The Impact of Generative AI Technology on B2B Sales Process and Performance: An Empirical Study

*Michael Rodriguez, PhD
East Carolina University
3119A Bate Building
Greenville, NC 27858
Rodriguezmich24@ecu.edu

Dawn R. Deeter-Schmelz, PhD
College of Business Administration
Marketing Department
Kansas State University
2127 Business Building
Manhattan, KS 66506
ddeeter@ksu.edu

Michael T. Krush, PhD
College of Business Administration
Marketing Department
Kansas State University
3026 Business Building
Manhattan, KS 66506
mikekrush@ksu.edu

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*Contact Author

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Structured Abstract

Purpose: This paper addresses the research gap in the use of Generative AI (GenAI) technology by empirically testing a model that explores the effects of upper management support and technology self-efficacy on GenAI technology use and its impact on sales outcomes.

Design/Methodology/Approach: The sample consisted of sales representatives from a healthcare company that utilized GenAI as part of their sales process. The pre-test included in-depth interviews and feedback from leadership to develop a preliminary questionnaire, followed by a survey assessment with a pilot sample. The main study used an online survey distributed to a larger sample. Data were analyzed using partial least squares (PLS).

Findings: The results indicate that GenAI technology has a positive impact on the effectiveness of the sales process, administrative efficiency, and sales performance. Furthermore, upper management support influences the use of GenAI technology and positively moderates the relationship between technology self-efficacy and the use of GenAI technology.

Originality: This study addresses a significant research gap by empirically testing a model that examines the use of GenAI technology. It extends prior studies on AI in sales by investigating the underexplored domain of GenAI and highlights the impact of GenAI on key sales outcome variables.

Research Limitations: The study focuses on a single healthcare company, which may limit its generalizability to other healthcare companies. Additionally, it relies on self-reported data from sales professionals.

Research Implications: Drawing on the Technology Acceptance Model (TAM), the study contributes to existing research by empirically testing the value of GenAI in enhancing sales process effectiveness, administrative efficiency, and sales performance.

Practical Implications: The findings underscore the significance of upper management support in successfully adopting and utilizing GenAI technology within the B2B sales process.

Keywords: Generative AI, GenAI, artificial intelligence, AI, sales, sales process, sales performance

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Introduction

Artificial intelligence (AI) capabilities have captivated both sales experts and scholars. Sales-oriented organizations have consistently demonstrated a willingness to invest in cutting-edge technology to enhance their sales processes and strengthen their competitive advantage (Alavi and Habel, 2021). A recent poll indicated that organizations implementing AI had a 39% enhancement in customer experience and a 33% increase in workforce efficiency (IDC Report, 2022). Academic studies have also quantified AI's influence, demonstrating a favorable correlation between AI innovation and organizational results, including sales performance (Singh *et al.*, 2019; Paschen *et al*., 2020). While AI technologies such as Salesforce Einstein have advanced steadily over the years, recent developments in Generative AI (GenAI) technologies (Salesforce GPT, IBM Watsonx, and Microsoft Copilot) represent a significant leap, prompting renewed scholarly interest in their implications for sales.

GenAI is a subset of AI that focuses on producing original content by learning the underlying structure of data (Zewe, 2023). Unlike traditional AI systems that analyze existing data for prediction or classification, GenAI generates new outputs, such as human-like text, images, videos, or music, that can create efficiencies within organizations. As noted by Grewal *et al.* (2024a), GenAI "…shifts the focus from prediction to the production of new content, meaning that it can take over many tasks that previously appeared exclusive to human capabilities…" (p. 870). For example, Walmart has employed a GenAI-powered chatbot to negotiate with suppliers, resulting in savings and improved efficiencies in the supply chain (Van Hoek *et al.*, 2022). H&R Block utilizes GenAI tools for sales and advisor support, enabling tax professionals to provide better customer service by handling routine customer questions and

assisting in direct conversations with customers (Microsoft, 2024b). Researchers predict that GenAI will lead to significant changes in marketing and sales strategies (e.g., Davenport *et al.,* 2020).

In the sales sector, GenAI technologies, such as Gong Engage or Outreach Kaia, can augment productivity and improve sales efficiency across the sales process (e.g., Salesforce.com, 2024), facilitating the creation of tailored materials for clients, augmenting forecasting accuracy, refining lead scoring, and enhancing the technological infrastructure of sales organizations, including components such as CRM (IBM Institute of Business Value, 2023). Sales users can manage technology and utilize its creative content within the sales context. Sales executives see the potential of GenAI to revolutionize the whole sales process, encompassing prospecting and pre-call preparation (Alavi and Habel, 2021) through to opportunity management. This connection may allow the salesforce to concentrate more on sales and less on administrative responsibilities.

Still, investments in GenAI within sales functions remain limited despite clear benefits. Gartner (2023) reported that merely 12% of sales functions had invested in GenAI; additionally, Korst and Puntoni (2023) highlight that sales and marketing leaders lag their peers in general management, human resources, and IT in utilizing GenAI. Potential reasons for this cautious approach may include concerns about employees' practices, such as relying excessively on AI-generated content at the expense of personalized human interaction with customers, which can diminish relationships. Other concerns about GenAI persist, including job loss, skill erosion resulting from reliance on GenAI, plagiarism, and customer discomfort, among other issues (Davenport *et al.*, 2020; Grewal *et al.*, 2024b; Zewe, 2023). From a research standpoint, there is limited literature available to guide practitioners on the influence of GenAI, particularly

regarding its impact on sales success. Sales personnel are crucial for revenue growth in business-to-business (B2B) companies (Lopez and McMillan-Capehart, 2009). Consequently, scholars and practitioners must understand how GenAI may influence sales productivity and performance to assess the relationship between benefits and costs. Given the limited research on GenAI, we aim to address the existing research gap and establish empirical data to support the use of GenAI technology within the sales process. While existing literature highlights AI's impact on sales process efficiency and forecasting (Luo *et al.*, 2021; Rodriguez and Peterson, 2024), our study uniquely examines the role of GenAI in facilitating personalized customer interactions and reducing administrative burdens, therefore filling a critical gap. We aim to empirically explore how organizational factors, particularly upper management support and technology self-efficacy, impact the adoption of GenAI among sales professionals and subsequently influence key sales performance metrics, including sales process effectiveness, administrative efficiency, and overall sales outcomes.

The Technology Acceptance Model, or TAM (Davis, 1989) and its extension TAM3 (Venkatesh and Bala, 2008), inform our study. As noted by Feng *et al.* (2021), TAM and its extensions (e.g., Venkatesh and Davis, 2000; Venkatesh and Bala, 2008) are commonly used in studies investigating technology adoption and use. Although other more complex theories are available to explain technology adoption, such as the User Acceptance of Information Technology, or UTAUT (Venkatesh *et al*. 2003), TAM has been argued to be preferable due to its parsimony (e.g., Agudo-Peregrina *et al*., 2014). Recent research results have identified TAM as providing valuable explanatory power within the context of digital transformation (Park *et al*., 2022) and attitudes towards AI use (Ibrahim *et al*., 2025). We therefore selected TAM due to its simplicity and focus on explaining individual technology adoption in the workplace.

