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The Agentic GTM Maturity Model: A Framework for AI-Driven Revenue Systems

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Abstract: *The aim of this review is to suggest the Agentic GTM Maturity Model as a simple matrix to evaluate how mature an AI-powered go-to-market revenue system and related organisations are in their transition from uncoordinated analytics to managed semi-autonomous revenue systems. The academic perspectives of the peer-reviewed journal articles reviewed herein build upon one another when it comes to understanding the agentic maturity of GTM and provide insights to AI-driven sales, B2B marketing automation, CRM intelligence, customer engagement, customer-retention analytics, and digital transformation. The literature indicates a higher probability of the revenue system developing more as an integrated process when the benefits of data integration, predictive modelling, workflow automation, human-agent interaction and outcome measurement are planned together as an integrated system, rather than developed individually. There are, however, several unknowns that need to be dealt with, including inadequate causal attribution, inconsistent handling of AI in sales, limited explanatory power, unclear functional governance, and limited evidence of when it is safe or appropriate to grant autonomy to AI to initiate, sequence, and/or adapt revenue-related actions within a human-defined commercial boundary. The author does not think that the 'mature agentic GTM' is a technology adoption, it is a capability of the revenue system. The benefit of the review is that it brings together research on AI decision support systems with responsible orchestration of revenue for acquisition, conversion, expansion and retention and clarifies the organizational environment in which agentic GTM systems can generate measurable and governed business value.*

Keywords: *Agentic AI, Customer Relationship Management, Go-To-Market Systems, Marketing Automation, Revenue Analytics*

I. INTRODUCTION

An integrated theoretical framework for agentic go-to-market (GTM) orchestration remains underdeveloped. Relevant research is distributed across AI-powered sales, AI-driven market knowledge, marketing automation, customer relationship management (CRM), retention analytics, and digital transformation. Machine learning can prioritize leads, augment salespeople, forecast sales outcomes, and change how selling is performed [1]. However, predictive tools create value only when they are embedded in organizational workflows, decision rights, and revenue processes. In B2B marketing, AI can enhance market knowledge by identifying patterns in disaggregated interaction data; however, this value is reduced when firms fail to connect intelligence with commercial action [2]. The evidence base for this review comes from adjacent but technically distinct literatures on AI-enabled revenue functions as there is no specific journal stream that is explicitly named as the Agentic GTM Maturity Model. GTM systems connect segmentation, positioning, demand generation, lead management, sales engagement, pricing, account expansion, retention, and customer success processes. This architecture could be direct and indirect channels such as partner marketing, resellers and demand-generation ecosystems. The second distinction is agentic capability: AI does not simply predict or report, but can recommend, sequence, trigger, personalize, and adapt GTM actions within prescribed commercial parameters. For the purposes of this review, commercial autonomy is defined as the limited authority given to AI-powered revenue systems to recommend, initiate, sequence, or modify GTM activities under pre-established rules and guidelines to ensure human oversight and maintain human accountability for these activities. According to marketing automation research, data capture, lead qualification, and handoff to sales processes are more effective when used as a unified process, and not done separately, when it comes to B2B content marketing [3]. Prior research also indicates that AI is transforming customer relations management (CRM) in various ways, such as changing when, how, and who is responsible for customer interactions. The results suggest that agentic GTM maturity is more than just a higher level of automation. Instead, it's a shift in the ability to turn customer, market and sales information into streamlined revenue action.

The concept is interdisciplinary, combining elements of marketing strategy, sales management, information systems, data science, and organizational design along with service research. It is a balance between algorithmic autonomy and commercial prudence that makes it so important. Published research indicates that revenue systems can have a negative effect on commercialization, if they are fragmented, sales adoption is limited, governance is not developed, or the predictive output of the systems is opaque and hard to translate into action. Several studies are narrowly focused on specific topics such as chatbots, churn scoring, CRM, and digital transformation. These components have yet to be sufficiently woven together into a coherent narrative of agentic GTM systems. Based on the peer-reviewed literature from 2015 onwards, this review thus investigates how the evidence can be used to derive a concise maturity logic, outlines methodological approaches and pinpoints research gaps of relevance to AI-driven revenue systems.

