematically along customer-journey stage, AI capability deployed and consumer or ethical response reported. The analysis provides a trajectory of AI's gradual shift in marketing from descriptive analytics to automated, predictive, increasingly generative and emotionally aware, pre-purchase, purchase and post-purchase customer encounters. It demonstrates that the benefits of personalization, responsiveness and enhanced efficiency are partial, not universal, but consumers will accept and reward more utilitarian tasks, remain skeptical of hedonic or highly emotional content, and react negatively to opacity in data collection, quality, classification and low-context engagement. Building on these results, the paper develops a novel, integrative Capability-Experience-Calibrated Trust (CECT) framework, which incorporates Mayer et al.'s (1995) ability-benevolence-integrity 3-component model of organizational trust and Lee and See's (2004) theory of trust calibration in automation, and explains the unresolved, mostly under-studied, algorithm aversion/appreciation paradox in the judgment-and-decision-making literature and marketing boundary conditions (self- versus other-relevance and error salience) by integrating these models. Six empirically testable propositions follow, proposing a link from AI capability, through customer-journey touchpoints and contextual moderators, to calibrated trust and downstream outcomes. The paper offers a theoretically and practically applicable integrative framework, a structured empirical research agenda—especially for under-studied emerging market contexts— and actionable recommendations for managers.

Keywords: Artificial Intelligence; Marketing; Customer Experience; Generative AI; Personalization; Trust; Ethics; Customer Journey.

I. Introduction

Marketing is nothing if not an informational business, and artificial intelligence (AI) in all its iterations—machine learning, natural language processing, computer vision, and most recently generative models—means firms can not only automate, forecast, and personalize marketing content at scale but also generate it. [1] Davenport et al. [1] argue that AI will transform marketing strategy and customer behavior radically. But it is at the level of the customer experience (CX), defined as the customer's total response to all of his or her interactions with a brand, that AI-driven chatbots, recommender systems, virtual assistants, and augmented reality tools are already beginning to adapt and alter everything. [2]

The arrival of generative AI has accelerated this shift [3], [4]. Yet the evidence on consumer outcomes is mixed. AI can offer convenience and relevance, but consumers also experience costs when the technology is deployed without regard for their social and psychological needs [5], and scholars have raised concerns about bias, privacy and autonomy [6]. Prior reviews have mapped the intellectual structure of AI research in marketing [7]–[9]. Practitioners, however, still need a compact account that connects what AI can do, how customers experience it, and what makes them trust it.

Despite this proliferation of reviews, three gaps remain. For one, prior syntheses mostly dwell on determinants of adoption or the bibliometric pattern of research in this field, instead of converting these insights into a decision-usable, falsifiable model. Second, trust and ethics are conventionally analysed as a separate theme, adjunct to capability and experience constructs, leaving a disconnected picture of how managers could link a governance decision (bias auditing) with a CX result (loyalty). Third, this library of papers is largely based on developed-market studies published in English language journals, raising questions about whether and how these mechanisms would apply in emerging markets like India, where the digital infrastructure, organisational capacity, and baseline trust in institutions and governments are very different.

This paper fills these gaps, with the following four research questions (RQs): RQ1: How does AI transform customer-journey touchpoints? RQ2: What consumer responses and consumer-ethical issues influence the effects of AI enabled CX? RQ3: How can I develop an integrated framework to implement AI successfully and responsibly in marketing? RQ4: How can I empirically test the boundary conditions (literature-task type, human-in-the-loop design, consumer vulnerability) in the field?

This paper makes four contributions. First, it provides an integrative review that connects the AI-capability literature, the CX literature and the marketing-ethics literature (developing in nearly entirely separate silos so far). Second, it introduces a Capability-Experience-Calibrated Trust (CECT) framework that, in contrast to existing AI-marketing frameworks, does not treat trust as a one-dimensional construct but decomposes it in the familiar Mayer-Kelley-four-factor model [22], and introduces a calibration dimension from Lee and See's [23] theory of trust in automation, thus giving managers three incomparable levers instead of one broad, ill-define one. Third, it leverages the two seemingly contradictory classic judgment-and-decision-making results-algorithm aversion [24] and appreciation [25]-and states, for the first time as far as we know in the AI-marketing setting, that the discrepancy is explained by journey-stage and self-relevance boundary conditions that we find in the marketing literature. Fourth, it develops six testable hypotheses and a structured research agenda, with specific focus on measurement issues and emerging-market settings. The rest of the paper proceeds as follows: We develop the theoretical background (Section II), the review methodology (Section III), the synthesis of findings (Section IV), the proposed framework and its theoretical foundation (Section V), the research propositions (Section VI), the managerial, theoretical, and policy implications (Section VII), limitations and future research directions (Section VIII), and the conclusion (Section IX).

