

From voice-of-field to product strategy: Operationalizing sales feedback loops in AI product go-to-market systems

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Abstract

In AI product go-to-market contexts, sales feedback should be treated as a formal component of product planning, rather than a peripheral input. This topic is important because it sits at the intersection of sales digitalization, artificial intelligence adoption in customer relationship management, product innovation governance, and data-driven market sensing. This review explores how voice-of-field data derived from sales conversations can be translated into replicable product-strategy mechanisms for AI products, because customer objections, adoption barriers, implementation challenges, and feature requests often emerge before they are captured in formal market research. The literature reviewed suggests that structured capture, semantic interpretation, prioritization and governance, and feedback return to the sales organization are essential for effective feedback loops. Fragmented evidence across sales, marketing, and innovation research, the lack of longitudinal validation, insufficient consideration of bias in salesperson-generated data, and the limited empirical research in AI-product contexts remain unresolved issues. This review presents a concise framework for feedback-loop maturity and identifies methodological priorities for future research on AI product go-to-market execution.

Keywords: AI product strategy; B2B sales; Customer feedback loops; Go-to-market systems; Sales analytics

1. Introduction

Customer needs, objections, perceived risks, integration challenges, and buying-committee concerns can shift more rapidly than formal product-planning cycles, creating a distinctive information challenge for AI-based product teams. In this context, salespeople occupy a boundary-spanning role between field evidence and strategic product decisions. Therefore, operationalizing sales feedback loops is not solely a sales-management problem, but a product-strategy challenge involving the translation of voice-of-field data into strategic decisions in a context of technical uncertainty, adoption uncertainty, and evolving value propositions for AI.

The literature regarding the use of AI in sales highlights the potential for technology to influence prospecting, qualification, forecasting and interaction support, but this literature also reveals that technology does not necessarily lead to a better product strategy [1]. Similarly, sales digitization scholarship suggests that AI is shifting the sales profession from information sharing toward judgment, advice, and cross-functional analysis of customer evidence [2]. This observation is central to AI product go-to-market systems: sales feedback is not just raw demand data. It is embedded in evidence generated during conversations, negotiations, trials, handling of objections, implementation planning, and post-sale expansion activities.

Collaborative-intelligence research demonstrates that the benefits of human and artificial intelligence can work together throughout the B2B sales funnel [3]. For product strategy, this means that the sales feedback loop needs to be

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a socio-technical system, not a repository. Customer relationship management records, call transcripts, win-loss notes, usage signals, support escalations, and account plans require machine-assisted structuring, but strategic interpretation still requires domain knowledge, product judgment, and governance. A broader body of research on AI in marketing points to the ability of predictive technologies to reconfigure sensing, personalization, engagement, and decision automation, while also creating risks of opacity, bias, and misalignment between operational metrics and marketing learning [4]. Strategic frameworks for AI in marketing further suggest that tasks should be allocated according to the type of intelligence required, including mechanical, analytical, intuitive, and empathetic intelligence [5].

There is not yet a substantial, self-contained peer-reviewed literature on the specific topic of translating voice-of-field data into product strategy. The scholarly basis is therefore distributed across AI in sales, CRM analytics, B2B selling, marketing automation, customer experience management, customer knowledge in innovation, digital services, and analytics-driven innovation. This dispersion leaves a gap in research. Current research helps uncover parts of the missing puzzle of how the feedback loop works, but little research directly links field-generated sales evidence to AI product roadmap governance, go-to-market messaging, segmentation, adoption-risk management and post-launch learning.

This review aims to provide an interpretation of the recent and relevant peer-reviewed journal publications as a basis to further understand how sales feedback loops can be embedded within AI product go-to-market systems. The review is based on three questions. First, what types of field evidence are collected in sales and related industrial systems? Second, how is that evidence converted into product strategy at organizational and computational levels. Third, what are the limits to the trustworthiness, comparability, and strategic usefulness of feedback collected from sales for AI products? The article provides topic-specific conceptual framing, explains methodological options, and outlines some research priorities for developing accountable, analytically valuable and strategically relevant sales feedback loops.