II. LITERATURE REVIEW

This literature review is organized around four evidence streams: (1) strategic AI capabilities in marketing and market knowledge; (2) AI-assisted sales and customer-facing interaction; (3) AI integrated CRM and retention decision analytics; and (4) customer experience management, digital transformation and redesign of the revenue process. Marketing studies show that AI can automate mechanical tasks, augment analytical tasks, and support more intuitive marketing decisions, depending on the nature of the task and the maturity of the organization [5, 6]. These studies are pertinent to GTM maturity because the alignment of data, decision support, workflow design and organizational capability are required to move from the generation of insights to adaptive commercial action. However, much of the strategic AI literature remains broad and does not fully specify how marketing, sales, retention, and customer-success systems should be operationally integrated in an agentic revenue architecture.

The second line of evidence is the use of AI for sales and customer interactions. In sales-coaching research [8] it is shown that the commercial performance of the frontline can be improved with AI recommendations when they are aligned with the task the salesperson must perform and their level of skill. Likewise, research on chatbots indicates that while customer-facing AI can impact purchase decisions, disclosure of AI, perceived autonomy, and timing of interactions can also impact trust and conversion [9]. The results suggest that agentic GTM maturity is dependent on strategic delegation: commercial action should be supported, sequenced or automated by AI only if the complexity of the task, customer sensitivity, and measurable revenue impact all support it.

The third evidence stream is related to AI-powered CRM and retention decision analytics. The studies on AI CRM adoption show that organizational agility, usefulness of the system, and compatibility of the system are key factors for its adoption [7]. Predictive retention studies suggest using hybrid classification methods to improve churn identification [10] and churn-intervention research suggests that high churn risk does not automatically imply profitable action as action value depends on incremental responsiveness and not just churn risk [11]. This is important to note when discussing maturity in GTM since more mature systems are required to optimize decision making and interventions, not just the identification of risk.

Table 1: Summary of Key Findings

Ref	Focus	Key Findings
[5]	AI transformation in marketing	AI alters marketing through task automation, prediction, personalization, and decision augmentation, but value depends on managerial integration.
[6]	Strategic AI capability in marketing	AI value differs across mechanical, analytical, and intuitive tasks, supporting staged maturity across GTM functions.
[7]	AI-integrated CRM adoption	CRM intelligence adoption depends on agility, compatibility, and organizational readiness, not only technical sophistication.
[8]	AI sales coaching	AI advice can improve sales performance, yet benefits vary by salesperson skill and decision context.
[9]	AI chatbot disclosure	Customer-facing AI may affect conversion depending on disclosure timing and perceived machine agency.
[10]	Churn prediction methods	Hybrid classification improves churn identification, but predictive performance remains separate from intervention value.
[11]	Retention targeting	High churn-risk targeting can be commercially weak when models ignore incremental responsiveness.
[12]	Customer experience management	Revenue outcomes depend on coordinated touchpoints, organizational alignment, and experience governance.

The fourth evidence stream is about customer experience management, digital transformation and revenue-process redesign. Customer experience research has identified the touchpoints, culture, and process design as the factors that can strongly influence the commercial performance of a business [12]. The research efforts in AI business value and digital transformation also offer a system-level perspective by showcasing the reconfiguration of processes, data flows and decision rights to embed digital capabilities [16, 17]. These studies serve to situate agentic GTM maturity as a capability of the organization and its revenue system, and not just a collection of isolated AI tools.

Table 1 indicates that the current evidence base is strongest at the component level, whereas system-level evidence for integrated agentic revenue architectures remains limited. The reviewed studies support specific mechanisms such as marketing automation, adopting AI-CRM, sales coaching, chatbot sales, churn modelling, retention targeting, and customer-experience governance, but they do not yet provide a complete and validated agentic revenue architecture. Another line of research is about the limitations of customer-facing AI. Subjective decisions or identity-relevant decisions (in situations where customers have personal preferences, trust, perceived fairness, or relationship sensitivity) might lead customers to more strongly oppose algorithmic decision-making [13]. As a result, revenue agents need clear delineations to determine what customer exchanges can be automated, which require human approval and which should remain human-led. Experiential research also reveals that customers consider the efficiency of AI output but also the social, emotional, and identity aspects of dealing with AI [14]. The results indicate that agentic GTM is not necessarily synonymous with more autonomy. A mature system must determine where automation improves revenue efficiency and where human involvement is necessary, legitimacy and persuasion quality.

III. METHODOLOGY

This article uses a narrative, theory-building review approach rather than an original empirical design. Peer-reviewed journal studies published from 2015 onward that are directly relevant to the theme of AI in sales, B2B marketing automation, CRM, retention analytics, customer experience, digital transformation, and AI business value were reviewed. As the Agentic GTM Maturity Model is not yet established as a labelled research stream, this review draws on adjacent literatures and maps their findings to GTM functions, maturity layers, and governance requirements. The aim is not to quantify pooled effects but to formulate an integrative maturity logic and identify gaps for future empirical testing.