We begin our analysis by providing an overview of AI research and developing our conceptual framework. We then formulate and evaluate our model while delineating our analytical process. Through this study, we contribute to the broader understanding of AI integration in sales by highlighting not only the significant benefits of GenAI technology but also the organizational dynamics affecting its widespread adoption and effective utilization in practice. Finally, we provide the consequences of our study for both research and practice, highlighting various limitations and outlining a roadmap for future research opportunities.

AI and the Evolution of Sales Technology

Because GenAI is a type of sales technology, we start our examination with the literature on sales technology. Technology, in the context of sales, refers to the application of digital tools and systems to enhance the efficiency, effectiveness, and outcomes of sales activities (Avlonitis and Panagopoulos, 2005). Sales technology has evolved significantly over the years, progressively reducing information asymmetry between sellers and buyers and enabling more transparent and insightful interactions (Goel *et al.*, 2025).

The evolution of sales technology has followed a trajectory of increasing intelligence and interactivity, beginning with Sales Force Automation (SFA) tools. Early sales technologies, such as SFA were designed primarily to automate basic, repetitive tasks, including scheduling meetings, pipeline management, and call tracking. These tools reduced manual effort, allowing salespeople to focus more on selling activities (Badrinarayanan *et al.*, 2022). However, information sharing remained limited, with salespeople essentially controlling customer interaction data.

Subsequently, customer relationship management (CRM) systems centralized customer data to foster relationship-building (Rodriguez and Honeycutt, 2011; Goel *et al.*, 2025). CRM

technology marked a substantial advancement by providing salespeople with deeper, actionable insights into customer behavior, preferences, and history. It reduced information asymmetry by making customer insights accessible throughout the sales organization, rather than solely with individual salespeople.

By the 2010s, the incorporation of social media platforms further transformed sales processes, providing digital channels for prospecting and customer engagement (Marshall *et al.*, 2012; Agnihotri *et al.*, 2017; Agnihotri, 2020). Social media has uniquely facilitated interactive exchanges between salespeople and customers, enabling immediate feedback, nurturing relationships, and fostering continuous dialogue.

Building upon foundational technologies, AI has introduced significant advances, including predictive analytics, personalized recommendations, and enhanced decision-making processes (Singh *et al.*, 2019; Paschen *et al.*, 2020). AI refers to computer systems designed to execute activities that typically require human intellect (Baidoe-Anu and Ansah, 2023); it encompasses the discipline of creating intelligent machines and the ability to achieve defined objectives (McCarthy, 2007). AI can learn from data, facilitating predictive analysis (Marr, 2023). AI has been progressively integrated into current sales technology (Chatterjee *et al.*, 2021), notably enhancing predictive capabilities, which enable sales professionals to anticipate customer needs and adjust their strategies accordingly (Alavi and Habel, 2021).

The advancement of sales professionals to AI technology is a notable milestone in the market (Chatterjee *et al.*, 2021). AI has enabled functionalities like predictive analytics, AI-powered chatbots, and sophisticated recommendation systems, transforming the B2B sales environment (Alavi and Habel, 2021). Predictive analytics utilizes AI to analyze trends in consumer data, allowing sales professionals to anticipate future purchasing behaviors and

identify sales opportunities before they emerge (Tan *et al.*, 2022). AI-powered chatbots deliver prompt replies, allowing human sales representatives to focus on more complex tasks. Utilizing AI in sales technology enhances operational efficiency and enhances the customer experience, ultimately increasing customer satisfaction and loyalty. As AI technology advances, sales personnel get capabilities that facilitate strategic decision-making, improved resource allocation, and enhanced sales results (Longoni and Cian, 2022). This trend signifies a shift toward more sophisticated, data-driven sales methodologies that adapt to the industry's evolving demands and individual consumers, paving the way for a future where technology and human expertise converge to achieve exceptional sales performance (Chen and Zhou, 2022).

Technology-enabled sales capabilities, as described by Badrinarayanan *et al.* (2022), emphasize the integration of technology into sales processes and activities. These capabilities significantly contribute to organizational financial performance and customer relationship outcomes by leveraging technological resources effectively.

Rodriguez and Peterson (2024) propose a conceptual framework that outlines AI's significant impacts across various stages of the B2B sales process, emphasizing improved sales process effectiveness, administrative efficiency, and enhanced customer performance. They argue that the strategic integration of AI into existing sales workflows not only enhances task efficiency but also fundamentally changes the nature of interactions between sales professionals and customers, creating a data-driven and predictive sales environment.

Further emphasizing AI's integration in sales, Casenave and Schmitt (2025) explore the comparative effectiveness of AI coaching versus traditional sales manager coaching. Their findings highlight the nature of AI adoption, suggesting AI's success depends significantly on how information is delivered, which aligns with the perceived psychological distance of AI

compared to human managers. This highlights the importance of framing technological interactions appropriately to enhance salesperson self-efficacy and intention to use AI.

Additionally, Chakraborty *et al.* (2025) provide empirical evidence for the effectiveness of AI in assessing and enhancing sales skills through conversational analytics. Their AI-human hybrid approach shows superior results in predicting latent sales abilities compared to either AI or human judgment alone, underscoring AI's potential in transforming sales recruitment and coaching practices. Comprehensive analyses by Goel *et al.* (2025) further highlight the broader implications of technology use in B2B sales, emphasizing the need for a holistic approach to understanding the transformative impacts of both established and emerging sales technologies.

One of the most captivating areas of AI is GenAI**.** Unlike traditional, rule-based AI systems that rely on historical data for prediction or classification, GenAI generates entirely new outputs, such as images, text, music, or videos, that mimic or resemble human-created content (see Table 1, IBM Institute of Business Value, 2023). This technology substantially further reduces information asymmetry, empowering customers with hyper-personalized information and salespeople with innovative, customized solutions for client interactions.

[Insert Table 1 here]

Within the current sales literature, research has increasingly focused on AI rather than GenAI (Singh *et al.*, 2019; Paschen *et al.*, 2020; Hoffman *et al.*, 2022; Daviet *et al.*, 2022; Bharadwaj *et al.*, 2022; Tan *et al.*, 2022; Longoni and Cian, 2022). McClure *et al.*'s (2024) most recent study provides a detailed discussion of GenAI's impact on the sales process, but is limited in empirical support. Thus, although there has been an increased focus on AI research, the body of research on the use of GenAI technology in sales is limited. Our study aims to help bridge this research gap and lay a foundation for the use of GenAI technology in the B2B sales process.

Theoretical Foundation and Conceptual Framework

Our conceptual framework (Figure 1) is grounded in the Technology Acceptance Model (TAM) (Davis, 1989). When salespeople are provided with sales technology options, TAM provides guidance regarding factors impacting how and if those salespeople will use the technology.