2. Literature Review

The reviewed literature provides a foundation for understanding sales feedback loops in a digital go-to-market system. B2B content marketing automation research shows how customer actions, segmentation, lead scoring, and sales handoff can be linked, but such systems tend to focus on campaign efficiency rather than product-learning depth [6]. This distinction is important when it comes to AI products because market feedback should not only support funnel conversion but also inform product strategy. It should also determine whether product claims, technical integrations, pricing assumptions, model performance factors, and deployment needs align with customer expectations.

Customer experience management (CEM) literature extends the unit of analysis from transactional selling to end-to-end journeys [7]. This work is highly relevant as the typical stages of AI product adoption include discovery, pilot evaluation, data-readiness assessment, security review, integration of the product into operations, and internal change management. The value of sales feedback loops is strategic when field signals are connected with journey stages and decision roles instead of being collected as individual salesperson notes. Marketing analytics research, on the other hand, demonstrates that data-rich environments can enable segmentation, attribution, experimentation, and predictive decision-making [8]. As analytics studies tend to take available data for granted, however, sales feedback is influenced by incentive programs, product selection, conversation quality, CRM practices, and subjectivity.

Research on customer knowledge in innovation has shown that it is possible to achieve better new product outcomes when customer knowledge is timely, interpretable and linked to decision authority [9]. This is very similar to the voice-of-field problem. While sales teams might be able to see the unmet needs earlier than formal research functions, turning observations into product strategy demands filtering mechanisms that separate individual account needs from market-level evidence. Big-data marketing research also shows that high-volume data can also produce marketing inferences that are spurious, weakly supported, or strategically misleading despite an abundance of data, which can introduce more noise than information [10]. In practice, AI product feedback loops need evidence weighing, rather than simple aggregation.

There are also more specific studies on sales strategy and social selling, which also contribute intelligence from the field. Research in value-based selling has shown that selling performance depends on salesperson customer orientation and organizational sales strategy [11]. Social media sales research can be used to enrich relationship management and to gain a competitive advantage based on customer engagement data, but the adoption of social media, managerial support, and integration into the sales process condition the value of these tools [12, 13]. Social-selling literature also identifies digital sales activities as sources of market-sensing information, although most studies emphasize sales outcomes rather than product-strategy outcomes [14, 15]. Solution selling research is particularly relevant for the go-to-market systems for AI products, as it indicates that product-led sales teams need organizational support, incentives

and knowledge management to sell solutions [16]. For AI products, feedback-loop design must consider the complexity of solution configuration, implementation complexity, and customer capability gaps.

Table 1 provides an overview of the key literature that has informed the understanding of voice-of-field operationalization. Table 1 shows that few studies examine the end-to-end sales-to-product feedback loop. This gap supports the need for a cross-domain conceptual model rather than a simple extension of CRM practice.

Table 1 Summary of key findings

Ref	Focus	Key Findings
[6]	B2B marketing automation and sales handoff	Automation improves lead nurturing and sales coordination, but product-learning value depends on disciplined interpretation of behavioural traces.
[7]	Customer experience management	Journey-based governance links customer signals to organizational action, supporting feedback beyond isolated transactions.
[8]	Marketing analytics in data-rich environments	Analytics expands predictive and diagnostic capacity, but data quality and managerial interpretation remain limiting conditions.
[9]	Customer knowledge in innovation	Customer involvement improves innovation outcomes when knowledge is actionable and connected to product decisions.
[10]	Big data consumer analytics	High-volume data can transform market sensing, although noise, bias, and weak causal inference limit strategic reliability.
[11]	Value-based selling strategy	Customer orientation supports performance when sales strategy and organizational execution remain aligned.
[12]	Social media adoption in sales	Digital engagement creates additional customer insight, but adoption depends on individual and organizational antecedents.
[13]	Social media and B2B satisfaction	Social interaction data can support responsiveness and satisfaction when integrated into relationship processes.
[14]	Competitive intelligence and adaptive selling	Social media supports intelligence collection and adaptive selling, indicating field relevance beyond lead generation.
[15]	B2B social selling foundations	Digital selling expands relational and informational channels, but conceptual boundaries remain underdeveloped.
[16]	Product-focused salesforce transition to solutions	Solution selling requires organizational alignment, not only salesperson willingness or product training.

