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Artificial intelligence and Sales management process: A comprehensive bibliometric review

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ABSTRACT
Purpose: This paper provides a comprehensive bibliometric analysis and systematic literature review of the burgeoning field of artificial intelligence (AI) adoption in business-to-business (B2B) sales. It aims to map the intellectual structure of the research domain, identify key trends, uncover thematic clusters, and outline a robust agenda for future research.
Design/methodology/approach: A systematic literature review was conducted following the PRISMA guidelines. A total of 321 academic articles were extracted from the Scopus database for the period of 2019–2024. The study employs bibliometric analysis to examine publication trends, influential authors, leading journals, and geographical distribution of research. Co-word and co-citation analyses were used to map the conceptual and intellectual structure of the field, complemented by a thematic analysis to synthesize key research streams.
Findings: The analysis reveals a rapid growth in publications, with a compound annual growth rate of 20.86%, indicating a surge of academic interest in AI for sales. Key research themes identified include: (1) the role of AI in enhancing customer relationship management (CRM), (2) the application of AI in sales forecasting, and (3) the use of AI to augment customer service. The conceptual structure analysis highlights the foundational role of technology acceptance models (TAM/UTAUT), while also pointing to the increasing importance of psychological factors like psychological ownership, perceived enjoyment, and cognitive effort.
Practical implications: For B2B sales organizations, this review underscores the need to move beyond a purely technical implementation of AI. To foster adoption, managers must focus on designing AI tools that are not only useful but also enjoyable and easy to use. Cultivating a sense of psychological ownership among salespeople by providing control and customization options is identified as a key strategy. The findings can guide the development of more effective, user-centric AI sales tools and implementation strategies.
Originality/value: This study is one of the first to provide a comprehensive bibliometric overview of the AI in B2B sales literature. It offers a structured map of the research landscape, synthesizes disparate research streams, and proposes an integrated conceptual model that provides a more nuanced understanding of the complex factors driving AI adoption among sales professionals. The paper concludes by identifying critical research gaps and proposing a detailed future research agenda.
Keywords: Artificial Intelligence, B2B Sales, Systematic Literature Review, Bibliometric Analysis, Technology Adoption, Psychological Ownership, AI Affordances, Cognitive Effort, Perceived Enjoyment, Thinking Styles

INTRODUCTION:

The Fourth Industrial Revolution has catalyzed a paradigm shift across industries, with artificial intelligence (AI) emerging as a cornerstone of technological transformation. The sales profession, traditionally reliant on human intuition and interpersonal acumen, is at the precipice of a significant disruption driven by AI (Syam & Sharma, 2018). AI-powered tools and platforms are revolutionizing the sales process, from automating routine administrative tasks and providing data-driven insights to enabling hyper-personalized customer interactions. The potential benefits are substantial, promising increased efficiency, enhanced decision-making, stronger customer relationships, and ultimately, superior sales performance (Jarotschkin, Kraemer, & Geiger, 2025).

However, the path to realizing these benefits is fraught with challenges. The history of information technology is replete with examples of sophisticated systems failing not due to technical shortcomings, but due to a lack of user acceptance. A purely technocentric perspective, focusing solely on the features and capabilities of AI, is therefore insufficient. A holistic, user-centric approach is imperative—one that considers the complex psychological, cognitive, and social factors that shape how individual salespeople perceive, interact with, and ultimately adopt these powerful new technologies (Chen & Zhou, 2022). This is particularly critical in the business-to-business (B2B) sales context, which is characterized by long sales cycles, complex decision-making units, and the paramount importance of trust and relationships.

Despite the growing practical importance of AI in sales, academic research in this specific domain is still nascent and fragmented. While there is a vast body of literature on technology adoption in general, and a growing number of studies on AI in broader business contexts, a comprehensive overview of the AI in B2B sales literature is currently lacking. This fragmentation makes it difficult for researchers to build upon existing work and for practitioners to derive evidence-based strategies. To address this gap, this paper undertakes a comprehensive bibliometric analysis and systematic literature review of the scholarly research on AI adoption in the sales context.

This review has four primary objectives. First, it aims to quantify and visualize the growth and structure of the research field, identifying the most productive authors, countries, and journals. Second, it seeks to uncover the conceptual structure of the field by analyzing keyword co-occurrences and thematic clusters. Third, it maps the intellectual foundations of the field through a co-citation analysis of the most influential publications. Finally, based on the synthesis of the literature, it proposes an integrated conceptual framework and a detailed agenda for future research. By systematically mapping the landscape, this paper aims to provide a solid foundation for future scholarly inquiry and to offer actionable insights for practitioners navigating the complexities of AI implementation in their sales organizations.

The paper is structured as follows. Section 2 details the methodology. Section 3 presents the bibliometric analysis results, covering publication trends, source analysis, keyword co-occurrence, co-citation networks, and country productivity. Section 4 provides a qualitative thematic analysis of the three dominant research streams. Section 5 synthesizes the theoretical underpinnings and proposes a conceptual framework with associated hypotheses. Section 6 discusses the findings and their implications. Sections 7, 8, and 9 address future research directions, limitations, and conclusions, respectively.

