ESP-JETA
ESP Journal of Engineering & Technology Advancements
ISSN: 2583-2646 / Volume 6 Issue 3 July 2026
Paper Id: JETA-V6I3P106/ Page No: 43-51

Review Article

Designing AI-Augmented Content Management Systems for Sales Enablement: A Framework for Measuring Engagement-to-Revenue Impact

Nisha Gopinath Menon
The University of Texas at Austin, Texas, USA

Received Date: 22 July 2026 Revised Date: 28 July 2026 Accepted Date: 01 August 2026

Abstract: *Digital content is an important sales enabler and AI-augmented CMSs play a crucial role in making content easily accessible for sales teams, relevant to sales teams' needs and buyer contexts, personalized, compliant, measurable and revenue-generating. This article reviews peer-reviewed journal articles published between 2015 and 2023 on the topics of AI in sales, B2B content marketing, marketing automation, CRM analytics, customer engagement, and revenue attribution. The research base is relevant, but remains fragmented, as content studies look at the quality of the engagement, sales studies look at the skills and abilities of the salesperson, and analytics studies look at attribution, customer value and decision support. A recurring challenge is how content interactions can be correlated with opportunity progression, sales productivity, win probability, retention and revenue by creating measurable frameworks. The article suggests a concise conceptual model for the engagement-to-revenue impact in the AI-powered sales enablement context. Fragmented data, lack of causal identification, reliance on platform metrics, and underrepresentation of governance are key challenges. Longitudinal designs, multi-touch attribution validation, explainable AI, and seller-in-the-loop experimentation should be areas of focus for future research.*

Keywords: *AI-Augmented Content Management, Customer Engagement, Revenue Attribution, Sales Analytics, Sales Enablement*

I. INTRODUCTION

AI-powered sales enablement content management systems (CMSs) represent a convergence point at which content operations, seller workflows, buyer engagement, CRM intelligence, and revenue analytics are integrated. Rather than functioning merely as tools for administrative efficiency, AI-enabled sales systems are increasingly positioned as structural changes to the selling process and create a new approach to value presentation and account prioritization [1]. The sales enablement challenge is no longer limited to storing content or training. It concerns the design of intelligent content environments that select, adapt, deliver, and evaluate content assets against buyer stage, account context, seller behaviour, and business results.

This topic is particularly relevant in light of collaborative intelligence in B2B selling. Research examining the human–AI interaction across the sales funnel indicates that AI delivers the most value when algorithmic pattern recognition is combined with human relational interpretation and negotiation skills [2]. It is important for any content management system particularly when it comes to sales content, which is not valuable just because it is correct or copious. Content becomes commercially significant when a seller can identify the right asset, customize it for the buyer's context and needs, share it with the buyer at an appropriate time and then observe the resulting engagement. A measurement architecture is required to connect content exposure, seller adoption, buyer engagement, opportunity movement and revenue contribution to operationalize AI-augmented content management.

This architecture is based on B2B content marketing and marketing automation research. Studies on B2B content marketing and marketing automation showed that the relevance of the content, lead nurturing, data quality, and sales–marketing alignment have an impact on the commercial value of digital content [3]. There is a large body of literature, however, that focuses on engagement, response to campaigns or CRM adoption at the asset or campaign level, rather than tracking revenue pathways. While the marketing analytics research has emphasized data-rich environments, attribution, and decision support, These tools have not always been applied effectively in content management design for sales enablement [4]. Similarly, customer value research calls for linking interactions with value, retention and profitability over a longer period of time, although it remains difficult to link content-level interaction with revenue in multi-actor and nonlinear buyer journeys [5].