Table 2: Comparison of Methodological Approaches in the Reviewed Literature

Ref	Method	Strengths	Limitations
[3]	Qualitative B2B case analysis of marketing automation	Shows process-level linkage between content, behavioural data, and lead management.	Limited generalizability and weak causal testing of revenue impact.
[7]	Survey-based adoption modelling	Identifies organizational antecedents of AI-CRM adoption.	Adoption perceptions do not directly measure realized GTM performance.
[8]	Field evidence on AI sales coaching	Captures performance implications of AI recommendations in live selling.	Context-specific sales setting limits transferability across GTM models.
[9]	Field and experimental chatbot analysis	Tests customer response to AI-mediated selling and disclosure.	Conversion focus provides limited insight into long-term relationship value.
[10]	Predictive modelling for churn classification	Compares model structures relevant to retention automation.	Prediction is evaluated more directly than intervention profitability.
[11]	Empirical retention targeting analysis	Distinguishes churn risk from incremental responsiveness	Findings depend on available intervention and response data.
[16]	Multidisciplinary digital transformation review	Links digital capability to organizational redesign.	Broad scope requires translation into revenue-system constructs.
[17]	AI business-value literature review	Connects AI value to resources, capabilities, and deployment context.	Limited function-specific evidence for GTM orchestration.

The reviewed literature uses three broad methodological approaches. Conceptual and agenda-setting articles classify the capabilities of AI, link them to the strategic implications, and list task categories [5, 6, 15]. Their strength lies in their breadth, as they connect AI capabilities to marketing strategy, sales roles, customer management, and value creation. However, these studies also have limitations because they often provide limited empirical detail; maturity statements are often presented only at the level of capability categories rather than quantifiable GTM stages. Second, empirical studies examine specific GTM functions, including AI-integrated CRM adoption, sales coaching, chatbot-mediated selling, churn forecasting, and retention targeting [7]–[11]. These studies provide stronger outcome-oriented evidence than conceptual articles, but most remain limited to single GTM functions. Third, reviews of digital transformation and AI business value link firm-level capabilities to data architecture, process redesign, and decision rights [16, 17]. These articles help frame agentic GTM maturity as a system-level property.

The proposed framework defines maturity in terms of five stages. At stage 1, fragmented insight, dashboards are disconnected, there is limited connectivity and function-specific analytics. Stage 2 adds assisted execution, AI-generated recommendations and guided selling, with most workflows being controlled by people. Stage 3, automated workflow, connects triggers across marketing automation, CRM, and retention systems. In stage 4, agentic orchestration, bounded AI agents can orchestrate interactions across the entire demand generation, sales engagement, customer success and account expansion journey. Stage 5 represents governed revenue autonomy, in which adaptive commercial execution is supported by human oversight, causal measurement, explainability, and risk controls. The proposed framework is derived from a recurring theme in the literature, which asserts that data, action, governance, and organizational capability are crucial to creating value in AI [15]–[18].

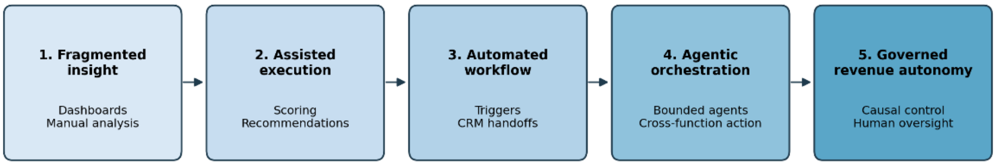

Figure 1: Five-Stage Architecture of the Agentic GTM Maturity Model

Figure 1 presents the topic-specific maturity logic of the Agentic GTM Maturity Model. The model is useful because it distinguishes automation intensity from governed commercial agency, and it is not based upon the number of tools but upon their coordination in the revenue system. The figure represents five maturity stages, ranging from fragmented insight to governed revenue autonomy. For peer-reviewed evidence on AI sales, B2B marketing automation, CRM intelligence, customer relationship AI, digital transformation and AI business value [1]–[8] and [15]–[18] are cited for conceptual interpretation.