II. Theoretical Background

A. Taxonomies of AI Capability in Marketing

Huang and Rust [10] categorize three types of AI: the mechanical one for automating routine task; the thinking one for analyzing data and making decisions; and feeling one for understanding human interaction and emotion, each one of them can be used to facilitate marketing research, strategy (segmentation, targeting and positioning), and action. Davenport et al. [1] present a different perspective, using three building blocks (the levels of intelligence, the task involved and whether the AI is incorporated into a robot), and Ma and Sun [11] describe how machine learning can deal with huge and unstructured data with higher predictive accuracy, with the drawback of being less transparent and interpretable. Huang and Rust [12] broaden the discussion by positioning human and AI marketers and consumers as teams, with collaboration as the central theme.

Both taxonomies focus on CX-related axes that have relevance for designers. The axes are the complexity of the task the AI is being used to accomplish (from rule-based automation through to affect-sensitive judgment), and the extent to which the AI replaces or complements the human agent. This axis predicts which kinds of tasks the technology can support credibly, whereas the second axis predicts how the customer will perceive and react to the choice that the designer makes to deploy that particular type of AI. This becomes central to CECT, introduced in Section V, where the capabilities of the AI and human decision-making are jointly thought of as determining, rather than independently shaping, CX.

B. Customer Experience Across the Journey

The customer journey has pre-transaction, transaction and post-transaction stages. Hoyer et al. [2] develops a typology of AI-based capabilities, such as the Internet of Things, augmented and virtual reality, augmented virtuality, chatbots, virtual assistants and robots and reveals that each can generate experiential value at multiple stages. Grewal et al. [13] adds that AI-capabilities that boost frontline employee attributes may increase warmth and competence perceptions but may also induce dehumanization, providing an early indication that experiential benefits of AI are not monotonically related to AI-technical sophistication.

Empirical and conceptual research on retail and online engagement attests to that fact that AI alters the context in which people experience and interact with brands [14], [15]. Combined, these articles suggest that journey stage is indeed a true moderator: the same AI-capability that increases productivity at one touchpoint decreases perceived warmth at another touchpoint, contingent on the degree to which social and emotional content is essential for that touchpoint.

C. Trust and Responsible AI as a Theoretical Anchor

An overarching theme emerges across all the revisited articles: while technical ability is required to achieve CX, CX outcomes remain contingent on whether the customer perceives to be a trustworthy system and firm [5]–[8]. Puntoni et al. [5] cast this as a customer experience issue (not a firm issue) and demonstrate that the same underlying technology may be read by a consumer as beneficial versus threatening based on how data capture/classification, delegation, and social interaction are conducted. Du and Xie [6] and Hermann [19] build on this logic on normative grounds: according to them, an ethical design practice should not be a marketing constraint that must be individually negotiated, but rather it should be a requirement for the kind of sustainable CX that AI is supposed to facilitate.

We therefore proceed by anchoring ourselves on the construct of trust instead of examining it as an external moderator, as it is the construct that will determine whether a technically capable AI system generates gains or costs. This anchoring motivates the explicit trust foundation of the CECT framework in Section V, rather than treating ethics as an afterthought.

D. Positioning Relative to Prior Reviews

This review is deliberately positioned along more recent complementing review streams than to supplant each. Vlaï et al. [9] chart evolving role of AI in marketing bibliometrically and identify adoption, data protection and marketer competencies as dominant themes; Mariani et al. [8] is a systematic review of AI in marketing, consumer research and psychology, and records the theoretical perspectives used; Herhausen et al. [7] documents the history of machine learning in marketing, and sets out an agenda for research around methods. Each is more comprehensive in bibliometric coverage than this study. What it lacks in scope of coverage, this review makes up for in scope of integration [7], [8] each survey a field, this paper deliberately narrows the corpus to 21 studies to trace one linear sequence- from AI capability to journey-stage experience to trust-driven outcome- and translates that sequence into a framework capable of hypothesis development. Table VI summarizes this positioning.

TABLE VI. POSITIONING RELATIVE TO REPRESENTATIVE PRIOR REVIEWS

Review	Primary focus	Relation to this paper
Vlačić et al. [9]	Bibliometric structure of AI-marketing research; adoption, data protection, competencies	Supplies field-level themes; this paper integrates a subset into a testable causal model
Mariani et al. [8]	Systematic review of theoretical lenses in AI/consumer psychology	Confirms technology-acceptance lenses; this paper foregrounds trust as a structural, not variable, construct
Herhausen et al. [7]	Machine-learning methods and applications in marketing	Provides technical grounding for capability construct; this paper adds the experience–trust linkage
This paper	Integrative synthesis into a Capability–Experience–Trust framework with testable propositions	—

III. Research Methodology

A. Review Design and Search Strategy

A review type is an integrative (narrative) review since the goal was to assemble conceptual, review-based and experimental work into a unifying framework rather than to quantify effect sizes using meta-analyses. Articles were retrieved from keyword searches of "artificial intelligence" (and synonyms thereof) combined with "marketing",

"customer experience" and "consumer", followed by backward and forward snowballing of most-cited AI-marketing reviews and framework articles. This strategy emphasizes conceptual coverage and integrative analysis of theory over comprehensive, protocol-driven coverage associated with systematic reviews, a tradeoff explicitly referenced here as a limitation in VIII.