[Insert Figure 1 here]

Technology Acceptance Model (TAM)

TAM began as a framework to help understand why employees may be averse to using available information technology (Davis, 1989), and has since been extended (Venkatesh and Davis, 2000; Venkatesh and Bala, 2008). Within the sales literature, TAM is widely used to assess and explain the factors influencing technology adoption (Ahearne *et al.*, 2004; Hunter, 2019; Igwe *et al.*, 2020). For example, sales researchers have utilized TAM to investigate the use of sales technology (e.g., Robinson *et al.*, 2005a, 2005b) and social media use among business-to-business salespeople (Kumar and Srivastava, 2022). In the broader literature, TAM has provided the foundation for studies examining artificial intelligence use (e.g., Ibrahim *et al*., 2025). In their review of 60 articles examining user acceptance of AI technologies, Kelly *et al.* (2023) identified the extended TAM as the most frequently used theory.

When users are presented with a new technology, several factors influence how and when they use it. TAM proposes that an individual's acceptance of technology depends upon perceived usefulness and ease of use (Davis, 1989). Perceived usefulness refers to the belief that using the system will enhance performance, while perceived ease of use refers to the belief that using the system will require little effort (Davis, 1989). Furthermore, TAM and its extensions suggest that external variables can influence these beliefs and attitudes (Davis, 1989; Venkatesh, 2000), including self-efficacy (Venkatesh and Bala, 2008). We submit that TAM provides theoretical

guidance and support for understanding why and how salespeople may adopt technological tools like GenAI.

Drawing from TAM, we position technology self-efficacy as an antecedent variable influencing GenAI technology use. Additionally, we seek to extend TAM by examining upper management support as an antecedent to GenAI technology use. GenAI, in turn, affects the key outcome variables of sales process effectiveness, administrative efficiency, and sales performance. We discuss the proposed model more fully in the following sections.

Upper Management Support

We suggest that upper management support plays a crucial role in the salesforce's use of technology, especially emerging technologies like GenAI. Within TAM, upper management support is considered an external variable that influences beliefs and attitudes (Davis, 1989). Traditionally, upper management support refers to the degree to which management promotes the adoption and use of sales technology (Rai and Patnayakuni, 1997), offering strategic advantages for the business's long-term success (Sanders and Carpenter, 2003). Research demonstrates a positive relationship between the level of upper management support and observed innovation behavior within organizations (Rai and Patnayakuni, 1997). In the case of GenAI, this support becomes even more critical. GenAI tools—such as Salesforce's Einstein GPT or Microsoft's Dynamics 365 AI—require changes to existing workflows, training investments, and visible endorsement by leadership to be successfully adopted (D'Angelo *et al.*, 2023; Deveau *et al.*, 2023).

Past research has shown that managerial support is crucial to the successful implementation of technological change, such as CRM or SFA tools (Morgan and Inks, 2001). More recent studies emphasize that upper management must actively champion GenAI to

overcome organizational resistance and encourage experimentation (Korst and Puntoni, 2023). When upper management models GenAI usage and provides resources, such as training on AI-driven prospecting or personalized content creation, sales professionals are more likely to perceive the technology as applicable and align with its adoption (Jöhnk *et al.*, 2021). For example, when leaders share how GenAI streamlines administrative tasks (e.g., automated meeting notes or customized email generation), they reinforce the practical value of the technology for sales reps (Sinha *et al.*, 2023; Bicanic *et al.*, 2023). Thus, upper management support enables adoption and accelerates GenAI's integration into the sales process.

> H1: There is a positive relationship between upper management support and the use of GenAI technology.

Technology Self-Efficacy

Our second antecedent, technology self-efficacy, plays a significant, positive role in the salesforce's adoption of GenAI (Venkatesh and Bala, 2008). Self-efficacy is one of the most important variables that affect human behavior, as it is the compilation of judgments about an individual's capabilities (Senemoğlu, 1997) and reflects a person's beliefs in their ability to accomplish a mission (Kurbanoğlu, 2004). For our study, technology self-efficacy is defined as an individual's belief in their ability to use technology to perform tasks effectively (cf. Venkatesh and Bala, 2008). Research indicates that individuals with high technology self-efficacy are more likely to embrace and effectively deploy technology solutions (Makarius *et al.*, 2020). This aspect of technology self-efficacy is crucial for utilizing GenAI, as AI tools are becoming increasingly advanced and may be intimidating to many salespeople (McBeth, 2021). When sales professionals feel confident in their technological capabilities, they are more likely to engage with and explore the functionality of emerging tools. This confidence fosters favorable

perceptions of the technology's ease of use and usefulness. As individuals interact with GenAI, they tend to experience fewer frustrations, recognize its practical benefits more quickly, and are less discouraged by technical challenges. This belief in one's ability reduces anxiety and promotes a sense of mastery over time, which positively influences actual technology use behavior. In summary, we argue that technology self-efficacy leads to greater ease of use of GenAI technology. Salespeople who believe in their ability to use technology are more likely to find it easy and, therefore, will be more inclined to use it.

H2: A positive relationship exists between technology self-efficacy and the use of GenAI.

We expect upper management support to positively moderate the relationship between technology self-efficacy and the use of GenAI technology. One of upper management's key responsibilities is to provide the training and resources necessary for their salesforce. When upper management supports initiatives such as training, it equips salespeople with the knowledge and understanding necessary to utilize GenAI technology effectively. Salespeople with higher levels of technology self-efficacy are more likely to build upon these training efforts, enhancing their confidence in their technological abilities to use GenAI.

Additionally, upper management can champion the use of GenAI technology by modeling its application in their work responsibilities (Campbell, 1998). The salesforce often sees role modeling as a suitable example to emulate (Rich, 1997). This demonstration of GenAI technology use by upper management promotes the value of the technology and enhances its usefulness and ease of use in the sales process. When upper management models the use of GenAI, it serves as an example that might enhance the technology self-efficacy beliefs of salespeople. Salespeople with high technology self-efficacy may improve their confidence when

they observe upper management effectively using GenAI technology. Thus, upper management support may further encourage salespeople to use GenAI technology in their sales practices.

> H2b: Upper management support will positively moderate the relationship between technology self-efficacy and the use of GenAI technology.

GenAI Technology Use and Sales Process Effectiveness

A sales process is a series of repeatable steps that potentially deliver customer value and increase the firm's sales performance (Enyinda *et al.*, 2021). As such, sales process effectiveness refers to the ability to achieve immediate results within the sales process, such as reducing sales cycles and facilitating meetings with key decision-makers (Stoddard *et al.*, 2006). Key elements of the sales process include generating client rapport, effectively identifying the client's needs, proposing a solution aligned with the buyer's needs, addressing hesitations and concerns, and facilitating a decision (Futrell *et al.*, 2018).

Research has explored the impact of sales technology on the effectiveness of the sales process. For instance, social media technology has also assisted salespeople by enhancing prospecting and new market development (Bocconcelli *et al.*, 2017; Agnihotri, 2020). Other studies discuss AI's potential applications within the sales process, including improving prospecting and opportunity management, as well as shortening sales cycles (Fischer *et al.*, 2022).