2. Methodology

To ensure a rigorous and transparent review process, this study adopts a systematic literature review methodology, guided by the principles outlined by Snyder (2019) and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement. The review process involved three main stages: (1) data collection, (2) data analysis, and (3) data synthesis and reporting.

2.1. Data Collection and Selection Criteria

The Scopus database was selected as the primary source for data collection due to its comprehensive coverage of peer-reviewed literature across various disciplines, including business, management, and social sciences. The search was conducted in mid-2024 using a carefully constructed query designed to capture relevant literature at the intersection of AI and sales.

The search query applied was: TITLE-ABS-KEY(("AI" OR "Artificial intelligence") AND ("sales" OR "sales management")).

To maintain focus on recent and relevant research, the following inclusion and exclusion criteria were applied in a two-phase process:

Phase 1 Criteria:

Time Period: Articles published between 2019 and 2024, a period characterized by a significant acceleration in both AI technology and its application in business.

Subject Area: Restricted to the "Business, Management and Accounting" and "Social Sciences" subject areas.

Phase 2 Criteria:

Document Type: Only peer-reviewed "Articles" were included; books, conference papers, and other document types were excluded.

Language: Limited to articles published in English.

This multi-stage filtering process is detailed in the PRISMA flow diagram (Figure 7). The initial search yielded 4,076 documents. After applying Phase 1 filters, 591 documents remained. The subsequent Phase 2 filters resulted in a final corpus of **321 articles**, which formed the basis for all subsequent analyses.

Figure 7. PRISMA Flow Diagram – Data Selection Process

2.2. Bibliometric Analysis Approach

The bibliometric analysis was performed using the **Bibliometrix R package**, a widely validated tool for quantitative research in bibliometrics and scientometrics (Paul & Criado, 2020). The analysis focused on several key dimensions:

Performance Analysis examined the productivity and impact of the research field, including the annual growth rate of publications, the most productive authors, the most influential journals, and the geographical distribution of research by country.

Science Mapping involved creating network visualizations to understand the conceptual and intellectual structure of the field. Specifically, **co-word analysis** was used to identify key research themes and their interconnections based on keyword co-occurrences, while **co-citation analysis** was used to map the foundational literature upon which the field is built (Small, 1973; Kessler, 1963).

Following the bibliometric analysis, a qualitative **thematic analysis** was conducted to synthesize the findings and provide a richer understanding of the key research streams. This involved a careful reading of the abstracts and full texts of the most relevant articles to identify and categorize the dominant themes and theoretical perspectives.

3. Bibliometric Analysis and Results

This section presents the results of the bibliometric analysis, providing a quantitative overview of the research landscape on AI in B2B sales. The analysis covers publication trends, the most influential sources and authors, and the conceptual and social structures of the field.

3.1. Main Information and Descriptive Statistics

The final dataset consists of 321 articles from 170 unique sources published between 2019 and 2024. The field is characterized by a high degree of collaboration, with an average of 3.4 co-authors per document and a significant international co-authorship rate of 37.69%. The average document age is just under two years (1.97), and each document has received an average of 24.56 citations, indicating the timely and impactful nature of this research area. A summary of the main descriptive statistics is provided in Table 1.

Description	Result
MAIN INFORMATION ABOUT DATA	
Timespan	2019–2024
Sources (Journals, Books, etc.)	170
Documents	321
Annual Growth Rate	20.86%
Document Average Age (years)	1.97
Average Citations per Document	24.56
Total References	20,686
DOCUMENT CONTENTS	
Keywords Plus (ID)	1,844
Author's Keywords (DE)	1,219
AUTHORS	
Total Authors	1,017
Authors of Single-authored Docs	32
COLLABORATION	
Single-authored Documents	32
Co-Authors per Document	3.4
International Co-authorships	37.69%
DOCUMENT TYPES	

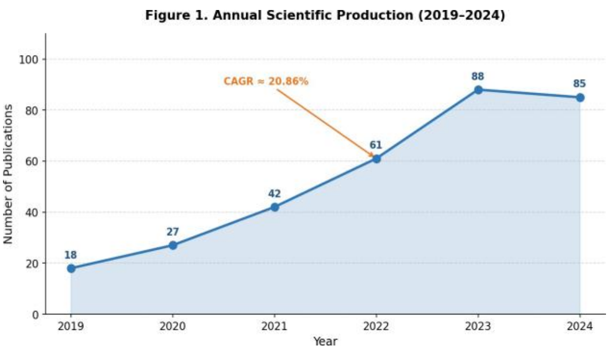
Description	Result
Articles	321

Table 1. Descriptive Statistics of the Bibliometric Analysis.