One major theme in the literature is the tension between sales urgency and product-strategy discipline. Sales feedback is time-sensitive, but suffers from recency bias, revenue pressures, strategic account distortion and inconsistent coding. Product strategy must encompass broad-based evidence, prioritization, and technical feasibility. While there are existing studies documenting digital tools and cross-functional mechanisms, limited research assesses the impact these have on product roadmaps, model governance, feature prioritization, market segmentation, or AI adoption strategy in the field. This divide is especially significant as AI products need to be trusted, explained, integrated with data, compliant and measurable in the workflow. Sales feedback loops, therefore, must be more than just CRM completion. Instead, these systems require an evidence architecture that preserves context while enabling product-level inference.

3. Methodology

The literature reviewed shows four major methodologies. The first methodology is platform-based behavioral analytics, as used in marketing automation, CRM, and digital-engagement research [6], [8]. This method can integrate lead behavior, engagement sequences, content interaction, pipeline movement and sales activity information. The strength associated with it is scalability. Its drawback is that there are many signals that reflect commercial activity rather than product learning. A failed opportunity can be caused by anything from budget timing to weak messaging to missing integrations, to poor model performance, to internal politics, or to a lack of evidence of value. If not qualified by a qualitative component, platform analytics can mistakenly attribute product strategy issues to a sales execution problem.

The second approach is survey-based and perceptual modeling, which has been adopted in digital sales adoption studies, customer orientation studies, social selling studies, AI-based CRM studies, and AI capability studies [12], [13], [19], [21]. This approach is used to predict how organizational capability and technology acceptance relate to competitive advantage and performance. It has strong capacity for cross-firm theory testing. One of its drawbacks is that it is not suitable for voice-of-field operationalization because it is not sufficiently close to the granular feedback objects that product teams require. While survey questions can include questions about the effectiveness of CRM or AI capability, there should be evidence that a product's strategy is making measurable progress (e.g., recurring comments on explainability, data-security concerns in regulated accounts, or inability to integrate with legacy workflow systems).

A third approach is customer-knowledge and co-creation research, where external knowledge becomes a source of innovation [9], [17]. This stream is more directly related to product strategy as it explains the linkage between customer input and product development and service innovation. One of its drawbacks is that sales-activity evidence is not often separated as a distinct knowledge stream with its own incentives and biases. When it comes to AI-product go-to-market systems, the difference between sales feedback and formal co-creation is that sales feedback is generated in persuasive interactions. This results in richness without neutrality.

The fourth approach is artificial intelligence and analytics capability research, which views AI as an organizational capability that requires data assets, technical infrastructures, human skill and decision routines [18], [20], [21]. This body of work is valuable because feedback-loop operationalization requires more than just defining topics from sales calls. The process must be governed so that repeated field signals can be transformed into product hypotheses, to connect product hypotheses to roadmap decisions, and to take product decisions back to the field as messages, enablement, and qualification criteria.

Table 2 Method comparison

Ref	Method	Strengths	Limitations
[6]	Qualitative case analysis of marketing automation practice	Reveals practical linkage between content behaviour, lead nurturing, and sales handoff.	Limited insight into roadmap change or AI-specific product learning.
[8]	Conceptual and analytical review of marketing analytics	Clarifies data-rich decision environments and analytics task types.	Limited treatment of salesperson-generated qualitative evidence.
[9]	Empirical modelling of customer knowledge and innovation	Connects customer involvement to new product performance.	Does not isolate field-sales evidence as a separate knowledge channel.
[12]	Empirical analysis of sales social media adoption	Identifies adoption antecedents and engagement effects.	Focuses on selling behaviour rather than product-strategy conversion.
[14]	Empirical study of competitive intelligence and adaptive selling	Links digital information collection to adaptive sales behaviour.	Product implications remain indirect.
[17]	Process analysis of agile co-creation in digital servitization	Explains iterative customer-linked innovation routines.	Context centers on servitization rather than AI go-to-market systems.
[18]	AI framework for B2B marketing decisions	Connects AI, knowledge creation, and marketing decision quality.	Framework requires stronger validation at feedback-object level.
[19]	Empirical analysis of AI-based CRM in B2B context	Links AI-enabled CRM to organizational performance and advantage.	Roadmap governance and feedback bias receive limited attention.
[20]	Empirical study of big data investments and service innovation	Shows how analytics affordances can support innovation outcomes.	Sales feedback is one possible input, not the central empirical unit.