IV. DISCUSSION

It is not enough to add individual projects, an AI-based revenue system matures when data, workflows, decision rights and outcome measurement are all included. Based on the research, AI tools can be leveraged in the marketing world if they can be linked to customer insights, content marketing, pricing, customer service, and management systems [5], [6], [15]. This pattern questions the notion of maturing the applications based on the deployment of AI applications. Firms that optimize isolated functions, such as predictive lead scoring, chatbots, AI content generation, and churn dashboards, may still operate fragmented revenue systems. In Agentic GTM Maturity Model, the system moves up the maturity stages only if its output of AI is followed by coordinated revenue action, with measurable constraints. This interpretation aligns with research on digital transformation in the digital world, which indicates that digital transformation has little to do with technology and much to do with reorganizing and redesigning organizations and decision architectures [16, 17].

In some revenue functions, the best evidence for bounded AI interventions exists. Research on sales coaching indicates that AI can support sales performance by offering suggestions for actions and communication strategies, but the impact of this might be different for various salespeople and sales interaction scenarios [8]. The result backs up a contingent perspective on agentic maturity, suggesting that the delegation of AI should be based on salesperson competence, customer complexity, and task ambiguity. Previous studies have also demonstrated that AI can be used for business activities that require customer interaction, and that disclosure effects can be noted with regard to customer trust and conversion rate [9]. The conclusions will guide the questions to be addressed about the conditions that promote human–AI interaction to support the effectiveness of GTM. Autonomy could have a negative impact if customers feel the interaction through AI is impersonal, manipulative, or not value-added.

A second important lesson is derived from retention analytics. A classification study using churn-prediction data has indicated that a hybrid model can be used to achieve better classification accuracy, especially for the combination of interpretable and nonlinear structures [10]. High churn risk does not automatically imply high retention-intervention value [11]. This distinction is at the heart of agentic GTM as it is often the case that some independent systems that simply act on prediction might not be optimal for commercial success. Such systems can be ineffective in quantifying treatment effects, incentivize wasted treatment, incentivize ineffective customer success strategies, and incentivize agents to focus more on the easily measured treatment risk score than the value of the treatment. So, the systems needed to be changed from prediction to decision intelligence in mature organizations. The important point to consider is not just model accuracy but incremental revenues under constraints on resources and on the customer experience.

The process-level view is provided by marketing automation evidence. The value of B2B marketing automation depends on linking content engagement, behavioural scoring, lead nurturing, and sales handoff [3]. This discovery implies that Stage 3 automated workflow is not enough for Stage 4 agentic orchestration. Poorly calibrated scoring models or marketing-qualified leads that are not accepted by sales teams can create handoff inefficiencies. Closed loop sales funnel feedback from conversion, sales cycle velocity, account expansion and retention must be applied to upstream targeting and content decisions to achieve agentic maturity. If this is not received, misalignment between the marketing and sales team can become more pronounced.

Table 3: Results Comparison

Ref	System / Context	Metric / Basis of Comparison	Outcome
[3]	B2B marketing automation	Lead nurturing, behavioural scoring, and sales handoff	Automation improved content-linked lead management when sales alignment was explicit.
[7]	AI-integrated CRM	Adoption drivers across agile organizations	Organizational agility and compatibility supported adoption more than technical novelty alone.
[8]	AI sales coaching	Sales-agent performance under AI guidance	AI advice improved performance in bounded selling tasks, with context-dependent caveats.
[9]	Customer-facing chatbot selling	Purchase conversion under AI disclosure	AI disclosure timing materially affected conversion, showing trust sensitivity in agentic selling.
[10]	Churn prediction	Hybrid classification versus single-model approaches	Hybrid modelling strengthened churn classification by combining segmentation and prediction.
[11]	Retention targeting	High-risk targeting versus intervention value	Risk-based retention was often insufficient without estimating incremental response.
[12]	Customer experience management	Touchpoint coordination and organizational alignment	Experience performance depended on coordinated governance across customer interactions.
[16]	Digital transformation	Organizational redesign and digital capability	Value emerged when digital tools changed processes, structures, and decision rights.

Research in customer experience management also suggests aligning revenue systems throughout the customer journey across customer touchpoints [12]. Agentic GTM takes this a step further by stating that the AI agents should behave based on the customer's journey state. For instance, the revenue agent who is tasked with outreach, discounting, support escalation and expansion should not optimize each action independently. Rather, the agent needs to consider the customer's lifecycle stage, the nature of the previous interaction, service history, and potential growth. This need is supported by research on consumer responses to AI that indicates that the task, the emotional salience of the task, and the perceived appropriateness of the AI application influence their acceptance of the AI [13,14]. Mature agentic GTM systems therefore require an interaction policy specifying when AI should act autonomously, when AI should recommend, and when humans should lead.