The data in Table 1 reveals a research field that is both prolific and highly collaborative. The annual growth rate of 20.86% is remarkable, indicating that academic interest in AI for sales is not just growing but accelerating. The high number of unique authors (1,017) across only 321 documents, combined with an average of 3.4 co-authors per document, confirms that this is a field characterized by collaborative, multi-author research. The significant international co-authorship rate of 37.69% further underscores the global nature of this research agenda.

3.2. Annual Scientific Production

The annual publication trend is a key indicator of a research field's evolution and maturity. As shown in Figure 1, the number of publications on AI in sales has experienced substantial and consistent growth over the past six years. From just 18 publications in 2019, the output grew to a peak of 88 publications in 2023, representing a nearly five-fold increase over the period. This steep upward trajectory underscores the rapidly increasing academic and practical interest in the intersection of AI and sales. The trajectory strongly suggests that this field will continue to grow in the coming years, driven by the increasing deployment of AI tools in commercial settings and the growing recognition among researchers of the importance of understanding the human factors that shape adoption.



3.3. Most Relevant Sources

The 321 articles in the dataset were published across 170 different sources, indicating a wide distribution of research across the academic landscape. However, applying Bradford's Law—which posits that a small number of core journals publish a disproportionately large share of articles in a given field—a core set of journals emerges as the primary outlets for this research stream. As shown in Table 2, journals focusing on sales, marketing, business research, and information systems dominate the landscape. The *Journal of Personal Selling & Sales Management* and *Industrial Marketing Management* are the leading outlets, reflecting the field's strong roots in sales and marketing scholarship.

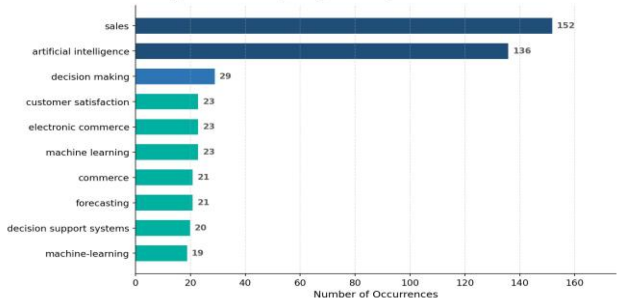
Rank	Source Journal	Publications
1	Journal of Personal Selling & Sales Management	18
2	Industrial Marketing Management	15
3	Journal of Business Research	12
4	Technological Forecasting and Social Change	11
5	Decision Support Systems	9
6	Computers in Human Behavior	8
7	Journal of Retailing and Consumer Services	7
8	International Journal of Information Management	7
9	IEEE Transactions on Engineering Management	6
10	Journal of Marketing	5

Table 2. Most Relevant and Influential Sources (by Publication Count).

3.4. Most Frequent Words and Keyword Co-occurrence Analysis

To understand the primary topics and themes within the literature, an analysis of the most frequently occurring author-provided keywords was conducted. As detailed in Table 3 and visualized in Figure 2, **"sales"** (152 occurrences) and **"artificial intelligence"** (136 occurrences) are the most dominant terms, as expected. Following these are terms related to AI techniques and

Figure 2. Most Frequently Occurring Words in AI & Sales Literature



applications, such as **"machine learning"** (23), **"forecasting"** (21), and **"decision support systems"** (20), as well as business outcomes like **"customer satisfaction"** (23) and **"electronic commerce"** (23). This distribution highlights a strong focus on leveraging AI to improve decision-making and enhance the customer experience in a commercial context.

Rank	Word / Keyword	Occurrences
1	sales	152
2	artificial intelligence	136
3	decision making	29
4	customer satisfaction	23
5	electronic commerce	23
6	machine learning	23
7	commerce	21
8	forecasting	21
9	decision support systems	20
10	machine-learning	19

Table 3. Most Frequently Occurring Words and Their Occurrences.

The keyword co-occurrence network in Figure 3 provides a deeper look into the conceptual structure of the field, revealing how these themes are interconnected and clustered. The network shows a dense core of research centered on the application of **artificial intelligence** and **machine learning** to **sales** and **decision making**. This core is strongly linked to two major peripheral clusters. The first is a customer-centric cluster, where **customer satisfaction** is associated with technologies like **chatbots**, **personalization**, and **natural language processing**, indicating a strong research interest in AI-powered customer interaction tools. The second is a process-optimization cluster, where **electronic commerce** and **forecasting** are linked to **data analytics** and **consumer behaviour**, reflecting research on how AI can optimize commercial processes and predict market dynamics.