However, GenAI provides even more opportunities throughout the entire sales process. For example, GenAI technology may enhance salesperson effectiveness by providing suggestions on objection handling, presenting personalized customer solutions (Huang and Rust, 2024), or sharing feedback for sales process improvement (D'Angelo *et al.*, 2023). Additionally, GenAI technology can aid salespeople in producing customer-focused communication and assist

with personalized follow-up emails (Deveau *et al.*, 2023), which may lead to more valuable interactions and information for buyers. For instance, Microsoft's Dynamics 365 AI for Sales utilizes GenAI to analyze sales call recordings and provide valuable insights throughout the client journey, including information on client sentiment, expressed objections, and key discussion points (Microsoft.com, 2024a). Similarly, Salesforce's Einstein, another GenAI technology solution, can examine client data and purchasing patterns to generate comprehensive consumer profiles (Salesforce.com, 2023). In summary, utilizing GenAI technology can help sales representatives tailor their approach to effectively address customer needs.

> *H*3: There is a positive relationship between the use of GenAI technology and the effectiveness of the sales process.

GenAI Technology Use and Administrative Efficiency

Sales professionals spend a significant amount of time on non-selling activities. Salesforce.com (2022) notes that most sales representatives spend a considerable amount of time on data entry and deal management tasks, with only 28% of their time devoted to selling. Trent (2021) reports that companies lose 38% of their revenue each quarter because salespeople spend 41% of their time on tasks other than selling. Sidhwani (2020) argues that sales representatives spend 66% of their time on non-selling tasks, while data from Workplace Analytics revealed that outside representatives at one company spent only 20% of their time with customers (Frick and Kovack, 2017). These findings underscore the potential of GenAI tools to enhance administrative efficiency by automating routine tasks.

Improving administrative efficiency can reduce the time spent on non-selling activities, which can pay dividends for salespeople and the organizations that employ them by increasing the time devoted to selling. Administrative efficiency refers to the extent to which salespeople

can complete tasks such as reporting and other non-selling activities, thereby creating more time to focus on sales-related activities (Gwin and Perreault, 1981). AI tools can facilitate various tasks, including data input, forecasting, analytics, and workflow optimization. (Hoffman *et al.*, 2022).

Sales professionals can reinvest their time in selling by automating repetitive tasks with GenAI technology (Chen and Zhou, 2022). For instance, GenAI technology can assist salespeople in generating reports and other forms of information, such as developing proposals and revising CRM data (Sinha et al., 2023), as well as creating meeting notes for client-salesperson interactions (Bicanic *et al.*, 2023). Later in the sales process, salespeople can utilize GenAI technology to provide post-sales information to clients, including training and key practices to leverage the solution (Deveau *et al.*, 2023). These examples demonstrate how GenAI technology can help salespeople reduce their effort while enhancing their productivity. Hence, GenAI can improve administrative efficiency in the sales process. This allows sales professionals to dedicate more time to activities that generate revenue.

> H4: There is a positive relationship between the use of GenAI and administrative efficiency.

GenAI Technology Use and Sales Performance

Our final hypothesis focuses on the effects of GenAI use and sales performance. Sales performance is defined as the results generated by a salesperson's selling activities, such as increased sales or market share through client development and retention, upselling, and cross-selling (Behrman and Perreault, 1982).

Scholars have documented prior research linking the use of sales technology and firm performance (Hunter and Perreault, 2007; Eggert and Serdaroglu, 2011; Rodriguez and Boyer,

2020; Chatterjee *et al.*, 2021; Mikalef *et al.*, 2023). While these studies provide a foundation for understanding how systems can enhance specific performance areas (e.g., productivity and forecasting), distinctions exist between sales technologies, such as SFA, CRM, and mobile CRM, and their impact on sales performance. Research suggests that sales technology, such as AI, may enhance sales professionals' ability to generate sales and increase market share (Chen and Zhou, 2022; Hunter and Panagopoulos, 2015). Accordingly, we argue that the effect of GenAI technology on sales performance will be positive. GenAI technology empowers sales professionals to enhance customer interactions and achieve more effective sales outcomes. For instance, GenAI technology can provide analytical insights into customer behaviors and preferences, thereby delivering a more personalized experience, which results in a higher probability of sales outcomes (Singh *et al.*, 2019; Luo *et al.*, 2021), including those of cross-selling or client retention.

H5: There is a positive relationship between GenAI use and sales performance.

Research Methodology

To examine the hypotheses and relationships between constructs, we collaborated with a company specializing in the sale and distribution of healthcare goods, ultimately used by end consumers. This company uses GenAI technology in its sales process. The study focused on a single medical company that is recognized for its adoption of advanced technologies in sales operations. Concentrating on the medical industry allowed for control over industry-specific factors that might influence technology adoption and sales performance, enhancing the study's internal validity (Eisenhardt, 1989). Through in-depth interviews with key sales leaders, including one Head of Sales, two Sales Managers, and one Head of Sales Enablement, we developed an initial questionnaire for the pre-test. The interviews included questions such as:

“How has GenAI impacted your team's closing rates and customer retention?”, “In what ways has GenAI streamlined administrative tasks?”, “How does upper management demonstrate support for GenAI?”, and “What training or resources are provided to enhance salespeople's confidence in using GenAI?”. These questions provided an exploration of key themes, including sales process effectiveness, administrative efficiency, upper management support, and technology self-efficacy. Insights from interviews helped develop our constructs and ensured the questionnaire accurately reflected the language and experiences of sales professionals using GenAI. This qualitative step significantly enhanced content validity, helping to align the survey closely with the real-world context of our target population. Our study aims to analyze the relationships between the use of GenAI technology and other discussed constructs, utilizing the partial least squares (PLS) methodology.

Measures

The GenAI technology measure was developed using the SFA measure from Eggert and Serdaroguls (2011). SFA was replaced with GenAI technology to measure sales professionals’ use of the tool in their current sales process. The adapted measure was used on a five-item, seven-point Likert scale.

Upper management support was measured using three items developed by Schillewaert *et al.* (2005), and technology self-efficacy was measured using a three-item scale developed by Brinkerhoff (2006). Both scales were rated on a seven-point Likert scale ranging from “strongly disagree” (1) to “strongly agree” (7).

The sales process effectiveness scale is based on a measure developed by Stoddard *et al.* (2006). Sales process effectiveness is the ability to effectively complete short-term outcomes in the sales process by analyzing opportunities and improving closing rates (Stoddard *et al.*, 2006).

The scale consisted of three Likert-type items, each on a seven-point scale anchored by “strongly disagree” (1) and “strongly agree” (7). The administrative efficiency construct focuses on how well a sales professional completes non-selling tasks (Hunter, 1999). It consists of three Likert-type items on a seven-point scale anchored by “Needs Improvement” (1) and “Outstanding” (7).

The salesperson performance measure, developed by Avlonitis and Panagopoulos (2005), focuses on how a salesperson performs compared to that salesperson’s peers. It consists of four Likert-type items on a seven-point scale anchored by “Needs Improvement” (1) and “Outstanding” (7).