There are very few peer-reviewed sources that make a direct connection between AI-supported content management systems and sales enablement. The most relevant evidence is spread out in adjacent, yet tightly connected, streams: AI in

This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/2.0/)

sales, AI in marketing, CRM analytics, digital content marketing, customer engagement, B2B digital marketing, and customer journey measurement. This division results in conceptual and methodological gaps. First, engagement is often defined as views, clicks, downloads, or even just being on a page, without necessarily establishing a link to sales. Second, studies on sales performance usually provide either seller or firm-level findings, obscuring the influence on asset level. Third, AI research often approaches recommendations, automation, personalization, or CRM intelligence as a single concept without any direction on how to approach structuring content governance or attribution. Lastly, there is weak causal evidence on the revenue value of content engagement beyond the correlation with account interest.

This paper conducts a literature analysis to identify design requirements for AI-enhanced sales enablement CMSs that have the ability to measure the engagement-to-revenue impact. The article constructs a framework in which content is a measurable commercial act that is a component of a human-AI sales process. This review draws together evidence from a number of studies, identifies some common study limitations and proposes a measurement logic for distinguishing content discoverability, seller activation, buyer engagement, opportunity influence, and revenue realization. The intended contribution is to provide a brief academic model for researchers and system designers who want to measure engagement-to-revenue—and do so defensibly—beyond platform analytics.

II. LITERATURE REVIEW

The literature on the topic of AI-enhanced sales enablement content management systems (CMSs) falls into four categories: digital content engagement, AI-powered CRM and marketing, seller-facing digital capability, and journey-to-revenue measurement. Table 1 summarises key findings from the peer-reviewed journal studies that inform this review.

Table 1: Summary of Key Findings

Ref	Focus	Key Findings
[6]	Digital content marketing and engagement	Content value, authenticity, and trust formation shape engagement quality, although revenue linkage remains conceptual.
[7]	Digital marketing framework	Digital environments require integrated data, targeting, interaction design, and measurement across customer touchpoints.
[8]	AI in marketing	AI changes targeting, personalization, service, and decision support but requires governance and human oversight.
[9]	Strategic AI in marketing	AI value varies by task type; mechanical, thinking, and feeling tasks require different degrees of automation.
[10]	AI and customer relationship management	CRM value depends on balancing prediction, personalization, privacy, and relationship quality.
[11]	Digitization and AI in sales professions	Sales roles shift toward analytical, relational, and technology-mediated capabilities.
[12]	Social media in B2B sales	Digital engagement supports competitive intelligence and adaptive selling when learning orientation is strong.
[13]	Sales-based CRM and social media	CRM and social media tools influence post-sale service behaviours through seller technology use.
[14]	AI-based CRM in B2B performance	AI-enabled CRM is associated with stronger organizational performance and competitive advantage under supportive conditions.
[15]	Digital transformation	Digital transformation requires strategic alignment of technology, data, organizational processes, and customer experience.
[16]	AI and personalized engagement marketing	AI can personalize engagement at scale but needs data integration, experimentation, and value-based evaluation.
[17]	Customer journey measurement	Customer experience should be assessed across touchpoints, stages, and dynamic journey paths.

One of the key messages of digital content marketing research is that engagement is not just about exposure. Digital content marketing influences engagement through value, trust, and relational mechanisms. In sales enablement, this means that sales content should support the buyer's evaluation process, rather than merely attracting attention [6]. Kannan and Li extend this notion by placing digital marketing within systems of interaction that integrate marketing data, including targeting, customer response, channel selection, and measurement [7]. These studies suggest that, for AI-facilitated content management, a content repository can only be useful when there is a connection between asset metadata, audience context, behavioural signals, and downstream outcomes. However, a limitation is that content engagement research tends to view

engagement as a marketing metric, while sales enablement research needs to measure it on the asset–seller–account–opportunity level.