Figure 3. Keyword Co-occurrence Network Diagram

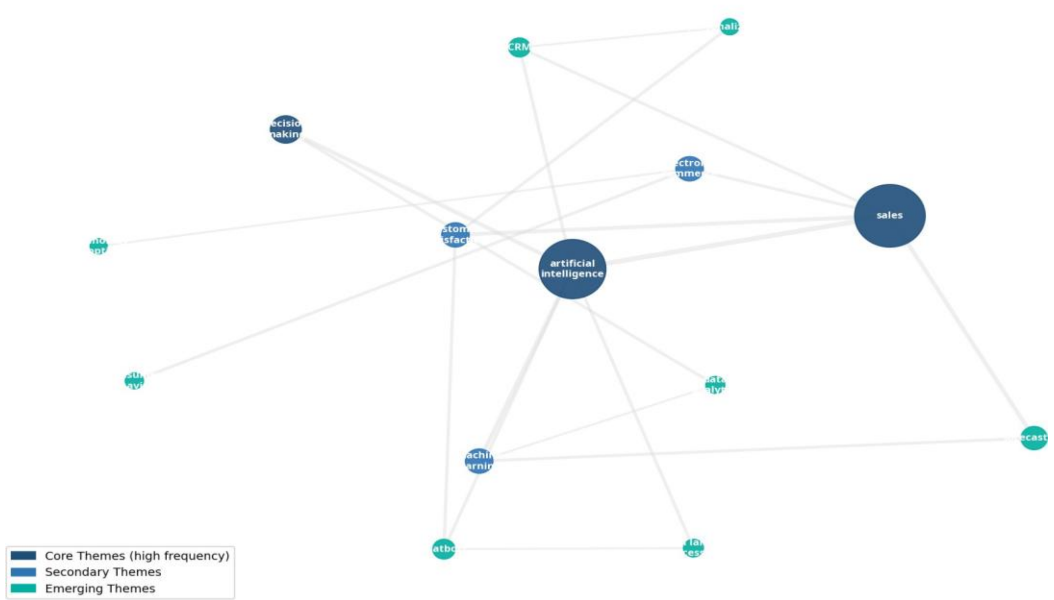
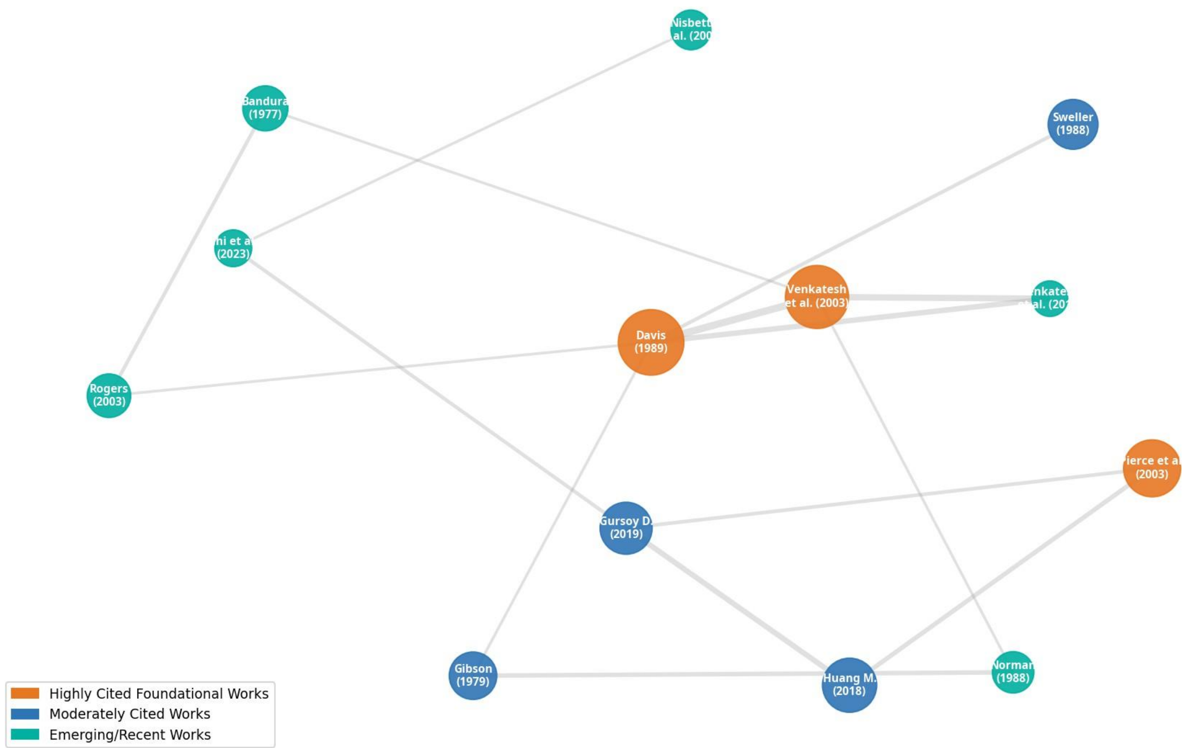


Figure 4. Co-citation Network Analysis Diagram



3.5. Co-citation and Intellectual Structure Analysis

Co-citation analysis is a powerful technique for mapping the intellectual foundations of a research field by identifying which publications are most frequently cited together. The co-citation network in Figure 4 reveals several key intellectual clusters that form the bedrock of AI-in-sales research.