[21]	Capability measurement and empirical performance modelling	Defines AI capability as a multidimensional organizational resource.	Abstract capability measures obscure product-specific loop mechanics.
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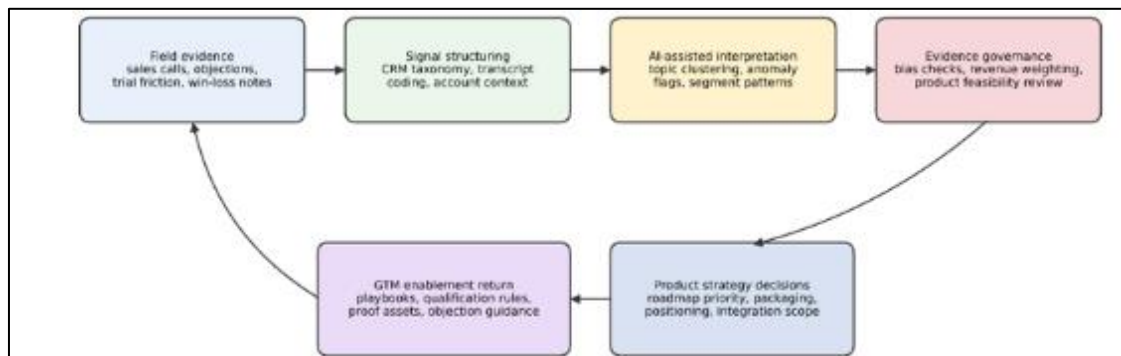


Figure 1 Voice-of-field operationalization framework for AI product go-to-market systems

Figure 1 outlines the process of transforming voice-of-field data into information that can inform AI-product strategy. It is not a catch-all pipeline since it splits signal origination, semantic structuring, evidence governance, product decisioning and mutual go-to-market enablement. There are many examples of failed feedback systems in which field data are gathered but no organizational function has the authority to (1) separate signal from noise, (2) convert observations into reusable evidence, or (3) communicate the rationale for product decisions back to the sales organization. The figure represents a closed learning system where the sales interactions are recorded as structured evidence, evaluated based on product and commercial governance, and returned to the market through positioning, enablement and qualification, and roadmap decisions. The framework provides a tool to recognize control points in the learning journey that may create strategic-learning bias, weak taxonomies, lack of ownership, or poor feedback to sales. The conceptual model was developed from literature on sales digitalization, marketing automation, customer knowledge management, AI-enabled CRM, and analytics-driven innovation [6, 21].

4. Discussion

The studies presented in this research indicate that the strategic value of sales feedback loops is determined by how the feedback is translated from a series of intermittent observations into comparable evidence. Although behavioral traces are helpful for B2B handoff, marketers need to be cognizant that marketing research suggests that marketing metrics do not always reveal product–market misfit [6]. Moreover, CEM research indicates that a journey-based interpretation would be better suited to the AI-product adoption, as there are multiple evaluators, and sequential risk checks that need to be performed during the journey [7]. While marketing analytics research has the most rigorous methodological foundation for organizing such evidence, other literature suggests that the value of marketing analytics depends on data governance, data measurement clarity and managerial interpretation [8]. All the outcomes of these findings support the idea of a feedback-loop model, with the need to annotate sales evidence by segment, buyer role, adoption stage, technical barrier, and strategic consequence.