AI and CRM research offers stronger insight into algorithmic capability than into content governance. AI has the potential to revolutionize marketing by customizing and segmenting content, automating tasks, and forecasting trends, yet it also comes with challenges of transparency and control [8]. Huang and Rust extend this view by distinguishing between applications of AI based on the type of task performed. This distinction is valuable for content systems because tagging, retrieval, translation, recommendation, and coaching each involve different risk levels and human oversight requirements [9]. Customer relationship management in an AI-enabled environment requires attention to customer response, privacy, and relationship quality, as demonstrated by Libai and colleagues [10]. The findings from these studies indicate that AI-powered content management should not be based solely on predictive ranking of assets. It should also provide a rationale for recommending an asset, maintain brand and regulatory integrity, and measure whether improved asset recommendations influence revenue-relevant behaviour.

Sales digitization studies bring the seller into the analysis. Singh et al. outline the transformation of the sales role in the age of AI and digitization, with a focus on data analysis, hybrid human–machine interactions and technology-driven customer interactions [11]. Research by Itani, Agnihotri, and Dingus indicates that B2B sellers can use social media to collect competitive information and improve their ability to adapt their selling strategies when their organisational learning orientation enables them to act on digitally acquired information [12]. Agnihotri et al. also demonstrate that sales-based CRM technology and social media use have an impact on post-sale service behaviours, which indicates that platform value is not merely a function of tool availability; it also depends on the behaviours implemented through the platform [13]. That implies that engagement-to-revenue value should not be assessed through buyer-side metrics alone within AI-driven content management. The causal chain includes seller adoption, content selection behaviour, follow-up timing, and CRM discipline.

AI-powered CRM, digital transformation, personalization, and customer-journey research provide a useful basis for measuring revenue impact. Chatterjee and colleagues explain that, in B2B contexts, AI-powered CRM systems can influence firm performance and competitive advantage, as long as they are tailored to strategy and capability [14]. Verhoef et al. state that digital transformation requires coordinated transformation of technology, business models, processes, and customer experience [15]. Kumar et al. call AI-powered personalized engagement marketing a path to scalable relevance while noting the need to measure personalization in the context of customer value, not just individual interactions [16]. To situate engagement within the customer journey, Lemon and Verhoef offer a customer journey lens to help define content engagement as a staged problem of measurement across touchpoints and time [17]. In these studies, there is a common theme: Engagement signals are frequently noted, but the revenue mechanism is less well specified.

This is reinforced by other B2B marketing and social selling research conducted via digital channels. Vieira and colleagues demonstrate that the orchestration of digital resources and capabilities in relation to performance outcomes is crucial to a successful B2B digital marketing strategy [18]. Terho and colleagues describe B2B social selling activities and outcomes; this is particularly important since an increasing amount of content is distributed via digital channels that are mediated by the salesperson [19]. According to Bleier et al. [20], the effectiveness of online customer experiences depends on the context, sensory design, informativeness, and customer goal states. Combined, the literature suggests that the architecture of AI-supported CMSs can be designed as engagement infrastructures, although few studies attempt asset-level causal attribution from content interaction to closed revenue. This defines the central research opportunity that is the subject of this article.

III. METHODOLOGY

The richness and fragmentation of evidence are reflected in the methodological approaches that have been used in the literature. Conceptual frameworks are especially prevalent in AI-in-marketing research because system capabilities are evolving quickly and longitudinal empirical evidence takes time to develop [8], [9], [10]. While these frameworks are useful for identifying mechanisms such as personalization, automation, prediction, privacy risk, and human oversight, they are less useful for estimating revenue effects. Empirical sales and B2B marketing research more commonly correlates technology use with performance through the use of surveys, structural equation models, case-study designs, and scale development [12], [13], [14], [18], [19]. These designs yield meaningful organizational and behavioural results, but the level of attribution for content is typically indirect. Customer journey and experience studies provide stronger touchpoint logic, but are difficult to apply when multiple channels, sellers, and buyer roles interact over long B2B cycles [17], [20].