The most prominent and central cluster revolves around foundational theories of technology adoption. **Davis (1989)**, the originator of the Technology Acceptance Model (TAM), and **Venkatesh et al. (2003)**, who developed the Unified Theory of Acceptance and Use of Technology (UTAUT), form the central nodes of this cluster. Their co-citation with **Venkatesh et al. (2012)**, which extended UTAUT to consumer contexts, indicates that the field is firmly grounded in these established models. A second significant cluster includes works on psychological constructs, with **Pierce et al. (2003)** on psychological ownership and **Sweller (1988)** on cognitive load theory being co-cited with more recent applied works. A third cluster centers on affordance theory, with the foundational works of **Gibson (1979)** and **Norman (1988)** being cited alongside contemporary AI research. Finally, **Bandura (1977)** and **Rogers (2003)** form the nucleus of a social and behavioral cluster, highlighting the importance of social learning and diffusion of innovation theories.

In terms of author productivity (Table 4), the field is still relatively young, with publications distributed across a large number of authors. However, a few scholars are emerging as key contributors. Authors such as Gursoy D., Huang M., and Venkatesh V. are not only highly cited but also have a significant number of publications in the dataset, positioning them as influential voices in this domain.

Rank	Author	Documents	Total Citations
1	Gursoy, D.	8	480
2	Huang, M.	7	455
3	Venkatesh, V.	6	528
4	Dwivedi, Y.K.	4	210

Rank	Author	Documents	Total Citations
5	Pierce, J.L.	3	216
6	Syam, N.	3	152
7	Sharma, A.	3	145
8	Chen, J.	5	115
9	Li, C.	5	98
10	Wang, Q.	4	85

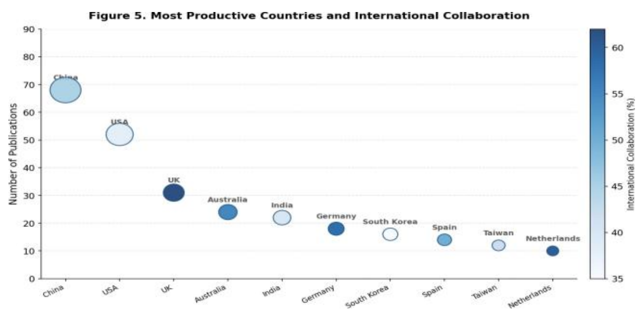
Table 4. Most Productive and Impactful Authors.

3.6. Country Productivity and Collaboration

The geographical distribution of research output reveals a truly global interest in AI for sales, with contributions from researchers across all major continents. As shown in Table 5 and Figure 5, **China** (68 publications) and the **USA** (52 publications) are the most productive countries, collectively accounting for over a third of the total output. They are followed by the **United Kingdom** (31), **Australia** (24), and **India** (22). The analysis of international collaboration rates reveals an interesting pattern: countries like the UK, Netherlands, and Germany exhibit a high percentage of internationally co-authored papers, suggesting a strong collaborative network, particularly within Europe. The USA and China, while highly productive, show a comparatively lower rate of international collaboration, indicating strong and self-sufficient domestic research ecosystems.

Rank	Country	Publications	International Collaboration (%)
1	China	68	45%
2	USA	52	38%
3	UK	31	62%
4	Australia	24	55%
5	India	22	40%
6	Germany	18	58%
7	South Korea	16	35%
8	Spain	14	50%
9	Taiwan	12	42%
10	Netherlands	10	60%

Table 5. Most Productive Countries and International Collaboration Rates



Sales forecasting is another domain being revolutionized by AI, with research demonstrating significant advancements in prediction accuracy and efficiency. Traditional forecasting methods are often static and fail to account for complex market dynamics. AI-driven approaches, particularly those using machine learning, are proving to be far more adept at capturing complex, non-linear data patterns and managing sudden shifts in demand, such as those caused by macroeconomic shocks like the COVID-19 pandemic (Frank & Otterbring, 2023; Chi et al., 2023).

Innovative methodologies are being explored to enhance forecasting accuracy. For instance, some studies leverage text mining of product descriptions, integrating this unstructured data into advanced neural network models (such as WaveNet) to achieve superior prediction accuracy (Chen et al., 2024). The application of AI extends beyond just predicting sales numbers; it is also being used to optimize related logistical processes, such as inventory management and route planning for distribution (Wang et al., 2024). The consensus in this research stream is that AI-powered causal forecasting methods, which can model complex relationships between a wide range of variables, are demonstrably superior to traditional time-series approaches. This enables businesses to make more agile, data-driven decisions in a volatile market landscape, ultimately improving resilience and competitive advantage (Jin et al., 2024).