Pre-Test Measure Assessment

The study employed a similar method to measure technology use by conducting a pre-test between independent (GenAI technology use) and dependent variables (sales process effectiveness, administrative efficiency, and sales performance) (cf. Kim and Pae, 2007). A systematic questionnaire was developed in collaboration with sales leadership at the participating organization. Following initial feedback on the design and objectives of the research, several adjustments were made to the question structure to align with the terminology used by the sales team.

Utilizing a pre-test sample identified by sales managers, seventy-two online surveys were distributed to the sales team on the East Coast. All sellers were business-to-business professionals using GenAI tools in their sales process. Sixty-four surveys were completed, yielding a 89% response rate. The sample consisted of 21 female (33%) and 43 male (67%) respondents. The goal of the pre-test was to assess the adapted GenAI technology construct and evaluate the relationships between AI and the dependent variables.

The pre-test measure assessment results (Table 3) show a highly reliable measurement for all scales tested, with Cronbach's α exceeding the minimum levels determined by past research (Nunnally, 1978). All measures' average variance extracted (AVE) exceeded the recommended minimum of 0.5 (Fornell and Larcker, 1981; Gefen and Straub, 2005). The PLS analysis confirmed that the use of GenAI technology was positively correlated with all three variables. The results in Table 3 show that the proposed relationships are theoretically sound.

[Insert Table 2 here]

Main Empirical Study

Survey and Data Collection

An online survey study was conducted to test the hypotheses using a similar approach to the pre-test, but with a larger sample size within the same organization. Sales managers sent the survey via email to their team during their yearly kick-off. As previously mentioned, all sellers within the organization use GenAI technology within their sales process. To improve response rates, sales managers emailed the team about the research project before the kickoff and encouraged them to participate in the survey. The email was followed by a second internal notice within their CRM systems. The company leadership had requested that the technology not be specifically named. Out of 184 responses, 163 passed the quality check question and were deemed usable, resulting in a response rate of 89%. Table 3 presents the demographic characteristics of the respondents.

[Insert Table 3 here]

Main Study Measure Assessment

Exploratory factor analysis revealed high loadings (>0.7) on a single factor, supporting the unidimensionality and construct validity of the model. Table 4 lists each construct with its source and associated items.

[Insert Table 4 here]

Table 5 illustrates the results of reliability and validity tests for our main empirical study, along with the correlation matrix. Cronbach's α met the threshold of .79 (Nunnally, 1978), and AVE calculations exceeded the recommended level of .50 (Fornell and Larcker, 1981; Gefen and Straub, 2005). Based on these analyses, the measurement model indicates acceptable reliability and validity.

[Insert Table 5 here]

To enhance the robustness of our findings, we controlled for several factors that previous research suggests might influence sales outcomes and technology adoption behavior (Ahearne *et al.*, 2008; Hunter and Perreault, 2006). Specifically, we controlled for sales experience and role type. Additionally, we employed best practices to minimize the potential for common method bias (Podsakoff *et al.*, 2003), including ensuring respondent anonymity, separating similar items, and utilizing informed and experienced respondents (MacKenzie and Podsakoff, 2012). Our respondents had an average of over 9.2 years of sales experience, with 82% of our sample having six or more years of experience. Finally, our model includes an interaction variable, which is not impacted by common method bias (Evans, 1985).

Structural Model Testing

After confirming the reliability and validity of the measurement model, the proposed hypotheses were analyzed by employing PLS to calculate weights and explained variance. PLS is an appropriate analytical tool since the research looks at the influence of antecedent variables on

outcomes (Chin and Newsted, 1995). PLS also accommodates smaller sample sizes (Cassel *et al.*, 2000). In Figure 2, the standardized path coefficients (β), the t-value and significance levels, and the explained variance of endogenous variables (R2) are visually represented. The structural model is verified by examining the coefficient of determination (*R2*) values, the effect size of predictor variables (*f2*), predictive relevance (Stone-Geisser *Q2*), and the effect size of path coefficients. To calculate the significance of estimates (t-value), a bootstrap analysis was run using 5000 resamples.

[Insert Figure 2 here]

The analysis of all results is summarized in Table 6. H1 and H2 pertain to two important antecedents of salespeople's GenAI technology use: upper management support and technology self-efficacy. The results indicate that upper management support ($\beta = .579$, $p < .01$) positively correlates with GenAI technology use. Therefore, H1 is supported. However, the relationship between technology self-efficacy ($\beta = .099$, $p < .01$) and GenAI technology use was not significant; H2 was not supported.

Next, we examined the moderating impact of upper management support on the interaction. The results showed that the path coefficient increased ($\beta = .104$, $p < .010$), which was higher than the main effect. We compared the R^2 in the main and interaction effect models to assess the interaction (Chin *et al.*, 2003). The interaction has a higher explanatory power than the main effect model; therefore, hypothesis 2b is supported.

In analyzing the impact of GenAI technology use on performance, we find that it has a significant and positive relationship on all three outcomes: sales process effectiveness ($\beta = .487$, $p < .01$), administrative efficiency ($\beta = .484$, $p < .01$), and sales performance ($\beta = .274$, $p < .01$). Therefore H3, H4, and H5 are all supported. The structural model explains 40% of the variance

for GenAI technology use (R^2 = 0.400), 23.7% for sales process effectiveness (R^2 = 0.227), and 23.4% for administrative efficiency (R^2 = 0.234). Sales performance presented an explained variance of 7.5% (R^2 = 0.075).

[Insert Table 6 here]

Post hoc analysis

The lack of support for H2, technology self-efficacy's direct positive impact on GenAI use, warrants further exploration, as it conflicts with established expectations (Venkatesh and Bala, 2008). To investigate this unexpected finding, we conducted a post hoc moderation analysis, examining upper management support as a potential boundary condition influencing the relationship between technology self-efficacy and GenAI use. While technology self-efficacy alone did not significantly predict GenAI use, its interaction with upper management support approached significance (p = 0.067). Specifically, in contexts where upper management support is low, technology self-efficacy plays a compensatory role, becoming more critical in influencing GenAI adoption. Conversely, in high-support scenarios, salespeople's use of GenAI was consistently high, regardless of their individual technology self-efficacy. This relationship suggests that strong managerial backing may diminish the individual variations in technology self-efficacy, providing broader access and encouragement that uniformly elevate GenAI usage across the sales team.

These results are particularly insightful, given recent calls by scholars (e.g., Goel *et al.*, 2025) for deeper examinations of the interplay between individual and organizational factors in technology adoption within sales. GenAI, characterized by its generative and content-creating capabilities, appears distinct from traditional sales technologies, where individual technological confidence alone has often been sufficient to drive usage. In this case, however, the complexity

and perceived risks associated with GenAI amplify the role of contextual enablers, most notably managerial support, in shaping technology adoption behaviors.

From a managerial perspective, these findings underscore the need for active organizational intervention, particularly through engagement and support. Companies intending to leverage GenAI technologies should prioritize creating organizational environments that foster confidence and minimize barriers to adoption.