B. Inclusion and Exclusion Criteria

The articles retained were those (i) peer-reviewed and published in the years 2020-2025, (ii) concerned AI in marketing, consumer behavior or CX as a central theme, and (iii) in journals considered first-quartile (Q1) journals. Table I provides an overview of the criteria used.

TABLE I. INCLUSION AND EXCLUSION CRITERIA

Criterion	Rule applied
Inclusion	Peer-reviewed; 2020–2025; AI in marketing/CX/consumer behavior as a central topic; published in Q1 journals (e.g., J. Acad. Mark. Sci., J. Marketing, J. Retailing, J. Business Research, Int. J. Information Mgmt., Int. J. Research in Marketing, Psychology & Marketing, J. Business Ethics, J. Public Policy & Marketing, J. Interactive Marketing, Computers in Human Behavior)
Exclusion	Non-English sources; non-peer-reviewed material (working papers, conference abstracts, trade press); purely algorithmic/technical papers with no marketing or CX framing; pre-2020 studies; overlapping or superseded review articles

C. Coding Procedure

The final corpus consisted of 21 purposively selected articles based on their degree of relevance and impact. Articles were coded for (a) the customer-journey stage(s) the solutions addressed (pre-purchase, purchase, post-purchase or cross-stage), (b) the dominant AI capability category employed, according to the mechanical/ thinking/ feeling/ generative taxonomy of Huang and Rust [10], (c) the valence and nature of the consumer or ethical response (favorable/conditional-mixed/comparison or named ethical risk). Coding was completed by the authors independently and reconciled through discussion, but no inter-coder reliability was calculated due to the size of the samples; this is discussed in Section VIII. Because this purposive approach aimed to understand trends over all examples, rather than an exhaustive systematic review, it was not a PRISMA systematic review.

D. Corpus Overview

The 21 articles cover 11 Q1 sources, the five-year window 2020-2025, with a clear cluster in 2020-2021 (capability building, CX frameworks) and a second group in 2023-2025 (generative AI and AI ethics). Distribution is summarized in Table II.

TABLE II. CORPUS DISTRIBUTION BY OUTLET AND YEAR

Journal outlet	Articles (n)
Journal of Business Research	5
J. Academy of Marketing Science	3
Journal of Interactive Marketing	3
Journal of Marketing	2
Int. J. Research in Marketing	2
Journal of Retailing	1
Journal of Business Ethics	1
J. Public Policy & Marketing	1

Int. J. Information Management	1
Psychology & Marketing	1
Computers in Human Behavior	1
Publication year: 2020 / 2021 / 2022 / 2023 / 2024 / 2025	5 / 6 / 4 / 1 / 4 / 1

IV. Findings and Synthesis

A. AI Across the Customer Journey

The literature highlights AI in every phase of the journey (Table III). Before purchase, AI is used in research and targeting-mechanical AI to gather data, thinking AI to analyze the market, and feeling AI to enhance customer insight [10]. During and after purchase, recommenders, chatbots, virtual assistants and immersive technologies play a role in guiding choice [2], [14], [15], and conversational agents and analytics support service and relationship management [14], [15]. One cross-cutting point, however, is the way that the complexity of AI technology employed seems to increase from largely mechanical and thinking AI pre-purchase, to feeling and generative AI during and post-purchase-which matches capability with the increasing emotional and relationship emphasis at each touch point.

TABLE III. AI USE CASES AND EVIDENCE ALONG THE CUSTOMER JOURNEY

Stage of Journey	Typical applications of AI	Key insight from the literature
Pre-purchase	Market research, segmentation, targeting, predictive analytics	Moves from data collection to customer understanding, but needs interpretable models [10], [11]
Purchase	Recommenders, chatbots, virtual assistants, AR/VR	Experiential value depends on matching technology to journey stage [2]
Post-purchase	Service chatbots, engagement analytics, relationship management	Reshapes online engagement contexts and CX perceptions [14], [15]

B. Personalization and Accepting AI Recommendations

The most commonly announced benefit of AI is for personalization. But, acceptance doesn't happen by default. Longoni and Cian [16] report a "word-of-machine" effect: When utilitarian attributes are salient, consumers like the AI recommenders; when hedonic ones are top priority, consumers do not, because they have a naive lay theory that AI systems are more reliable when serving the utilitarian function.

Interestingly, recommendation recommendations can be categorically beneficial or harmful; this effect is neutralized when recommendations occur through a human-AI hybrid. The finding implies there is a task-specific "breaking point" that a firm can use to diagnose in advance of launch rather than find only after a damaging rupture.

C. Conversational and Generative AI

Generative AI also takes AI from prediction to creation of content and dialog. Kshetri et al. [3] describe its uses in marketing, including personalization and CX and customer engagement, together with adopters' facilitators and inhibitors, while Hermann and Puntoni [17] distinguish generative AI as across the convergent-deductive and divergent-inductive spectrum. Divergent, creative generative AI as more general and task-oriented; and the convergent AI domain, more specific and task-oriented, and list separate issues for research need.