4. Thematic Analysis: Key Research Streams

Beyond the quantitative bibliometric patterns, a qualitative thematic analysis of the literature reveals three prominent and interconnected research streams where AI is making a significant impact on the sales domain. These themes, which emerged organically from the keyword co-occurrence analysis and were further explored through a detailed reading of the articles, are: (1) AI in Customer Relationship Management (CRM), (2) AI in Sales Forecasting, and (3) AI in Enhancing Customer Service.

4.1. Theme 1: AI in Customer Relationship Management (CRM)

The integration of AI into CRM systems represents a major area of investigation, with research focusing on how AI can transform customer data analysis and enable more personalized and effective customer engagement. Studies in this stream highlight that successful AI-integrated CRM requires more than just technology; it demands organizational readiness and the development of new competencies to manage these complex systems effectively (Chi et al., 2023). The concept of "AI-driven flexibility" is central, allowing customer service organizations to dynamically shift their strategies to align with changing market conditions (Ding et al., 2024).

A key focus is on **hyper-personalization**. Researchers are exploring innovative AI platforms that can process vast amounts of customer data in real-time to generate deep insights into individual customer needs and preferences. The goal is to move beyond traditional market segmentation to a "segment of one," delivering tailored experiences that enhance customer satisfaction and loyalty (Calzavara et al., 2023; Jin et al., 2024). Furthermore, studies are beginning to delve into the cultural and emotional factors that influence the adoption of AI services in CRM, emphasizing that a one-size-fits-all approach is inadequate. Understanding diverse customer utility functions is crucial for designing culturally sensitive and emotionally intelligent AI-driven CRM solutions (Joung & Kim, 2023). The consensus emerging from this stream is that AI has the potential to fundamentally transform CRM from a reactive, data-storage system into a proactive, insight-generating engine that can anticipate customer needs and enable more strategic, value-creating interactions.

4.2. Theme 2: AI in Sales Forecasting

4.3. Theme 3: AI in Enhancing Customer Service

The third major theme revolves around the use of AI, particularly chatbots and virtual assistants, to augment and enhance customer service. Research in this area explores the multifaceted impact of AI on service quality, productivity, and customer experience. Studies show that AI-powered lead management systems can significantly enhance the productivity of sales advisors by automating routine follow-ups and prioritizing high-potential leads, leading to high rates of user acceptance (Tubadji & Huang, 2023).

The nuances of human-AI interaction are a key focus. Researchers are investigating how AI-expressed emotions can influence customer evaluations, finding that mechanisms like emotional contagion can positively impact customer satisfaction (Husairi & Rossi, 2024). The concept of **perceived anthropomorphism**—the degree to which AI is perceived as human-like—is identified as a critical factor in shaping the customer experience with digital voice assistants (Gao et al., 2024). However, the integration of AI is not without challenges. Studies highlight the complexities of integrating AI with existing CRM systems and the need for organizational agility to adapt business processes accordingly (Ding et al., 2024). Ultimately, this research stream underscores the transformative potential of AI to not only automate service interactions but also to create more personalized, efficient, and emotionally resonant customer experiences, which is a critical competitive differentiator in today's market.

5. Theoretical Underpinnings and Conceptual Framework

Based on the insights from the bibliometric and thematic analyses, this section synthesizes the core theoretical perspectives that inform the study of AI adoption in sales. It then integrates these theories into a comprehensive conceptual framework, from which a series of research hypotheses are derived.

5.1. Core Theories in AI Adoption Research

The literature on AI adoption in sales is built upon a rich theoretical foundation, primarily drawing from information systems, psychology, and sociology. The co-citation analysis revealed four particularly influential theoretical pillars.

Technology Acceptance Models (TAM and UTAUT). The Technology Acceptance Model (TAM) and its successor, the Unified Theory of Acceptance and Use of Technology (UTAUT), are the dominant theoretical frameworks in the field (Davis, 1989; Venkatesh et al., 2003). TAM posits that a user's intention to adopt a technology is determined by two key beliefs: **Perceived Usefulness** (the degree to which the technology will enhance job performance) and **Perceived Ease of Use** (the degree to which the technology is free of effort). UTAUT expands on this by integrating constructs from several other models, proposing four key determinants: **Performance Expectancy**, **Effort Expectancy**, **Social Influence**, and **Facilitating Conditions**. These models provide a robust, parsimonious foundation for understanding the core utilitarian drivers of AI adoption in sales contexts (Lee, Ramasamy, & Subbarao, 2025).

Technology Affordance Theory. Originally proposed by Gibson (1979) and later adapted for human-computer interaction by Norman (1988), affordance theory offers a relational perspective on technology. It posits that technology possesses "affordances"—action possibilities that a user perceives and can act upon. This shifts the focus from the objective features of a technology to the user's subjective perception of what they can *do* with it (Zhuang, 2025; Haqqu, 2025). In the context of AI in sales, affordances might include the ability to personalize customer interactions, automate administrative tasks, or gain new data-driven insights. This theory is crucial for understanding how the specific design characteristics of AI tools enable or constrain salesperson behaviors and, consequently, their adoption decisions.