The second trend concerns customer knowledge versus sales-generated knowledge. When customer knowledge is timely, interpretable, and connected to decision-making authority, customer participation in innovation can improve product or service outcomes [9]. Sales-generated knowledge is valuable because sales teams encounter implementation barriers, competitive comparisons, pricing resistance, and proof-of-value expectations before these issues appear in usage analytics. However, when dealing with a large volume of data, data volume may obscure validity concerns [10]. A third implication concerns the weighting of sales feedback. Repeated objections from high-value enterprise accounts may indicate weakness in a product area, whereas numerous low-value requests may point to qualification or messaging problems. So, the number of feedback items should not be the sole unit of analysis. Evidence should instead be weighted according to evidence quality, strategic alignment, technical feasibility, segment fit, revenue exposure, and recurrence.

The feedback loops are also revealed to be part and parcel of the sales force design system in sales research. Value-based selling is based on customer orientation that needs to be converted to a coordinated approach [11]. Social selling has been shown to benefit the intelligence gathering, customer engagement and adaptive selling via digital channels

[12]–[15]. There is, however, a danger from these studies, too: that digital activity does not always generate product insight, particularly when this insight results in a lot of poorly developed commentary. Sales teams may overweight vocal accounts, late-stage deals, or highly compensated or strategically important opportunities. Without a consistent structure, product teams may consider sales input anecdotal. This mistrust can also obstruct the implementation of a strategy based on market signals for AI products.

This is emphasized by research into solution selling. For product-centric sales teams, a problem arises when they are attempting to sell complex products without organizational support, training, and appropriate incentives [16]. AI products go to market systems add to this challenge as the product can become embedded in a customer's workflow, data environment, governance policies, and change-management processes. If only “feature request” categories are included in the feedback loop, it may exclude more significant strategic evidence that is related to customer readiness, explainability expectations, deployment services, legal concerns, integration dependencies, and buyer education. Accordingly, field-evidence taxonomies should capture both product-function gaps and adoption conditions.

Table 3 Results comparison

Ref	System / Context	Metric / Basis of Comparison	Outcome
[6]	B2B marketing automation	Lead nurturing, content engagement, sales handoff	Improved commercial coordination, with limited direct roadmap linkage.
[7]	Customer experience management	Journey integration and organizational responsiveness	Stronger cross-functional action when customer signals are mapped to journey stages.
[8]	Data-rich marketing analytics	Segmentation, prediction, attribution, decision support	Better analytic capacity, constrained by data quality and interpretive governance.
[9]	Customer knowledge in innovation	Customer involvement and new product performance	Positive innovation value when knowledge is actionable and decision-linked.
[10]	Big data marketing environments	Data volume, velocity, variety, and marketing transformation	Expanded sensing potential, paired with noise and validity risks.
[14]	B2B digital sales intelligence	Competitive intelligence and adaptive selling	Improved adaptive selling through richer external signal collection.
[16]	Solution-selling transition	Individual and organizational support conditions	Solution performance requires structural alignment, not only salesperson effort.
[17]	Digital servitization co-creation	Iterative micro-service innovation process	Rapid customer-linked learning supports modular product and service adjustment.
[19]	AI-based CRM in B2B firms	Organizational performance and competitive advantage	AI-enabled CRM contributes to performance when embedded in firm processes.
[20]	Big data investment and service innovation	Marketing affordances and innovation outcomes	Analytics value materializes through organizational affordances and service innovation.
[21]	AI capability in firms	Multidimensional capability and performance	AI value depends on technical infrastructure, human skill, and organizational routines.

Digital servitization and co-creation research introduces an additional emphasis on iterative product learning. The results of agile co-creation work demonstrate that close interaction, modular learning, and short cycles are beneficial for customer-linked innovation [17]. This helps prioritize roadmap items in a go-to-market strategy that relies on learning from pilots, proof-of-concept implementation friction, model performance, and lessons learned. But the literature does not focus as much on the reconciliation of sales-generated insights with engineering feasibility, data-science uncertainty, and compliance requirements. AI-product teams should determine whether a field signal reflects a feature gap, a model limitation, a service-design gap, a documentation problem, a target-segment mismatch, or product immaturity.