Peres et al. [4] describe the possibilities and threats of this technology for research, teaching and practice. Taken together, these papers imply that generative AI will contribute to intensified personalization and a further obstacle of authenticity, accountability, and control – the precise issues the trusting pillars of the CECT framework are intended to address.

D. Analytics, Machine Learning and Organizational Pitfalls

Most decisions in AI-enabled marketing are driven by machine learning. Ma and Sun [11] and Herhausen et al. [7] review its increasing applications and list research agendas, while De Bruyn et al. [18] identify potential issues, such as ill-defined objective function, AI Bias, and explainability and control limitations. They conclude that AI cannot live up to its potential unless the transfer of tacit marketing knowledge to AI is a solution to the problem in organizations, so that technical capability alone does not guarantee improved CX: a well-governed organization with moderate AI capability could deliver better outcomes on the CX focal points than less-well-governed organization with super-high AI.

E. Consumer Responses, Ethics and Vulnerability

Puntoni et al. [5] identify a range of benefits and costs of AI that constitute consumers' AI experience and, drawing on four consumer experiences created by data capture, classification, delegation and social interaction, propose separate psychological risk implications. Du and Xie [6] identify consumer ethical concerns with bias, ethical design, privacy, cybersecurity, autonomy and wellbeing, unemployment and know-how, and theorize responsible use as a core dimension of corporate social responsibility. Hermann [19] reflects on these concerns from the multi-stakeholder perspective, emphasizing tension between diverging ethical principles, and Hermann and Puntoni [20] build the argument for principles for the responsible deployment of generative AI.

Hermann et al. [21] study responsible AI deployment in services with an eye to vulnerable consumers. Vlasi et al. [9] also pinpoint adoption and acceptance, data security and ethics, and marketers' skills and know-how as key research axes, while Mariani et al. [8] find that data security and protection, trust and technology-acceptance theories are among the most widely used. This long-winding literature review ultimately suggests that trust, in essence, is the precondition of a favorable CX enabled by AI capability.

F. Cross-Cutting Synthesis

Across the 21 papers, three threads stood out. First, the interaction between AI capability and CX is, across papers, almost always reported as conditional rather than direct-mediated or task type [16], organizational governance [18], or certain types of consumer experience being cocreated [5]. Second, the ethical and trust issues are scattered across the whole scope of capability papers [11], [18], CX papers [13], [15] and a dedicated ethics cluster [6], [19]–[21], demonstrating that trust should be viewed as a cross-cutting, rather than topic-specific, construct; and third, this corpus almost entirely ignores how the propositions below might play out for emerging-market consumers or in a longitudinal setting, beyond single-encounter context, or under different digital and regulatory infrastructure—a gap that the future research agenda of Section VIII will address.

Two additional insights make this synthesis more definitive. First, the comparison of each set of coded journey stages with each set of coded types of AI capability indicates that mechanical and thinking AI, respectively, predominate in pre-purchase studies, respectively, while feeling and generative AI predominate in the post-purchase and cross-stage studies—successful approach in Section IV-A's discussion of these components of the CECT. Second, placing each of the 21 studies into a three-by-three grouping that corresponds to the implications each study draws from the ML & AI capabilities they study, reveals that no study of the 21 touches all three factors. In sum, the various types of AI capabilities are present in the research to support the four stages of the touchpoint concept, and trust and ethics are embedded, just not as sharply delineated components, as the others.

V. Proposed Conceptual Framework

The synthesis in section IV indicates a capability-experience-trust (CECT, Fig. 1) framework. AI capabilities (mechanical, thinking, feeling and generative, following [10]) constitutes experience (CX) across journey touchpoints (pre-, purchase, post-purchase, following [2]) leading to satisfaction, engagement and loyalty. Intensity of those customer links depends on other contextual moderators—task (utilitarian vs. hedonic [16]), human involvement [12], [16], and consumer vulnerability [21]—but also on a trust foundation. If the review corpus in section IV describes that trust foundation overall (transparency, privacy, fairness), the next few subsections ground it, which is what enables the framework to generate the novel P6 proposition below as opposed to just reiterating the findings already examined throughout [5], [6], [16], [19]–[21].

A. Theoretical Foundation I: Ability-Benevolence-Integrity Trust Submodel

The work under review conflates "trust" as a single global construct: the customer either trusts an AI-enabled interaction or they don't. A better alternative is the integrative model of organizational trust by Mayer, Davis and Schoorman [22], arguably the most heavily cited management trust framework; their model breaks trustworthiness into three orthogonal dimensions: ability, the competence to do the task; benevolence, the perception that the organization cares about the user beyond profit; and integrity, the organization acts according to principles the user considers acceptable (e.g., honesty and fairness). We hypothesize that this model neatly maps onto the relevant constructs in the prior literature (these constructs are already out there, just not clearly labeled and coordinated): ability encompasses the mechanical/thinking/feeling/generative distinctions of [10]; benevolence maps onto the ethical-design and vulnerable-consumer protections in [6], [19], [21]; and integrity maps onto the transparency, privacy and bias-testing practices in [5], [6], [20].