Therefore, the lack of support for the direct effect of technology self-efficacy emphasizes an essential shift in understanding technology acceptance in advanced technological contexts, demonstrating that individual efficacy beliefs must be understood within and alongside organizational contingencies to predict adoption behaviors. This new insight contributes to existing theoretical frameworks, emphasizing the evolving complexity of human-technology interactions in modern sales environments.

Discussion

The evolution of sales technology, specifically in the form of Generative AI, has significant implications for research and practice. Our study aims to build and empirically test a conceptual model regarding the use of GenAI in the sales process and its impact on several performance areas. Our evaluation possesses value considering the ongoing evolution of the sales environment. For instance, Moncrief and Marshall (2005) have discussed how the emphasis on relationship selling has modified the sales process to place the client at the center. Catering to the requirements of B2B buyers often necessitates developing customized solutions for individual customers (Chang, 2022). Tailored solutions require significant time investment and a comprehensive understanding of the client, industry, solutions, and other relevant factors. Consequently, there is a growing trend among organizations to adopt sales technology to

enhance their ability to meet customer demands and equip salespeople with innovative tools to handle current challenges (Agnihotri *et al.*, 2023).

Our study on the use of GenAI technology provides insight into the relationships between GenAI technology use and several sales outcomes, including sales process effectiveness, administrative efficiency, and sales performance. We found that sales professionals' use of GenAI technology will positively impact these three areas if the technology is supported by management and their confidence and understanding in using GenAI technology. Contrary to expectations, technology self-efficacy did not significantly impact the use of GenAI technology use. Prior research has consistently emphasized self-efficacy as an influential factor in technology adoption, asserting that individuals confident in their technological abilities are typically more inclined to adopt new technologies (Mathieu *et al*., 2007; Román and Rodriguez, 2015). Our results differ from this pattern, suggesting GenAI is distinct from other sales technologies previously examined in the literature. This warrants a deeper exploration into why GenAI differs from both theoretical and practical perspectives.

GenAI's unique attributes likely contribute to diminishing the traditional impact of self-efficacy observed in other technology adoptions. Unlike earlier forms of sales technology, such as CRM, GenAI represents a significant departure in that it actively generates new content rather than merely analyzing existing data. Consequently, GenAI may be perceived as a technology that requires specialized skills beyond general technological competence, including an understanding of prompts, evaluation of AI outputs, and consideration of ethical implications (Zewe, 2023). This specialized nature could lead to uncertainty or apprehension among users regardless of their previous technological confidence, thereby overshadowing the traditional role of self-efficacy. Additionally, GenAI's inherent complexity may reduce users' confidence in their ability to

master it independently, highlighting the need for structured organizational support rather than individual technological self-confidence. Our findings demonstrate that upper management support significantly moderates the relationship between self-efficacy and GenAI usage, suggesting organizational influences substantially outweigh individual technological beliefs when it comes to GenAI.

This finding may stem from the complexity of GenAI tools, which could overshadow individual confidence without adequate training or managerial guidance. Future research should explore whether training programs or peer influence mitigate this effect.

Implications for Research

Our results highlight the interplay between individual and organizational factors in the use of GenAI. Specifically, we examine how upper management support and technology self-efficacy influence the use of GenAI and its impact on sales performance. Our research makes several contributions to the field of sales and marketing thought.

First, our research contributes to the literature regarding the impact of AI on sales performance. While previous studies have explored the general relationship between AI and performance (Singh *et al.*, 2019; Paschen *et al.*, 2020) and the impact of sales technology on performance (Hunter and Perreault, 2006, 2007; Ahearne *et al.*, 2008), our study is among the first to examine the use of GenAI technology empirically within the sales function. Our research contributes by providing robust empirical evidence that validates GenAI's impact on sales outcomes, thereby highlighting the value of GenAI in terms of its impact on sales effectiveness and administrative efficiency.

Second, our study addresses the research gap concerning the applications and benefits of GenAI technology in the sales domain. While AI adoption in sales is still in its early stages

(McBeth, 2021), our findings suggest significant potential for GenAI technology to improve sales productivity and performance. This finding is especially valuable considering recent research regarding the dynamics of the sales environment. As Hartmann *et al.* (2018) noted, salespeople face an extended sales cycle duration and an expanding number of stakeholders within the decision-making process. Participation of stakeholders in the decision-making process involves an average of 6.8 individuals (Toman *et al.*, 2017). As such, salespeople are undoubtedly seeking methods for greater productivity within the sales process. Our results demonstrate the value of GenAI technology within the sales process and expand our understanding by providing insight into its value, considering the current environment.

Third, the positive and significant result between upper management support and GenAI technology use highlights the critical role of upper management in influencing salespeople's use of GenAI. While management support is acknowledged in prior literature (Rai and Patnayakuni, 1997; Morgan and Inks, 2001), our study clarifies explicitly the moderating role that upper management support plays in amplifying the benefits of technology self-efficacy, particularly for sophisticated technologies like GenAI. This moderation effect provides a new managerial insight into effectively implementing GenAI. This finding contributes to the literature on management support (e.g., Campbell, 1998; Karahanna and Straub, 1999; Morgan and Inks, 2001; Rai and Panayakoni, 1997; Yim *et al.*, 2004) as it shows the value of upper management and their ability to champion the use of GenAI technology.

Our study did not reveal a significant relationship between technology self-efficacy and the use of GenAI technology. Although technology self-efficacy has been considered an essential element in technology adoption (Mathieu *et al.*, 2007; Román and Rodriguez, 2015), it appears to play a lesser role in technologies such as GenAI. This finding provides a unique contribution,

suggesting that upper management support is predominant in the salesforce's use of GenAI technology. Our findings indicate that in scenarios involving GenAI, external organizational encouragement and support might override individual psychological determinants.

Similarly, the significant interaction term comprising technology self-efficacy and upper management support shows that strong upper management support can enhance the impact of individual self-efficacy on technology use. This finding suggests that technology self-efficacy is effectively leveraged when upper management support is present. Given that GenAI's effectiveness heavily depends on the user's understanding of the outputs, rather than merely operating the technology, managers should consider ongoing education that enhances not only technical proficiency but also critical thinking and evaluative skills relevant to AI-generated content. Our study also examined the downstream effects of GenAI technology use on three important sales outcomes (i.e., sales process effectiveness, administrative efficiency, and sales performance). This is a significant contribution, as our literature review revealed a scarcity of empirical studies investigating GenAI.

Managerial Implications

Recent research suggests that 50% of senior executives hesitate to incorporate GenAI technology into their firms (de Bellefonds *et al.*, 2023). McKinsey & Company also found that only 21% of sales organizations have implemented GenAI into their sales process (2024). Our results show that utilizing GenAI technology can substantially benefit the firm's salesforce, including enhancing sales processes and improving sales efficiency. Our research also provides empirical evidence that may reduce executive hesitation or unease in adopting GenAI technology. We also offer some potential managerial opportunities based on our research results.