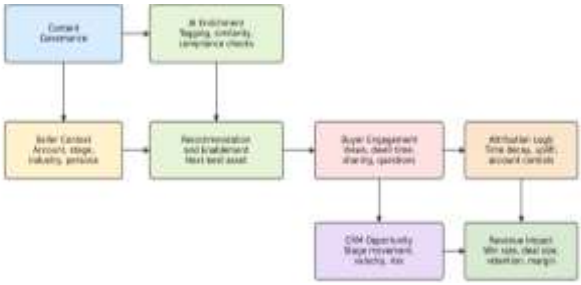

Figure 1: AI-Augmented CMS Architecture for Engagement-To-Revenue Measurement

The literature thus suggests that the use of AI-powered content management is not a one-size-fits-all solution but a measurement architecture. The proposed architecture represents the core of the solution, connecting the elements of content governance, AI enrichment, seller activation, buyer engagement, opportunity influence, and revenue attribution, as shown in Figure 1. It aims to help separate operational metrics from commercial metrics like opportunity progression and revenue contribution. The architecture demonstrates how AI services can enhance content, suggest next best assets, help sellers, record buyer engagement and bring content signals together with CRM opportunity outcomes.

Table 2: Method Comparison

Ref	Method	Strengths	Limitations
[3]	Qualitative B2B marketing automation case analysis	Captures process change in content marketing and lead nurturing	Limited generalizability and limited causal revenue estimation
[6]	Conceptual framework development	Clarifies engagement, trust, and content value mechanisms	Does not test asset-level sales outcomes
[8]	Managerial and conceptual analysis of AI applications	Maps AI functions across marketing tasks	Limited empirical measurement of revenue contribution
[10]	Conceptual analysis of AI in CRM	Integrates personalization, relationship quality, and governance	Does not operationalize CMS-specific attribution
[12]	Survey-based B2B sales model	Connects digital use to intelligence and adaptive selling	Relies on perceptual measures and seller-level outcomes
[14]	Empirical AI-CRM performance model	Links AI-enabled CRM to competitive and performance outcomes	Firm-level measures obscure content-specific effects
[17]	Customer journey framework	Supports multi-touch, multi-stage measurement logic	Requires granular longitudinal data rarely available
[19]	Scale development and empirical testing	Provides social selling activity and outcome measures	Content asset properties receive limited attention
[20]	Empirical online experience study	Shows contextual effects of digital experience design	Mostly customer-experience focused rather than sales-enablement focused

The framework calls for measures that can be used for mediation and attribution. Seller activation may moderate the relationship between AI recommendation quality and buyer engagement, and opportunity state may moderate the relationship between buyer engagement and revenue. This logic points to the value of longitudinal, CRM-linked event data, quasi-experimental designs, A/B testing of content suggestions, and account-level controls for deal size, buying stage, industry, and previous relationship quality. While there are survey and conceptual designs in place, future empirical studies need to capture more granular content-event data than the firm- or campaign-level measures that currently dominate.

IV. RESULTS AND DISCUSSION

The most consistent result from the literature is that engagement-to-revenue impact is not driven by any single AI capability, but rather by integration. While these capabilities (recommendation, personalization, segmentation, prediction, and decision support) can all benefit from AI, revenue relevance emerges only when these capabilities are integrated into sales workflows and connected with CRM outcomes [8], [9], [14], [16]. Content engagement studies reveal that informational value and the building of trust are important for the quality of engagement [6]. Sales technology studies reveal

that technology use must translate into adaptive selling action [12], [13]. This is at the heart of AI-powered content management. Optimizing content relevance alone is insufficient if seller adoption and buyer response are not measured. On the other hand, a system that does not connect buyer engagement to opportunity context may overvalue content that captures attention but does not move a buyer toward purchasing.