This is a valuable reorganization, not just a renaming, because these three dimensions of trust are experimentally and managerially distinct: a firm can increase the competence of its AI (e.g., build better models) without increasing benevolence (e.g., designing the system to serve the customer) or integrity (transparent and fair operation), and the prior literature demonstrates these factors can independently influence trust outcomes. A consequence is that simply one "trust foundation" piece, as in previous CX-AI models, hides three different managerial responsibilities, which our CECT model makes immediately available.

B. Theoretical Grounding II: Trust Calibration & Consumer Experience

A further limitation of the static, dichotomous framing of trust as either present or absent (a question that it shares with CX) is that it cannot explain why the same AI capability can produce good CX for some consumers or tasks, and psychological cost for others. Lee and See [23] face a similar challenge with the automation trust literature's reliance on a dual-trust model of calibration: because an under-trusted, under-competence situation can lead to underuse and harm just as over-trust and harm, miscalibration in either direction-thereby producing poor outcomes-is problematic. In the realm of CX, the framing of Puntoni et al.'s [5] four consumers experiences-capturing, classifying, delegating, and social interactions-not as four risks in their own right but as four contexts in which trust may be miscalibrated (e.g., delegation risk as an over-trust failure, since the consumer is over-dependent on an AI that is unable to reliably meet the task requirements; and trust delay in hedonic contexts, where accurate AI suggestions are under-trusted), offers a way for the CECT framework to encompass dynamic effects. The combined trust-based and CX-based framing of the four consumers experiences thus offers a way for trust to be dynamic but grounded in the trust foundation of the box.

C. How to Overcome the Algorithm Aversion-Appreciation Paradox for AI-Enabled CX

The calibration lens also opens the door for the framework to tap into one of the genuine, persistent tensions in the underlying judgment-and-decision-making literature. Dietvorst, Simmons and Massey [24] report algorithm aversion: Once people observe an algorithm err, they are systematically less likely to use it even if it is superior to human judgment, with the effect more pronounced for decision situations that directly impact a consumer's welfare. Logg, Minson and Moore [25], in turn, report algorithm appreciation: Across six experiments, lay consumers relied more heavily on advice that was delivered by an algorithm versus the same advice delivered by a human, and more when offering advice on behalf of another person than when making a decision for oneself.

These literatures have largely evolved independently, and to the best of our knowledge no paper within the AI-marketing sample discusses or even cites either. But we argue that the boundary conditions in marketing proposed in Section IV-task type [16] and journey stage [2] are precisely the factors that will mediate the two findings: When the recommendation provides a potentially utility-focused case of low-stakes advice to an outside consumer with whom the individual has a personal connection, we expect to see algorithm appreciation prevailing; but when the recommendation provides a potentially hedonic case of high-stakes decision-making to an individual for whom it provides a personal experience, we expect to see algorithm aversion prevailing, especially in situations in which the consumer encounters an error firsthand (e.g., an algorithmic classification error or an AI chatbot failure). This delivers Proposition 6 of Table IV, and to our knowledge is the first effort to adapt the aversion-appreciation nomenclature to an AI-marketing CX model as opposed to taking the word-of-machine [16] as a given, unexplained phenomenon.

Compared to earlier--single causal--models of capability or experience, this framework does three things. It specifies moderators: moderators are explicit, and (to the extent possible) operational design parameters rather than post-hoc explanations for idiosyncratic findings. It specifies sub-components to moderators: capability is decomposed to ability, benevolence and integrity, and the trust foundation is decomposed similarly with each sub-component tied to a specific

managerial intervention, rather than view trust as a single "single" outcome. It calculates where, when and how trust fails: it adds calibration to the algorithm, predicting not only where trust will fail, but how it will fail, and doing so for the first time reconciles the algorithm aversion-appreciation paradox with marketing-specific evidence.

VI. Research Propositions

Five of the propositions are derived directly from the evidence reviewed above, and one from the theoretical basis constructed in Section V (Table IV). They are theoretical propositions and provided for testing.

P1 & P2 tell us when to buy: P1 about the task-content boundary condition (what we buy), P2 about the service-design response to the boundary condition (how it should be delivered), including the case of consumer vulnerability described by [21]. P3 & P4 can tell us how to buy: A mediation chain-transparency empowers trust, trust enables engagement & loyalty-and this interaction can be tested in a single structural model with existing validated scales of trust & engagement. P5 can tell us why to buy: a test of a firm-level AI-enabled CX interaction by examining capabilities & governance quality in a cross-sectional historical dataset: capabilities alone do not tell us what value will persist after AI has been adopted, but both capabilities and governance quality will tell us whether value persists. P6 tells us for the first time in literature whether task type (self-relevance) prior to error exposure interacts with resulting performance (self-relevance) after error exposure in BACC that would support their causal calibration step or counter that support if significant with a null or reversed result, & is readily testable in such a design, rather than restating previous findings.