The positive results of using GenAI technology in all three outcomes of our study show the value of this sales tool. This innovation could be integrated within the sales tech stack to assist salespeople through the sales process and administrative duties. As our manuscript describes, salespeople consistently face considerable demands on their time, which effectively reduces their available selling time. A GenAI technology investment can alleviate administrative responsibilities, increase efficiency, and improve overall sales performance.

The results also demonstrate the value of upper management in utilizing GenAI tools. Our results suggest that it would be wise for managers to understand their impact when using this sales technology tool. For instance, managers may want to demonstrate their use of GenAI sales tools to their teams, whether in team meetings, town hall meetings, or one-on-one mentoring sessions. By doing so, they can share firsthand knowledge of the value they derive from using GenAI tools, demonstrate their willingness to invest time in understanding the value of GenAI tools, and serve as exemplars of its value.

The results suggest managers include GenAI technology in salesperson training, especially during onboarding. This training could teach new sales representatives how GenAI technology could automate many routine tasks, such as email creation and note-taking during meetings. By doing so, the firm would create a foundation for greater sales administrative efficiency from the beginning of the new salesperson's career.

Our results also demonstrate the value of using GenAI technology in sales. Managers could provide additional training at annual sales meetings for more experienced salespeople. The sessions could focus on GenAI demonstrations and share case studies from other salespeople at the firm. The presenters could discuss and demonstrate how GenAI technology has enhanced the effectiveness of the sales process along the customer journey. Salespeople could be challenged to

integrate GenAI technology into the stages of the sales process that provide value to themselves and their customers.

Managers should integrate GenAI tools into sales processes through targeted training programs. For example, onboarding sessions could demonstrate how GenAI automates tasks such as email drafting and meeting preparation, allowing new sales representatives to adopt these tools seamlessly.

Lastly, Generative AI (GenAI) is poised to enhance other sales technology tools, such as social media and CRM systems, by transforming their usage. CRM, for instance, is typically a passive repository of customer data. Combined with GenAI, they evolve into proactive insight engines. They can analyze CRM records to auto-generate personalized emails, summarize client history before meetings, suggest next-best actions, and even draft follow-up messages.

Similarly, social media platforms, already rich with customer sentiment and behavioral signals, become even more powerful when integrated with GenAI. For example, GenAI can generate tailored social content for specific customer segments, summarize real-time engagement metrics, and offer predictive insights based on trend detection. GenAI can be a catalyst that amplifies the value of existing sales force automation tools, signaling a shift from siloed digital tools to intelligent, integrated ecosystems. As such, organizations should not view GenAI as a replacement for existing tools but as a strategic layer that enhances the utility and productivity of their current sales tech stack.

Limitations and Future Research

Our study does have limitations. First, GenAI technology use is a modified construct. Although the results indicate that the variable is highly reliable, a more rigorous assessment is needed for future research. Second, GenAI technology measures performance from the sales

professional's perspective rather than the organization's perspective. Future studies should analyze the impact of GenAI technology use on overall firm performance. Third, the research only focuses on the seller's perspectives on GenAI technology use. Researchers could measure how GenAI technology use impacts buyers' experiences and their perspective on how GenAI is utilized in the process.

We used TAM (Davis, 1989; Venkatesh and Bala, 2008) as the theoretical foundation informing our study. Other theoretical models exist, including the UTAUT (Venkatesh *et al.*, 2003). Researchers have identified pros and cons associated with both theoretical frameworks (see, for example, Kelly *et al.*, 2023; Schorr, 2023). Still, AI research has leaned toward TAM (Kelly *et al*. 2023). Future research should examine the pros and cons of these alternative models, as well as other models that hold promise for GenAI research.

Another limitation is our focus on one industry. Future studies involving multiple organizations representing different industries can yield compelling results on each firm's use of GenAI. Finally, the last limitation relates to the study's empirical design. While the results show a positive effect of GenAI technology use in sales, inferences regarding causality should be made with caution. Future research could investigate the impact of GenAI on buyer satisfaction, specifically examining how personalized content creation influences decision-making. Longitudinal studies could also assess how GenAI adoption evolves, particularly as sales professionals become more familiar with the technology.

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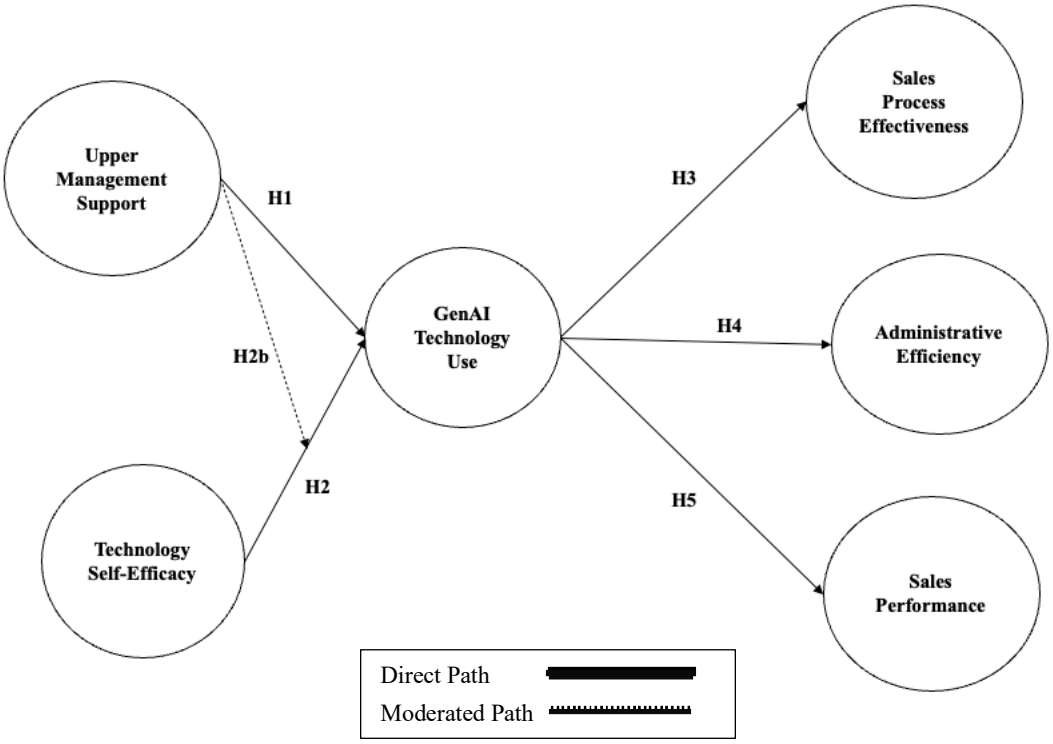
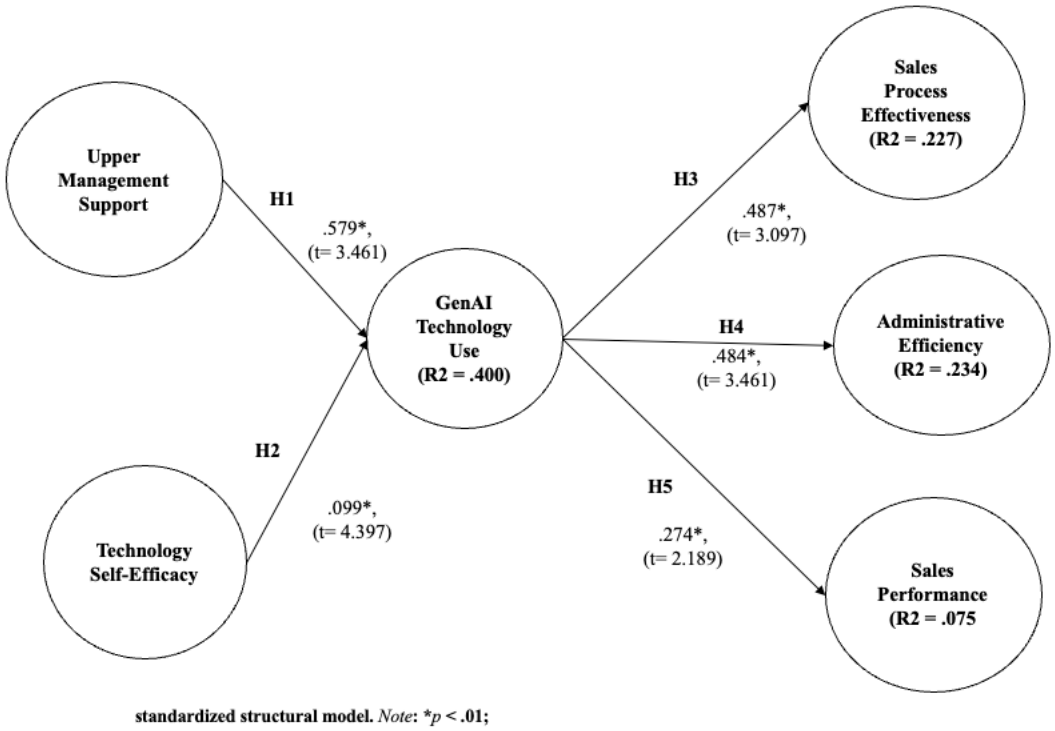
Figure 1. Conceptual Model