Table 3: Results Comparison

Ref	System / Context	Metric / Basis of Comparison	Outcome
[3]	B2B marketing automation for content marketing	Lead nurturing, content relevance, data integration	Content impact improved when marketing automation was aligned with the sales process and customer data.
[6]	Digital content marketing	Engagement, trust, perceived value	Engagement quality was theorized as a relational mechanism rather than a click-based outcome.
[10]	AI-enabled CRM	Personalization, prediction, relationship management	AI value depended on customer relationship quality and responsible data application.
[12]	B2B social media selling	Competitive intelligence and adaptive selling	Digital signals improved sales behaviour when sellers had a learning orientation.
[14]	AI-based CRM in B2B firms	Organizational performance and competitive advantage	AI-CRM capability was positively associated with performance-related outcomes.
[16]	Personalized engagement marketing	AI-based personalization and customer value	AI personalization requires value-based evaluation rather than surface interaction metrics.
[17]	Customer journey management	Touchpoints and journey stages	Multi-stage journey mapping clarified how engagement accumulates across interactions.
[18]	B2B digital marketing strategy	Digital capability and performance	Performance required strategic orchestration of digital assets and market-facing capability.
[19]	B2B social selling	Activity measures and performance outcomes	Social selling metrics captured seller-mediated engagement relevant to sales results.
[20]	Online customer experience	Informativeness, experience design, customer response	Experience effects vary by context, indicating that content impact is conditional.

Evidence is distributed across content engagement, AI and CRM, sales enablement behaviour, and journey or analytics measurement, as shown in Figure 2. The figure shows that no single stream provides a full engagement-to-revenue model. This is important because AI-powered CMS solutions must include all four of the evidence domains – content quality, algorithmic intelligence, seller activation and revenue attribution. The figure indicates the dominant studies referenced and illustrates the literature's focus on content engagement, AI/CRM, sales enablement, and journey analytics. The count data in Figure 2 are based on qualitative coding of the studies summarized in Tables 1–3.

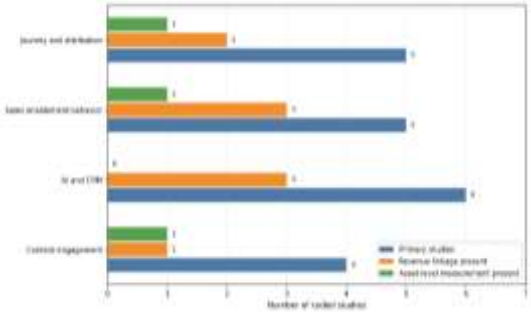

Figure 2: Evidence Distribution Across Engagement-To-Revenue Design Domains

A second trend is to consider engagement as an intermediate variable and revenue as an aggregate variable. This indicates a measurement gap. Engagement is linked to trust, value, and relationship building in the context of content marketing [6]. Sales technology research shows that digital engagement can influence adaptive selling and post-sale service [12], [13], while AI-CRM research often evaluates performance at the firm level [14]. However, these studies are analytically useful but insufficient for determining whether any content influenced a buying committee, which seller actions, if any, magnified that influence, or which engagement signals led to movement in an opportunity. This means for sales enablement CMS design that the unit of analysis needs to move from the campaign-level engagement to event-level content interactions that are linked to account and opportunity records.

Personalization and journey logic are the strongest conceptual areas of alignment. AI marketing research identifies data integration and governance as key conditions for improving the relevance and value of personalization [8, 9, 16]. Customer journey research provides a temporal lens for mapping interactions across stages [17]. Applied to sales enablement, this means that content discoverability can influence seller adoption, buyer exposure, engagement quality, opportunity progression, and ultimately revenue. However, existing literature rarely quantifies these stages as a causal sequence. This leaves a central question unresolved: whether AI-based recommendation improves revenue directly, through seller-mediated content use, or only under specific sales-context conditions.

To clarify the relationship between the selected studies and the engagement granularity, revenue linkage, and AI augmentation relevance, Figure 3 presents a comparative map of the selected studies. The pattern is that studies with a higher level of conceptual or system scope tend to have higher relevance to AI, and studies with a higher level of engagement detail tend to have lower relevance to revenue. This visual comparison shows the design space of future empirical studies: the content-event data need to be coupled with more robust revenue modelling. The figure shows the selected studies by dimension of granularity of the engagement measure and strength of the revenue linkage coded in the review. Bubble size reflects each study's relevance with regard to AI enhancement or smart CRM development. Values are the analytical coding categories from the article's interpretations in Tables 1–3, not effect sizes.