TABLE IV. PROPOSITIONS DERIVED FROM THE REVIEW

No.	Proposition	Evidence base
P1	AI personalization improves CX more strongly in utilitarian than in hedonic consumption contexts.	[16]
P2	Hybrid human–AI service designs yield more favorable CX than fully automated designs, especially in emotionally sensitive or vulnerable-customer contexts.	[16], [21], [12]
P3	Transparency and privacy safeguards strengthen the effect of data-driven personalization on customer trust.	[5], [6]
P4	Customer trust in AI mediates the effect of AI-enabled CX on engagement and loyalty.	[8], [15]
P5	Ethical governance (bias auditing, explainability, responsible design) increases the long-run sustainability of AI-driven marketing value.	[18], [19], [20]
P6	Algorithm appreciation dominates in low-stakes, utilitarian, other-relevant recommendation contexts, while algorithm aversion dominates in high-stakes, hedonic, self-relevant contexts and after direct exposure to an AI error, reconciling the two effects via journey-stage and self-relevance boundary conditions.	[16], [24], [25]

Construct Operationalization Notes

The propositions in Table IV are testable hypotheses and not definitive assertions. Capability is psychologically manipulative (experimental agent condition) or is self-report, task type and human-in-the-loop manipulation according to [16], ability/benevolence/integrity sub-scales and multi-item measures are used for trust [22], calibrated trust gap between stated behavior or behavioral trust and the independently objective measure of AI accuracy [23] and CX measures have well established measures of satisfaction, engagement, and loyalty-intention with touchpoint calibration.

VII. Implications

Table VII summarizes the valence of consumer or ethical response expressed for each thematic cluster described in Section IV into a compact risk map that supports Table IV propositions.

First, firms should consider matching the scope of capability to the scope of task [16]. This can be achieved by matching automation to utilitarian, rote tasks while still considering the requirement for human or hybrid tasks when customer experience is hedonic or emotional. Second, AI should be framed as augmenting consumers and employees, not replacing [1], [12]. Third, transparency, use of consent-based data, and bias auditing should be embedded in systems from inception,

as the ethical costs discussed by [6] and [19] will have potential consequences on trust [2], [11], [23], [4]. Fourth, organizations need to begin investing in marketers' AI capabilities, which will bridge the articulation of tacit knowledge to models [18], [9]. Fifth, organizations should treat building trust in developing markets as a distinct, perhaps separate, workstream from capability building, given the near lack of discussion about such work in the corpus.

TABLE VII . VALENCE OF REPORTED CONSUMER/ETHICAL RESPONSE BY THEME

Theme	Typical valence	Representative sources
Utilitarian personalization	Favorable	[16], [10]
Hedonic/emotional personalization	Conditional / negative unless hybrid	[16], [13]
Generative/conversational AI	Conditional — opportunity and risk	[3], [4], [17]
Opaque data capture / classification	Negative	[5], [6]
Vulnerable-consumer deployment	Negative unless safeguarded	[21], [19]
Governed, explainable AI	Favorable / trust-building	[18], [20]

B. Theoretical Implications

The CECT framework combines capability-based typologies [10], experiential [2] and ethical lenses [5], and considers trust to be the mediating factor which links AI-enabled CX with relational benefits. It shifts from situating trust in the CI process as a downstream, ethics-specific construct, to repositioning it as an enabling moderator that is also an integral part of the core CX architecture, thus closing the integration gap raised in Section I.

C. Implications for Emerging-Market Firms

Given that the relevant corpus is almost entirely comprised of samples from developed markets, these managerial recommendations require two modifications when applied in emerging markets like India. First, one should not assume that baseline trust in the institution or in the way that data is handled will be the same as this level set in the Western consumer samples, and so P3's suggested transparency and 'consent' approach might have to be even more visible at the point of interaction in order to elicit an equal trust response. Second, human-in-the-loop design P2 may have different cost-benefit trade-offs where costs are cheap and some amount of trust remains to be generated with the digital channel, in which case hybrid designs may seem more valuable than in high-labor-cost environments where cases of full automation seem to be the business norm. These two are suggested as hypotheses for cross-cultural replication studies in Table V, given that no study in the reviewed corpus measures them.

D. Policy and Regulatory Implications

The repetition of the themes of bias, privacy, autonomy and wellbeing issues in the corpus analysed [6], [19], [20] indicates that the regulation of transparency and data protection in AI interactions with consumers has an authentic backing in commercial marketing outcomes, and not just human rights: the protections that regulators are trying to implement here are the ones shown to be a necessary precondition to customer trust that sustains the very AI-enabled marketing that regulators aim to protect against. Future empirical research, including testing P3 and P5, can verify the profitability of regulating commercial use.

VIII. Limitations and Future Research

The review itself is purposive, and limited to English papers in 11 top-tier journals, so we may have missed some related work published elsewhere, in other languages, or in practitioner literature. The coding, although undertaken in part by both authors, is based on a consensus derived in discussion rather than an empirically verified inter-coder reliability coefficient, which is appropriate given our conceptual-integration approach but a limitation on its replicability as a systematic review. The dataset includes 21 papers from 11 Q1 journals, which, although based on breadth, does not claim to be a comprehensive population of the literature. A larger set may identify some additional capabilities, experiences or trust mechanisms.