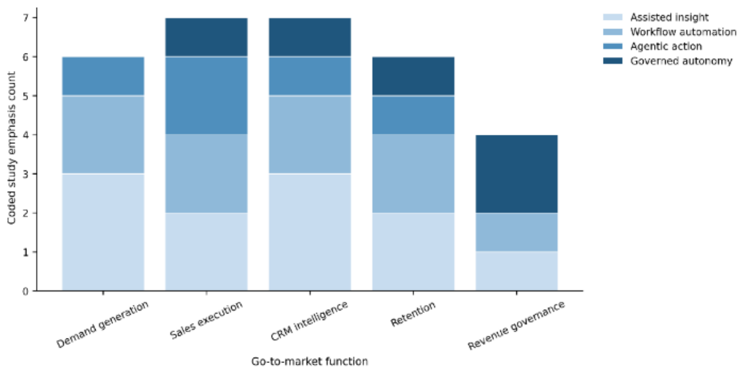

Figure 2: Author-Coded Evidence Concentration Across GTM Functions and Maturity Layers

The distribution of the evidence across the GTM functions and maturity layers presented in the reviewed literature is visualized in Figure 2. It is important because it indicates that there is evidence clustering at the extremes of assisted execution and functional autonomy rather than governed cross-functional autonomy. This figure shows a coded evidence distribution over the five GTM functions and four maturity layers. The figure reports counts of study emphases, rather than effect sizes, based on author-coded categorizations of the peer-reviewed studies summarized in Tables 1–3.

Figure 3 combines the review in a comparative capability profile by maturity stages. It is important because it illustrates that advancement in later-stage agentic GTM must also include advances in data integration and orchestration, human-agent collaboration, causal measurement, and governance. The radar chart reports the capability intensity in each of the early, intermediate and advanced maturity configurations. The scoring is conceptual and is based on patterns reported in the literature on AI sales, marketing automation, CRM, retention, AI acceptance, and digital transformation [1]–[18].

Figure 3: Capability Profile of the Agentic GTM Maturity Model

Several tensions emerge across the reviewed studies. Strategic AI literature suggests that more advanced AI capabilities may improve decision quality, whereas behavioural evidence indicates that perceived algorithmic agency can reduce acceptance in subjective or trust-sensitive situations [6], [13], [14]. Predictive-modelling research often emphasizes classification performance, whereas retention research emphasizes causality and customer responsiveness. The research for sales augmentation and CRM adoption has been linked to potential productivity benefits and organizational readiness and system compatibility, respectively [7], [8]. These tensions illustrate the central point of the maturity model: agentic GTM requires the coordinated management of algorithmic capability, human judgment, customer acceptance, and revenue measurement.

Finally, methodological issues are reported in the literature. Numerous studies offer only functional evidence rather than system-level GTM evidence. The causal inference from field experiments is more compelling, but they are uncommon and can be idiosyncratic. The survey studies define the adoption mechanisms, but they are likely to overestimate maturity since perceived usefulness is not the same as revenue-system performance. Conceptual studies provide integrative categories, but sometimes these studies are lacking in operational metrics. While predictive modelling studies are typically based on accuracy, area under the curve, or classification lift, GTM leaders are interested in such measures as incremental pipeline, compression of the sales-cycle, expansion propensity, churn intervention profit, and customer lifetime value impact. Better algorithmic-performance-to-commercial-outcome linkages are thus needed to support a mature research program on agentic GTM.

For AI-based revenue systems, maturity can be audited across five dimensions. Data maturity concerns the availability of seamless, trusted, timely, and context-aware data across marketing, sales, product usage, service, and finance. Action maturity refers to the capacity to connect and organize recommendations or agentic activities throughout the customer lifecycle. Collaboration maturity concern's role design among AI agents, sales teams, marketers, customer-success teams, and revenue operations. Measurement maturity moves beyond descriptive attribution toward causal evaluation of interventions. Governance maturity includes explainability, consent, risk thresholds, escalation rules, and auditability. A system may therefore be highly automated without being fully agentic if these dimensions are weak or absent.

V. FUTURE DIRECTIONS

Moving forward, the Agentic GTM Maturity Model should look at the use of AI in different scenarios and consider revenue systems as more holistic and longitudinal systems. A goal is to create and test maturity scales to differentiate between assisted analytics, automated workflow, agentic orchestration and governed autonomy. These scales should assess the level of tools deployment and cross-functional data quality, autonomy boundaries, feedback loops, causal evaluation, and human escalation design. While there are already some frameworks in place for the study of AI marketing and digital transformation, validated instruments or scales specific to agentic GTM maturity are still needed [15]–[16].