Artificial intelligence and CRM research shows that there are associations between organizational performance and analytics capability. According to AI applications in B2B marketing, AI can improve the creation of knowledge and decision-making [18]. Empirical studies on AI-based CRM are associated with competitive advantage in B2B [19]. Studies of big-data investment show how analytics affordances can support service innovation when organizational conditions allow data to be translated into action [20]. The analysis of AI capability literature also indicates that technical, human, and organizational resources, are critical for AI value [21]. A limitation of these studies is that the general sentiment is that AI tools are not a complete solution. The strategically valuable element is the structured decision routine, as it establishes ownership, a quality assessment of evidence and feedback for learning about the product and the sales execution.

The distribution of evidence in thematic areas is shown in Figure 2, in the reviewed corpus. The pattern has a strong foundation in analytics, CRM, and digital selling, and a thinner foundation in direct product strategy governance. This imbalance is why this topic needs further empirical investigation on the translation from field evidence to roadmap decisions. Figure 2 groups the reviewed articles according to their dominant contribution to feedback-loop operationalization. The chart demonstrates that literature is more robust on analytics capability and digital selling, compared to explicit product-roadmap governance, and suggests a disconnect between data capture and product action. Thematic coding of the 21 peer-reviewed journal articles, done manually. A single dominant contribution category is assigned to each article.

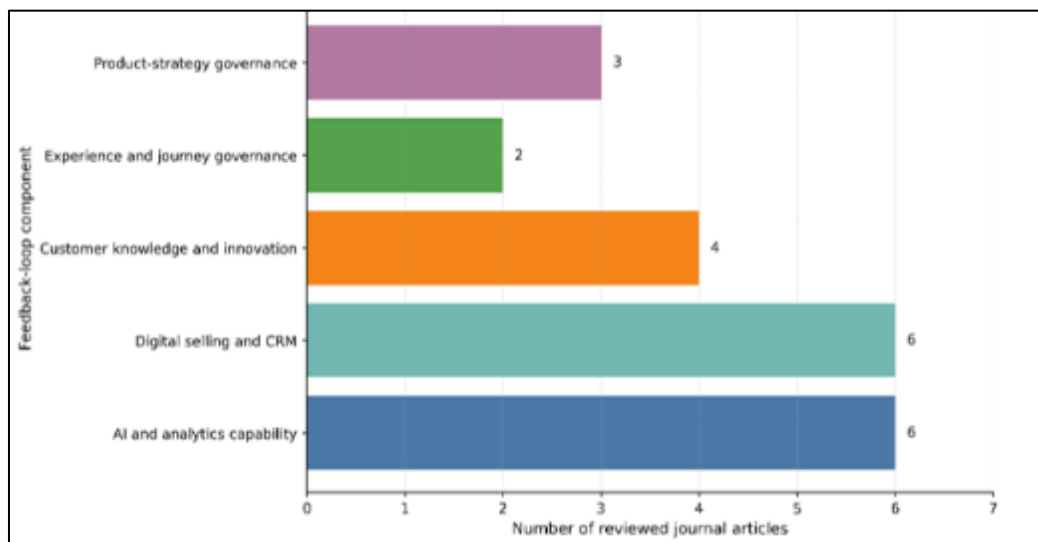


Figure 2 Evidence distribution across feedback-loop components

In Figure 3, methodological families are compared across five properties that are relevant to AI product go-to-market feedback loops. The matrix is not statistical, but it helps to explain why there is no single method that is enough. While platform analytics provides scale and latency benefits, co-creation and qualitative field review maintain context and strategic meaning. This figure is a comparison of the method families, based on their suitability to sales-to-product feedback-loop operation. Higher scores indicate greater suitability for the stated feedback-loop requirement. The matrix illustrates the necessity for blended methods as scalable methods may not be as interpretive, and qualitative methods may not be as standardized. The methodological approaches from the reviewed literature in Table 2 were translated into the codes as shown below: Scores are not pooled effect sizes.