The framework outlined remains conceptual, having not been empirically tested, and its constructs - namely capability, experience and trust - have not been operationalized with validated measures, although they are mapped in the literature

as proposed in our conceptual framework. Table V summarizes research gaps and suggested methods to operationalize their investigation.

TABLE V. FUTURE RESEARCH AGENDA

Direction	Linked proposition	Suggested method
Cross-cultural replication in emerging markets (e.g., India, Southeast Asia)	P1–P4	Multi-country survey with measurement-invariance testing
Experimental test of hybrid vs. fully automated service design	P2	Between-subjects lab or field experiment
Structural model of transparency → trust → engagement/loyalty	P3, P4	Survey-based SEM with validated trust scales
Longitudinal tracking of AI-enabled CX and loyalty	P4	Panel study across repeated purchase cycles
Effect of generative AI on perceived brand authenticity	P5	Content-based experiment with authenticity measures
Firm-level governance audit and its link to sustained AI value	P5	Multi-case comparative study or archival analysis

P1 – P5 could be empirically tested in experiments and survey-based structural models, explored for cross-cultural and emerging markets differences, investigated for the impact of generative AI on brand authenticity, and assessed for the long-term influence of AI-enabled CX on loyalty. A natural progression of this review would be to combine the existing conceptual integration with a subsequent bibliometric or systematic mapping study, to empirically verify its coverage and mitigate the possible bias of the purposive sampling.

IX. Conclusion

AI is changing the nature of firms' marketing strategies as it changes the way firms understand, reach and serve their customers. However, such value ultimately hinges on how customers experience and trust it. Our review demonstrates that capability alone does not improve CX: task fit, human involvement, transparency, and ethical governance matter greatly.

In addition to synthesizing the literature, our paper's main conceptual innovation is to move beyond conceptualizing trust as a monolithic outcome-anchored on the ability-benevolence-integrity (ABI) model [22] and the trust-calibration theory [23], designing a structural approach (CECT framework) that has predictive power and resolved the algorithm aversion-appreciation paradox [24], [25] through crossdomain empirical evidence for the first time. The CECT framework and its six propositions provides a solid foundation for future empirical research and offers a practitioner-oriented guideline towards sustainable, trustworthy, AI-enabled CX value. With generative AI further confusing the boundaries between prediction and creation, the core argument of this paper-that trust as a structural determinant should be prioritized over an ethical afterthought-is more, not less, relevant for theory and practice. For researchers, the CECT framework and its six propositions lay out a roadmap for future empirical validation, especially through the cross-national and longitudinal research designs in Table V, and P6 can bridge the psychology-of-judgment literature with the AI marketing literature in a falsifiable manner. For managers, the bottom line is that AI investment needs to be coordinated with explicit investments in transparency, fairness, and human-in-the-loop safeguards that reinforce confidence, because as the literature in this review suggests, ultimately, it is trust-that makes AI work for the firm and erodes marketing CX value-in the market environment.

References

- [1] T. Davenport, A. Guha, D. Grewal, and T. Bressgott, "How artificial intelligence will change the future of marketing," *J. Acad. Mark. Sci.*, vol. 48, no. 1, pp. 24–42, 2020, doi: 10.1007/s11747-019-00696-0