Causal research on agentic action is a second priority. The literature also suggests that AI sales coaching and the AI sales coaching and chatbot-based selling has positive functional outcomes, which should be measured in future studies for the added value of revenue in connected GTM stages and not in one function to another [8]–[11]. Randomized experiments, uplift modelling, longitudinal panel designs and quasi-experimental methods are methods that can disentangle prediction quality from action value. Further studies should investigate these relationships and connections at different levels, including AI-only, human-only, and hybrid configurations of human-AI products, as well as at different stages of product relationships.

Thirdly, there remains a governance and trust challenge. Research on algorithm aversion and AI experiences suggests that algorithmic decisions are accepted or rejected depending on the task and its appropriateness [13] [14]. Going forward, more research is required to distinguish between actions which can be fully automated, actions which must be reviewed by humans and remain human-led for GTM. Future research should integrate marketing ethics, information-systems governance, sales management, and service research. Finally, from a research perspective, institutional explanations for the integration of AI into business processes need to be developed.

VI. CONCLUSION

The Agentic GTM Maturity Model provides an understanding of how revenue systems develop from isolated insights to AI-driven revenue systems that have a governed commercial autonomy. From the literature review, the number of tools used that leverage AI does not directly reflect maturity rather, maturity is realized through the convergence of data, recommendations, workflows, human judgments, measurement, and governance around revenue outcomes. There are opportunities mentioned in the reviewed literature for the use of AI in aspects of sales coaching, chatbot selling, marketing automation, CRM adoption, churn prediction, targeting for retention, customer experience, and digital transformation; however, there are important gaps in implementation. The main contribution of the model to the scholarly world is the system perspective on the revenue system, which includes the functional AI evidence. These evidence streams point towards potential value, which relies on the causal impact, conditions of adoption, constraints of trust, and organizational redesign. Research gaps that have been prevalent for a long time are a lack of validated maturity metrics, lack of integration of causal inference in GTM automation, and lack of governance models for autonomous commercial action. Agentic GTM should be viewed as a socio-technical revenue architecture in which autonomy is bounded, measured, explainable, and aligned with customer and firm value creation.

VII. REFERENCES

[1] Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management, 69*, 135–146.

[2] Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business & Industrial Marketing, 34*(7), 1410–1419.

[3] Järvinen, J., & Taiminen, H. (2016). Harnessing marketing automation for B2B content marketing. *Industrial Marketing Management, 54*, 164–175.

[4] Libai, B., Bart, Y., Gensler, S., Hofacker, C. F., Kaplan, A., Kötterheinrich, K., & Kroll, E. B. (2020). Brave new world? On AI and the management of customer relationships. *Journal of Interactive Marketing, 51*, 44–56.

[5] Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24–42.

[6] Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50.

[7] Chatterjee, S., Ghosh, S. K., Chaudhuri, R., & Chaudhuri, S. (2021). Adoption of artificial intelligence-integrated CRM systems in agile organizations in India. *Technological Forecasting and Social Change, 168*, 120783.

[8] Luo, X., Qin, M. S., Fang, Z., & Qu, Z. (2021). Artificial intelligence coaches for sales agents: Caveats and solutions. *Journal of Marketing, 85*(2), 14–32.

[9] Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937–947.

[10] De Caigny, A., Coussement, K., & De Bock, K. W. (2018). A new hybrid classification algorithm for customer churn prediction based on logistic regression and decision trees. *European Journal of Operational Research, 269*(2), 760–772.

[11] Ascarza, E. (2018). Retention futility: Targeting high-risk customers might be ineffective. *Journal of Marketing Research, 55*(1), 80–98.

[12] Homburg, C., Jozić, D., & Kuehnl, C. (2017). Customer experience management: Toward implementing an evolving marketing concept. *Journal of the Academy of Marketing Science, 45*(3), 377–401.

[13] Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research, 56*(5), 809–825.
[14] Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of Marketing, 85*(1), 131–151.
[15] Vlačić, B., Corbo, L., Silva, S. C., & Dabić, M. (2021). The evolving role of artificial intelligence in marketing: A review and research agenda. *Journal of Business Research, 128*, 187–203.
[16] Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research, 122*, 889–901.
[17] Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers, 24*(5), 1709–1734.
[18] Rust, R. T. (2020). The future of marketing. *International Journal of Research in Marketing, 37*(1), 15–26.