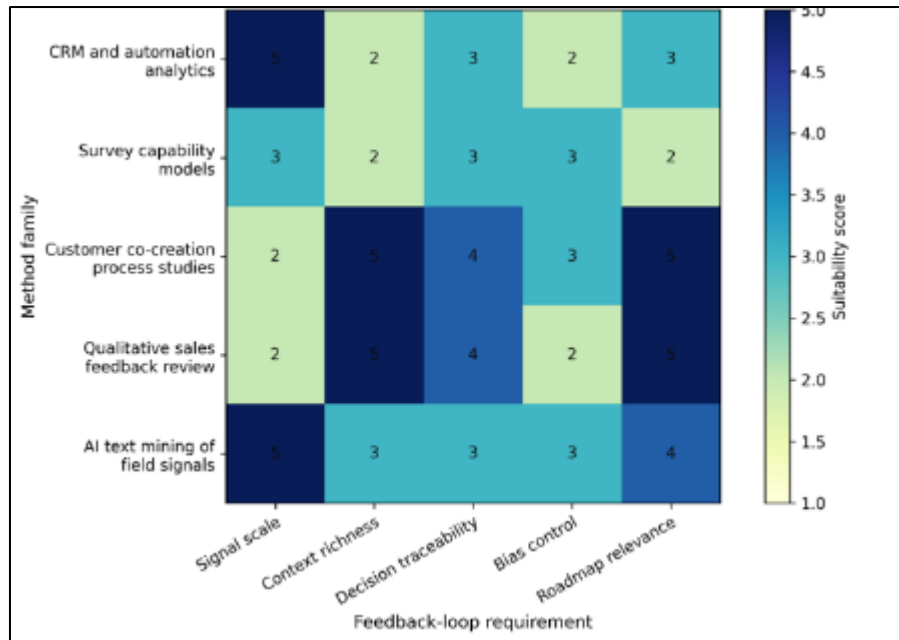


Figure 3 Comparative matrix of methodological suitability

Figure 4 presents an AI product go-to-market feedback loop maturity profile derived from the review. The figure shows an ad hoc CRM logging approach, a CRM-analytics approach, and a closed-loop AI approach to go to market. The comparison is significant because there are many organisations that invest in capture technology but do not invest in governance, prioritisation and reciprocal enablement. This radar chart visualizes three states of maturity and compares them across the dimensions required to transform voice-of-field data into product decisions. The closed-loop AI GTM profile works best when evidence capture, semantic consistency, governance, roadmap linkage, enablement return, and learning velocity are all part of a system. Conceptual scores were derived from a cross-study interpretation of CRM, analytics, sales digitalization, customer knowledge, and AI capability literature [6]–[21].