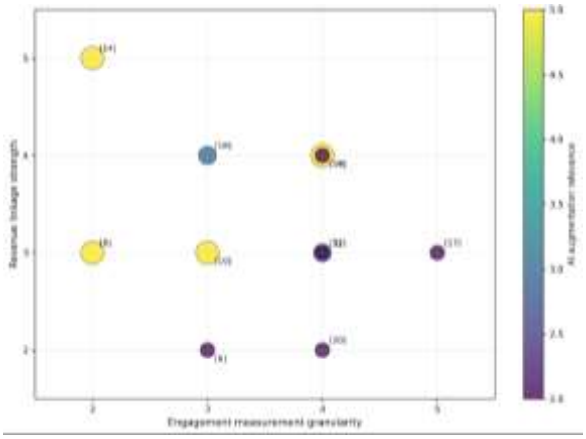

Figure 3: Comparative Positioning of Studies By Engagement Granularity And Revenue Linkage

A third issue concerns the lack of a "selling behaviour" dimension as an explanatory factor. Sales enablement content is different from consumer advertising content because sales content is often chosen, assembled, formatted, and presented by a salesperson. The evidence for the growing need among salespeople for analytical and technology-mediated skills [11] and the research on social selling reveal that sellers' learning orientation and digital behaviour affect the way that they use online signals to produce adaptive behaviour [12], [19]. This requires capturing not only buyer engagement but also seller actions, including search queries, recommendation acceptance, asset customization, sharing sequence, follow-up timing, CRM note quality, and use of follow-up content. This seller-side telemetry is necessary if the attribution is to be used to conclude whether content is effective or ineffective.

The fourth finding relates to governance. Even though the studies on AI marketing and AI-CRM highlight the benefits of algorithmic personalization, they also identify risks such as opacity, privacy issues, misalignment, and relationship quality [8, 10]. Permission boundaries, explainable recommendations, regulatory compliance, brand consistency, asset approval, and metadata quality are components of governance for sales enablement CMS design. Poor governance creates a measurement problem because engagement with inaccurate, outdated, or noncompliant content does not represent a valid revenue signal. Additionally, AI-generated summaries, recommendations, or different versions of content can introduce attribution contamination unless each variation is versioned and linked to downstream opportunity outcomes. While there is

a robust conceptual basis for responsible AI, the available empirical evidence on governance indicators for content systems is limited.

These findings are combined into a measurement spine in Figure 4. The figure illustrates the narrowing of an initial collection of content interactions as signals are linked to seller action, the quality of the buyer's engagement, opportunity movement, and revenue. The issue is not the absence of engagement data itself; the problem is that as signals shift from platform analytics to commercial outcomes, interpretability is lost. The figure depicts an illustrative normalized funnel for raw content events, which can be filtered into fewer but more commercially meaningful events when correlated to the seller, buyer, CRM, and revenue data. Mechanisms reported across marketing automation, AI-CRM, social selling, customer journey, and digital experience studies were normalized for conceptual interpretation, and the values are illustrative index values rather than empirical effect sizes.