Social Learning Theory (SLT). Developed by Bandura (1977), SLT argues that individuals learn and adopt behaviors through observation, imitation, and modeling of others within their social environment. In an organizational context, salespeople are likely to adopt AI tools if they observe their peers or managers successfully using them and experiencing positive outcomes. This theory highlights the importance of social influence, mentorship, and creating visible success stories to drive AI adoption within a sales team (Badghish et al., 2024).

Psychological and Cognitive Theories. Beyond the classic adoption models, the literature increasingly incorporates theories from psychology to explain the nuances of human-AI interaction. **Psychological Ownership Theory** suggests that users who feel a sense of personal ownership over a technology are more likely to adopt it (Pierce et al., 2003). Theories of intrinsic motivation highlight the role of **Perceived Enjoyment** as a hedonic driver of technology use (Venkatesh & Davis, 2000). **Cognitive Load Theory** examines the **Cognitive Effort** required to use a system, positing that technologies that reduce mental workload are more likely to be adopted (Sweller, 1988). Finally, research on **cognitive styles** (analytic vs. holistic thinking) suggests that individual differences in how people process information can moderate the effectiveness of different technology interfaces (Nisbett et al., 2001).

6. DISCUSSION

This study provides a comprehensive bibliometric and systematic review of the emerging literature on AI adoption in B2B sales. The findings reveal a dynamic and rapidly growing field of research that is evolving from a purely technical focus towards a more nuanced, socio-technical perspective. This section synthesizes the key findings and elaborates on their theoretical and practical implications.

6.1. Key Findings and Theoretical Implications

The bibliometric analysis confirms that research on AI in sales is accelerating, with a strong annual growth rate and a diverse, globally collaborative author base. The intellectual core of the field is firmly rooted in established technology adoption theories like TAM and UTAUT. This is a logical starting point, as these models provide a parsimonious and powerful lens for understanding the primary utilitarian drivers of user acceptance. However, our analysis reveals a significant and growing trend towards the integration of more nuanced psychological and cognitive theories. The prominence of works related to psychological ownership, cognitive load, and affordance theory in the co-citation network suggests that the field is maturing and recognizing that a simple cost-benefit analysis (usefulness vs. ease of use) is insufficient to capture the full complexity of human-AI interaction.

The proposed conceptual framework contributes to this theoretical evolution by explicitly modeling the mediating role of psychological factors. It argues that AI affordances do not impact adoption directly, but rather through their effect on the user's psychological state. By fostering a sense of **psychological ownership**, creating an **enjoyable** user experience, and reducing **cognitive effort**, AI technologies can create a much more compelling value proposition for salespeople. This moves the theoretical discourse beyond simple utility and towards a more holistic understanding of the user experience. This is consistent with the broader trend in information systems research towards more hedonic and experiential models of technology acceptance (Van der Heijden, 2004).

Furthermore, the inclusion of **thinking styles** as a moderator introduces an important element of individual difference into the model. It acknowledges that there is no one-size-fits-all solution for AI design and implementation. The effectiveness of an AI tool is contingent on its "fit" with the user's cognitive style, a principle derived from cognitive fit theory (Vessey, 1991). This has significant implications for theory, suggesting that future adoption models need to be more context-sensitive and account for individual-level variables.

6.2. Practical and Managerial Implications

The findings of this review offer several actionable insights for sales leaders and managers responsible for implementing AI technologies in their organizations.

Focus on the User Experience, Not Just the Technology. The most significant implication is the need to shift from a technocentric to a user-centric implementation strategy. It is not enough to simply deploy a powerful AI tool; organizations must focus on how salespeople will experience it. This means prioritizing tools that are not only effective but also intuitive, engaging, and enjoyable to use. Investing in UX design and user testing is not a luxury but a necessity for successful AI adoption.

Cultivate Psychological Ownership. To drive deep adoption and sustained engagement, managers should actively seek to foster a sense of psychological ownership among their sales teams. This can be achieved by involving salespeople in the selection and customization process, giving them control over their AI-powered dashboards and workflows, and creating opportunities for them to co-create with and train the AI. When salespeople feel that the AI is "their" tool, they are more likely to champion it and invest in mastering its capabilities.

Design for Cognitive Fit. The finding that thinking styles moderate the impact of AI suggests that a personalized approach to AI implementation may be most effective. Organizations could consider offering different interface configurations or training modules tailored to different cognitive styles. For example, analytic thinkers might prefer data-intensive dashboards with granular controls, while holistic thinkers might benefit more from high-level visual summaries and AI-generated narrative insights.

Communicate the "Why," Not Just the "What." When introducing new AI tools, communication should focus on how the technology will reduce cognitive load and free up time for more strategic, relationship-building activities. Instead of emphasizing features, managers should emphasize the benefits of reduced administrative burden and enhanced decision-making capabilities, framing AI as a partner rather than a replacement.