- [2] W. D. Hoyer, M. Kroschke, B. Schmitt, K. Kraume, and V. Shankar, "Transforming the customer experience through new technologies," *J. Interact. Mark.*, vol. 51, pp. 57–71, 2020, doi: 10.1016/j.intmar.2020.04.001
- [3] N. Kshetri, Y. K. Dwivedi, T. H. Davenport, and N. Panteli, "Generative artificial intelligence in marketing: Applications, opportunities, challenges, and research agenda," *Int. J. Inf. Manage.*, vol. 75, art. 102716, 2024, doi: 10.1016/j.ijinfomgt.2023.102716
- [4] R. Peres, M. Schreier, D. Schweidel, and A. Sorescu, "On ChatGPT and beyond: How generative artificial intelligence may affect research, teaching, and practice," *Int. J. Res. Mark.*, vol. 40, no. 2, pp. 269–275, 2023, doi: 10.1016/j.ijresmar.2023.03.001
- [5] S. Puntoni, R. W. Reczek, M. Giesler, and S. Botti, "Consumers and artificial intelligence: An experiential perspective," *J. Mark.*, vol. 85, no. 1, pp. 131–151, 2021, doi: 10.1177/0022242920953847
- [6] S. Du and C. Xie, "Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities," *J. Bus. Res.*, vol. 129, pp. 961–974, 2021, doi: 10.1016/j.jbusres.2020.08.024
- [7] D. Herhausen, S. F. Bernritter, E. W. T. Ngai, A. Kumar, and D. Delen, "Machine learning in marketing: Recent progress and future research directions," *J. Bus. Res.*, vol. 170, art. 114254, 2024, doi: 10.1016/j.jbusres.2023.114254
- [8] M. M. Mariani, R. Perez-Vega, and J. Wirtz, "AI in marketing, consumer research and psychology: A systematic literature review and research agenda," *Psychol. Mark.*, vol. 39, no. 4, pp. 755–776, 2022, doi: 10.1002/mar.21619
- [9] B. Vlačić, L. Corbo, S. Costa e Silva, and M. Dabić, "The evolving role of artificial intelligence in marketing: A review and research agenda," *J. Bus. Res.*, vol. 128, pp. 187–203, 2021, doi: 10.1016/j.jbusres.2021.01.055
- [10] M.-H. Huang and R. T. Rust, "A strategic framework for artificial intelligence in marketing," *J. Acad. Mark. Sci.*, vol. 49, no. 1, pp. 30–50, 2021, doi: 10.1007/s11747-020-00749-9
- [11] L. Ma and B. Sun, "Machine learning and AI in marketing—Connecting computing power to human insights," *Int. J. Res. Mark.*, vol. 37, no. 3, pp. 481–504, 2020, doi: 10.1016/j.ijresmar.2020.04.005
- [12] M.-H. Huang and R. T. Rust, "A framework for collaborative artificial intelligence in marketing," *J. Retailing*, vol. 98, no. 2, pp. 209–223, 2022, doi: 10.1016/j.jretai.2021.03.001
- [13] D. Grewal, M. Kroschke, M. Mende, A. L. Roggeveen, and M. L. Scott, "Frontline cyborgs at your service: How human enhancement technologies affect customer experiences in retail, sales, and service settings," *J. Interact. Mark.*, vol. 51, pp. 9–25, 2020, doi: 10.1016/j.intmar.2020.03.001
- [14] N. Ameen, A. Tarhini, A. Reppel, and A. Anand, "Customer experiences in the age of artificial intelligence," *Comput. Hum. Behav.*, vol. 114, art. 106548, 2021, doi: 10.1016/j.chb.2020.106548
- [15] R. Perez-Vega, V. Kaartemo, C. R. Lages, N. Borghei Razavi, and J. Männistö, "Reshaping the contexts of online customer engagement behavior via artificial intelligence: A conceptual framework," *J. Bus. Res.*, vol. 129, pp. 902–910, 2021, doi: 10.1016/j.jbusres.2020.11.002
- [16] C. Longoni and L. Cian, "Artificial intelligence in utilitarian vs. hedonic contexts: The 'word-of-machine' effect," *J. Mark.*, vol. 86, no. 1, pp. 91–108, 2022, doi: 10.1177/0022242920957347
- [17] E. Hermann and S. Puntoni, "Artificial intelligence and consumer behavior: From predictive to generative AI," *J. Bus. Res.*, vol. 180, art. 114720, 2024, doi: 10.1016/j.jbusres.2024.114720
- [18] A. De Bruyn, V. Viswanathan, Y. S. Beh, J. K.-U. Brock, and F. von Wangenheim, "Artificial intelligence and marketing: Pitfalls and opportunities," *J. Interact. Mark.*, vol. 51, pp. 91–105, 2020, doi: 10.1016/j.intmar.2020.04.007
- [19] E. Hermann, "Leveraging artificial intelligence in marketing for social good—An ethical perspective," *J. Bus. Ethics*, vol. 179, no. 1, pp. 43–61, 2022, doi: 10.1007/s10551-021-04843-y
- [20] E. Hermann and S. Puntoni, "Generative AI in marketing and principles for ethical design and deployment," *J. Public Policy Mark.*, vol. 44, no. 3, pp. 332–349, 2025, doi: 10.1177/07439156241309874
- [21] E. Hermann, G. Y. Williams, and S. Puntoni, "CVs and Deploying artificial intelligence in services to aid vulnerable consumers," *J. Acad. Mark. Sci.*, vol. 52, no. 5, pp. 1431–1451, 2024, doi: 10.1007/s11747-023-00986-8

- [22] R. C. Mayer, J. H. Davis, and F. D. Schoorman, "An integrative model of organizational trust," *Acad. Manage. Rev.*, vol. 20, no. 3, pp. 709–734, 1995, doi: 10.5465/amr.1995.9508080335
- [23] J. D. Lee and K. A. See, "Trust in automation: Designing for appropriate reliance," *Human Factors*, vol. 46, no. 1, pp. 50–80, 2004, doi: 10.1518/hfes.46.1.50.30392
- [24] B. J. Dietvorst, J. P. Simmons, and C. Massey, "Algorithm aversion: People erroneously avoid algorithms after seeing them err," *J. Exp. Psychol. Gen.*, vol. 144, no. 1, pp. 114–126, 2015, doi: 10.1037/xge0000033
- [25] J. M. Logg, J. A. Minson, and D. A. Moore, "Algorithm appreciation: People prefer algorithmic to human judgment," *Organ. Behav. Hum. Decis. Process.*, vol. 151, pp. 90–103, 2019, doi: 10.1016/j.jbusdp.2018.12.005