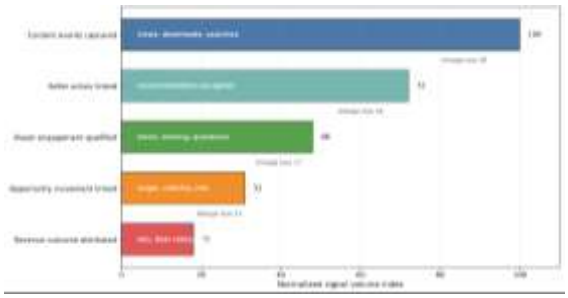

Figure 4: Engagement-To-Revenue Measurement Spine for AI-Augmented Sales Content

Based on the comparative evidence, four design implications are suggested. First, it is important to recognize that content metadata is a revenue-measurement asset. Product fit, buyer persona, stage of the sales journey, industry, objection type, compliance status, language, format, and intended sales motion are examples of metadata. Second, AI recommendations should be assessed using incremental gains rather than recommendation acceptance alone. A recommendation that is accepted can be a weak signal if it does not add value for engagement quality or opportunity movement, even after accounting for account intent. Third, engagement scores should be split into low-friction engagement (e.g., opening an asset) and high-intent engagement (e.g., forwarding content to other members of the buying committee, returning repeatedly to a pricing comparison). Fourth, rules-based and model-based approaches should be combined in the process of revenue attribution. Time-decay rules can be used for reporting that is operationally meaningful, whereas uplift models or causal forests can be used to evaluate whether there is a plausible causal effect of content exposure on opportunity outcomes.

Different units of analysis lead to a variety of apparent tensions in the literature. In content marketing research, the quality of relationships and the importance of depth of engagement are of primary concern [6], whereas in AI research, the focus is on scalable prediction and personalization [8, 9, 16]. Sales studies have focused on seller capabilities and adaptive behaviour [11], [12], [19]. Customer journey studies highlight multistage touchpoint accumulation in customer journey studies [17]. These viewpoints, when taken in isolation, are compatible but fragmented. The downside is that most of the current research focuses only on a single link in the chain, such as the AI content recommendation to the seller's actions, the buyer's interaction with it, or the opportunity's development or closure, resulting in closed revenue. This means that the reported outcomes align with the plausibility of engagement-to-revenue, but do not yet constitute a robust causal evidence base for the design of AI-supported sales enablement CMSs.

V. FUTURE DIRECTIONS

Future research should develop longitudinal datasets that allow for the connection between content asset metadata, AI recommendation logs, seller actions, buyer engagement events, CRM opportunity states, and closed revenue. These datasets would enable researchers to distinguish content effectiveness from pre-existing account intent, which has been a significant challenge in attribution research [4, 17]. Event-level designs need to capture seller identity, the context of the buying stage, account characteristics, content version, and the sequence of follow-ups, and timestamp each event or observation. This structure would support survival models (opportunity velocity), multilevel models (seller heterogeneity), and uplift models (incremental content influence).

The second priority is testing the AI recommendations within the sales enablement system. While there is existing AI marketing research with an emphasis on personalization and prediction, what has been missing is evidence that AI-selected assets outperform human-selected assets under the same selling conditions [8], [9], [16]. Randomized or quasi-randomized recommendation exposure could be used to examine the ability of AI to enhance the relevance of content, buyer reaction,

meeting conversion, opportunity progression, or win probability. These designs should not be click-optimized because optimization may shift attention away from revenue quality.

Explainability and governance are the third priority. AI-driven CMS platforms should reveal the rationale for recommending an asset, the metadata that influenced the ranking, and the compliance requirements that were satisfied. According to AI-CRM research, two key factors that play a pivotal role in value creation are 'relationship quality' and 'responsible data application' [10]. Explainability is also operational in sales enablement; a seller should understand why a recommendation is relevant to a buyer, and the manager should assess whether a recommendation is aligned with approved messaging and regulatory requirements.

A fourth priority is interdisciplinary model development. Marketing analytics can provide attribution and experimentation approaches [4]; sales research can provide constructs of seller behaviour [11], [19]; customer journey research can provide temporal touchpoint logic [17], information systems research can provide methods for platform governance and data integration [15]. The most promising research area is not a more general exploration of the role of AI in marketing. It is a specific research program on AI-augmented content systems as commercial measurement infrastructures with validated connections between content, seller, buyer, CRM, and revenue data

VI. CONCLUSION

Algorithmic content recommendation in sales enablement is a particularly challenging academic and practical problem because the usefulness of content relies on the interaction of three elements: algorithmic recommendations, seller behaviour, and buyer engagement, with attributable revenue outcomes representing the final stage of the proposed measurement framework. The review revealed that AI can support prediction and personalization capabilities, digital content can help engage and build trust, and sales technologies can drive adaptive selling behaviours. However, the existing evidence remains fragmented across marketing, sales, CRM, analytics, and customer journey research.