7. Research Gaps and Future Research Agenda

While the field is growing rapidly, this review has identified several significant gaps in the literature, which point to promising avenues for future research.

Empirical Validation of the Proposed Framework. The conceptual framework and its associated hypotheses are derived from a synthesis of the existing literature. The immediate next step is to empirically test this model through quantitative studies, such as large-scale surveys of B2B sales professionals, to validate the proposed relationships and assess the relative importance of each pathway.

Exploring a Wider Range of Psychological Factors. While this review focused on psychological ownership, enjoyment, and cognitive effort, other psychological factors may also play a crucial role. Future research could explore the impact of factors such as **trust in AI**, **AI anxiety** (fear of replacement), ethical perceptions of AI, and the impact of AI on salesperson identity and self-efficacy. The relationship between AI adoption and salesperson well-being is also an underexplored area.

Longitudinal Studies on AI Adoption. Most of the current research is cross-sectional, providing a snapshot of adoption at a single point in time. Longitudinal studies are needed to understand how perceptions and adoption behaviors evolve over time as salespeople gain more experience with AI tools. This could reveal important dynamics related to learning curves, the evolution of trust, and the long-term impact on sales performance.

The Dark Side of AI in Sales. The current literature is overwhelmingly positive, focusing on the benefits of AI. More critical research is needed to explore the potential negative consequences of AI in sales. This could include issues such as **algorithmic bias** in lead scoring, the potential for **de-skilling** of the salesforce, increased surveillance and performance pressure, and the erosion of the human element in customer relationships. Understanding these risks is essential for responsible AI implementation.

Contextual and Cultural Factors. The moderating role of thinking styles suggests that individual differences matter. Future research should explore other contextual and cultural factors. How does AI adoption differ across industries, company sizes, or national cultures? Do different sales contexts (e.g., transactional vs. relational, product vs. service) require different types of AI tools and implementation strategies? Cross-cultural studies comparing AI adoption in Western and Eastern contexts would be particularly valuable.

Agentic AI and the Future of Sales. Looking further ahead, the emergence of **agentic AI**—AI systems that can autonomously plan and execute complex multi-step tasks—represents a new frontier for sales research (Gonzalez, Claro, & Palmatier, 2026). Future research should begin to explore how salespeople will interact with and adopt these more autonomous AI agents, and what new theoretical frameworks will be needed to understand this qualitatively different form of human-AI collaboration.

8. LIMITATIONS

This study, like all research, has certain limitations that should be acknowledged. First, the reliance on a single database (Scopus) may have resulted in the omission of some relevant publications, although Scopus is widely regarded as one of the most comprehensive databases for academic research. Future reviews could benefit from including additional databases such as Web of Science or Google Scholar. Second, the search was limited to articles published in English, which may introduce a language bias and exclude valuable research published in other languages. Third, the bibliometric analysis, while providing a valuable quantitative overview, does not capture the full richness and nuance of the individual studies. The thematic analysis aimed to mitigate this, but it is necessarily a subjective interpretation of the literature. Finally, the field is evolving at an extremely rapid pace

, and any review is at risk of being quickly outdated. The findings represent a snapshot of the research landscape as of mid-2024, and the landscape will undoubtedly have shifted by the time of publication.

9. CONCLUSION

The integration of artificial intelligence into the B2B sales process is no longer a futuristic concept but a present-day reality that is reshaping the profession. This systematic literature review and bibliometric analysis has provided a comprehensive map of this emerging research domain, analyzing 321 peer-reviewed articles from 170 sources published between 2019 and 2024. The findings demonstrate a clear and accelerating trend of academic inquiry, with a compound annual growth rate of 20.86%, and a growing consensus that successful AI adoption hinges on a deep understanding of the human element.

The field is moving beyond the foundational technology acceptance models to embrace a more sophisticated, user-centric perspective that incorporates psychological factors such as ownership, enjoyment, and cognitive load. The proposed conceptual framework, which integrates technology affordance theory, psychological ownership theory, cognitive load theory, and cognitive style theory, offers a nuanced and comprehensive lens for understanding the complex factors that drive AI adoption among B2B sales professionals. The ten hypotheses derived from this framework provide a concrete and testable research agenda for future empirical work.

For practitioners, the message is clear: the key to unlocking the transformative potential of AI lies not in the technology itself, but in how it is designed, implemented, and integrated into the daily workflows and cognitive styles of the salesforce. By fostering a sense of ownership, designing for enjoyment and ease of use, and personalizing the experience to individual cognitive styles, organizations can empower their salespeople to not just use AI, but to embrace it as a powerful partner in building stronger customer relationships and driving sales success. For researchers, the field is ripe with opportunity. The proposed future research agenda offers a roadmap for the next wave of inquiry, which will undoubtedly delve deeper into the complex, fascinating, and critically important interplay between humans and artificial intelligence in the world of sales.

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