Source: Authors' own work

Figure 2. Empirical Results



standardized structural model. *Note*: ***$p < .01$;**

Source: Authors' own work

Table 1. Key differences between AI and GenAI

Dimension	Traditional AI	Generative AI (GenAI)
Objective	Automates decision-making, classification, and prediction based on input data	Generates new data outputs based on learned data patterns
Examples of Output	Product recommendations, fraud detection, customer segmentation	Chat responses, personalized emails, images, sales scripts
Training Approach	Supervised learning with labeled datasets	Unsupervised/semi-supervised learning, transformer-based models
Key Technologies	Decision trees, support vector machines, random forest	GPT (text), DALL·E (images), StyleGAN (videos/images), MusicLM (audio)
Use in Sales	Lead scoring, pipeline forecasting, churn prediction	Drafting emails, call summaries, proposal generation, product content generation
Data Dependency	Requires historical labeled data for training	Learns from vast data corpora to create contextually relevant new outputs
Nature of Tasks	Analytical (understanding and predicting)	Creative (producing and generating)
Human-like Interaction	Limited interactivity, relies on predefined rules and logic	Capable of dynamic, human-like dialogue and content creation

Source: Adapted from Zewe (2023), Marr (2023), Huang and Rust (2024), and IBM Institute for Business Value (2023).

Table 2. Pre-test Scale Reliability, Validity, and Path Coefficients

Variable	α	Composite Reliability	AVE
GenAI use	0.878	0.878	0.749
Sales process effectiveness	0.873	0.920	0.749
Administrative efficiency	0.747	0.795	0.578
Sales performance	0.771	0.778	0.537

Relationship	Path Coefficient
GenAI use → Administrative efficiency	.578*
GenAI use → Sales process effectiveness	.613*
GenAI use → Sales performance	.406*

Source: Authors' own work

Table 3. Respondent Demographic Characteristics

Factors	Category	Percentage %
Sex	Male	63%
	Female	35%
	Do not want to self-identify	2%
Years of Sales Experience	1 - 5	17%
	6 - 10	19%
	11 - 15	21%
	More than 15	42%
Sales Role	Sales Development Representative	30%
	VP/Sales Manager	15%
	Account Executive/Account Manager	44%
	Technical Sales/Engineer	11%

Source: Authors' own work

Table 4. Constructs and Items

Construct	Source	Items
GenAI technology use	Eggert and Serdaroglu (2011)	• I use GenAI to improve the quality of my sales process. • I use GenAI to creatively serve my customers. • I use GenAI to identify the most important customers from a list of potential customers. • I use GenAI to plan selling activities. • I use GenAI to prepare sales calls.
Upper management support	Schillewaert *et al*. (2005)	• I am continuously encouraged by my immediate supervisor to use our technology tool in my job. • My supervisor supports my use of our sales technology. • My supervisor believes in the benefits of our sales technology.
Technology self-efficacy	Brinkerhoff (2006)	• I am very confident in my abilities to use technology. • I can usually deal with most difficulties I encounter when using technology. • Using technology is something I enjoy.
Sales process effectiveness	Stoddard *et al*. (2006)	• Compared to my peers, I have higher closing rates. • Compared to my peers, I have higher customer retention. • Compared to my peers, I am able to analyze wins and losses.
Administrative efficiency	Hunter (1999)	• Getting the required paperwork done. • Submitting required reports on time. • Addressing my responsibilities promptly.
Salesperson performance	Avlonitis and Panagopoulos (2005)	• Generating sales volume. • Increasing market share. • New account development. • Servicing existing customers.

Source: Authors' own work

Table 5. Empirical Study: Reliability, Validity, and Correlation Matrix

Variables	1	2	3	4	5	6
1. Administrative efficiency	**0.702**					
2. GenAI use	0.484	**.721**				
3. Sales performance	0.260	0.274	**.741**			
4. Sales process effectiveness	0.501	0.487	0.246	**.714**		
5. Technology self-efficacy	0.402	0.374	0.212	0.622	**.768**	
6. Upper management support	0.642	0.626	0.343	0.615	0.475	**.793**
Cronbach's α	.858	.844	.864	.808	.826	.817
Composite reliability	.793	.881	.894	.862	.877	.868
AVE	.593	.52	.548	.51	.59	.524

Source: Authors' own work

Table 6: Path Coefficient Summary and Hypotheses Test Results

Structural Path	Path Coefficients	t-value	Results
H1: Upper management support → GenAI use	.579	3.461	Supported
H2: Technology self-efficacy → GenAI use	.099	4.397	Not Supported
H3: GenAI use → Sales process effectiveness	.487	3.097	Supported
H4: GenAI use → Administrative efficiency	.484	2.580	Supported
H5: GenAI use → Sales performance	.274	2.189	Supported

H2b: Moderation of Upper Management Support			Results
Model	**Path Coefficients**	**R^2**	
Main effect model	.099	.400	
Interaction effect model	.104	.510	Supported

Source: Authors' own work