The central implication is that engagement should not be interpreted as simple content activity, but as buyer interaction that may indicate stage progression, opportunity movement, or revenue relevance. A valid measurement model should therefore integrate content management, AI enhancement, seller activation, buyer response, opportunity movement, and sales results. To assess the effectiveness of a content asset in any defensible metric, asset-level metadata, recommendation logs, seller-side telemetry, buyer engagement quality, and CRM-tied revenue data need to be integrated at an asset level.

The remaining gaps are causal identification, availability of longitudinal data, design of recommendations that are explainable to users, and governance of AI-generated and AI-ranked content. Future scholarship should move beyond broad claims about the benefits of AI-powered personalization for sales toward robust evidence on the sales impact of specific content recommendations. A sales enablement CMS should be understood not as a storage repository but as a measurable decision system within the revenue process.

- **Interest Conflicts:** The author declares that there is no conflict of interest concerning the publishing of this paper.

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., Wilson, M., & Ferreira, J. J. (2020). Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. Business Horizons, 63(3), 403–414.

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

[4] Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. Journal of Marketing, 80(6), 97–121.

[5] Kumar, V., & Reinartz, W. (2016). Creating enduring customer value. Journal of Marketing, 80(6), 36–68.

[6] Hollebeek, L. D., & Macky, K. (2019). Digital content marketing's role in fostering consumer engagement, trust, and value: Framework, fundamental propositions, and implications. Journal of Interactive Marketing, 45, 27–41.

[7] Kannan, P. K., & Li, H. A. (2017). Digital marketing: A framework, review and research agenda. International Journal of Research in Marketing, 34(1), 22–45.

[8] 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.

[9] 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.

[10] 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.

[11] Singh, J., Flaherty, K., Sohi, R. S., Deeter-Schmelz, D., Habel, J., Le Meunier-FitzHugh, K., Malshe, A., Mullins, R., & Onyemah, V. (2019). Sales profession and professionals in the age of digitization and artificial intelligence technologies: Concepts, priorities, and

questions. Journal of Personal Selling & Sales Management, 39(1), 2–22.
[12] Itani, O. S., Agnihotri, R., & Dingus, R. (2017). Social media use in B2B sales and its impact on competitive intelligence collection and adaptive selling: Examining the role of learning orientation as an enabler. Industrial Marketing Management, 66, 64–79.
[13] Agnihotri, R., Trainor, K. J., Itani, O. S., & Rodriguez, M. (2017). Examining the role of sales-based CRM technology and social media use on post-sale service behaviours in India. Journal of Business Research, 81, 144–154.
[14] Chatterjee, S., Rana, N. P., Tamilmani, K., & Sharma, A. (2021). The effect of AI-based CRM on organization performance and competitive advantage: An empirical analysis in the B2B context. Industrial Marketing Management, 97, 205–219.
[15] 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.
[16] Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. California Management Review, 61(4), 135–155.
[17] Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69–96.
[18] Vieira, V. A., de Almeida, M. I. S., Agnihotri, R., da Silva, N. S. D. A. C., & Arunachalam, S. (2019). In pursuit of an effective B2B digital marketing strategy in an emerging market. Journal of the Academy of Marketing Science, 47(6), 1085–1108.
[19] Terho, H., Giovannetti, M., & Cardinali, S. (2022). Measuring B2B social selling: Key activities, antecedents and performance outcomes. Industrial Marketing Management, 101, 208–222.
[20] Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2019). Creating effective online customer experiences. Journal of Marketing, 83(2), 98–119.