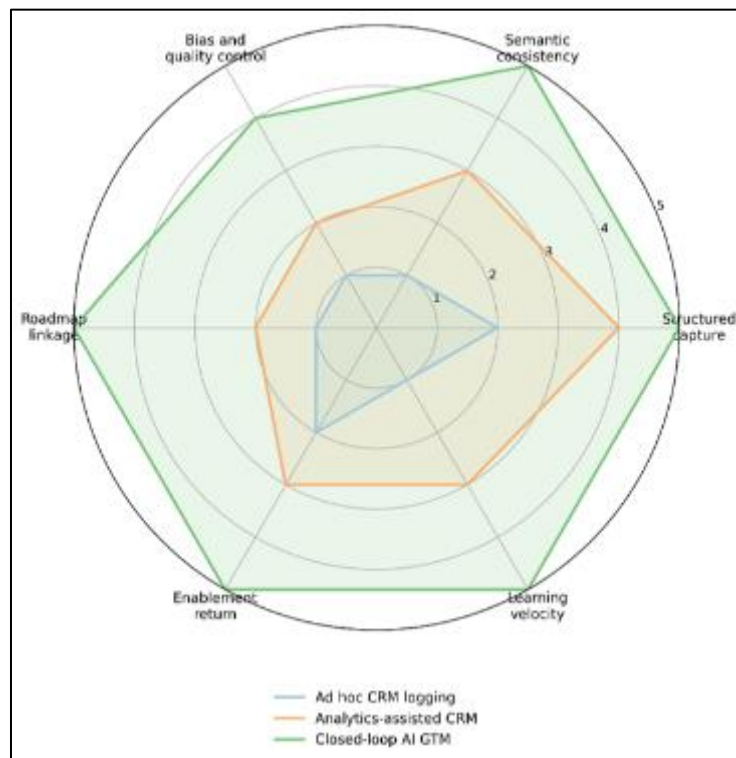


Figure 4 Maturity profile for operationalized sales feedback loops

The reviewed literature suggests four interpretive propositions. First, the value of a feedback loop is related to the coupling of commercial sensing and product governance. Second, AI-powered tooling enhances scale and pattern recognition without eliminating the need for human review of strategic significance. Third, field evidence requires critical evaluation and remains strategically important: dismissing it as anecdotal wastes market-proximate insight, whereas accepting it uncritically can lead to a skewed roadmap. Fourth, AI product go-to-market systems must be two-way streets: Product decisions should flow back to sales teams as new qualification criteria, proof assets, how to handle objections, how to package the product and which segments to prioritize.

5. Future Directions

Sales feedback loops should be considered as a product strategy system and not just as CRM adoption, sales enablement or analytics implementation. One key element is longitudinal research that follows field signals from capture and roadmap consideration through product decisions, market relaunch, and actual commercial outcomes. Existing research often involves measuring adoption, performance, or capability at a single time point, which limits understanding of feedback-loop latency and evidence decay, as well as delayed product impact [19, 21].

The second priority is related to feedback quality. Research should come up with standardized coding schemas for voice-of-field evidence for AI products, such as concerns about model performance, explainability objections, integration barrier, data-readiness gaps, security-review objections, price-value mismatch, workflow disruption, and buyer education deficit. The resulting taxonomies would make it possible to support comparisons across companies and minimize the tendency to lump different go-to-market issues together as feature requests. This direction should incorporate CRM data, transcript analysis, win-loss, pilot notes, and product-management decisions, and maintain account and segment context.

A third priority is to operationalize the measurement of bias rather than merely noting its presence. Future studies should examine how compensation structures, account size, sales stage, customer power, and salesperson expertise affect whether a field signal is captured, coded, escalated, and considered during product deliberation. This would shift the research agenda from a general recognition of sales-feedback bias to testable indicators of signal distortion across the feedback loop. Because big-data and analytics research have already shown that data abundance can create false confidence [8, 10], AI product feedback research should evaluate signals using more than frequency alone, incorporating recurrence, segment fit, revenue exposure, feasibility, and strategic alignment.

A fourth priority concerns governance design. Product councils, revenue-operations review boards, customer advisory boards and AI-assisted evidence triage mechanisms should be compared. The most helpful studies would measure the effectiveness of governance structures in improving the accuracy of the roadmap, quality of prioritization, efficiency of the sales cycle, success of the implementation, or retention. The concept of servitization and co-creation research in digital also indicates that incremental customer-driven learning can enhance innovation processes [17] but, in an AI go-to-market context there is a need to pay attention to the management of model risk, trust, regulatory exposure, and implementation capability.

Finally, interdisciplinary work should integrate sales management, product innovation, information systems, data science, and organizational learning. AI product feedback loops are not limited to commercial systems. They are decision systems that shape how market evidence disciplines product ambition. Studies that assess end-to-end loop integrity from data capture and interpretation through governance accountability, roadmap action, and enablement feedback will make the strongest future contributions.

6. Conclusion

When voice-of-field data is processed into structured, governed and actionable product evidence, sales feedback loops become a strategic capability of artificial intelligence product go-to-market systems. The literature reviewed reveals that the knowledge is fragmented across the following areas; sales digitalization, marketing automation, customer experience, analytics capability, customer knowledge and innovation research. There is limited research that explores the entire journey from interaction in the field to AI-product roadmap decisions to market execution.

The central argument is that sales feedback must not be ignored as anecdotal or treated as an unquestioned representation of market reality. Effective feedback loops require disciplined capture, semantic consistency, contextual weighting, cross-functional evaluation, and reciprocal enablement.

There are ongoing gaps, such as limited longitudinal evidence, limited evidence on measuring feedback bias, limited AI-product specificity, and underdeveloped methods to link field evidence to product-strategy outcomes. Future scholarship should treat sales feedback loops as sociotechnical systems that integrate data infrastructure, human expertise, product decision rights and market-learning accountability. This kind of research can strengthen both theory and practice of AI product strategy.

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