How Generative AI impacts B2B-Sales and Content Creation

Luca Braun luca.braun@fom-net.de
FOM University of Applied Science for Economics and Management Essen
Germany István Széchenyi Economics and Management Doctoral School,
University of Sopron
Sopron, Hungary

Corresponding Author: Luca Braun

Abstract

Sales processes that involve the customer can be a major time sink and a source of drag on efficiency and quality. This research focuses on specific areas of the sales process, from research and discovery meetings to the creation of sales-related materials. It explores the areas where the sales process creates loss and where gains can be made using generative AI (GenAI). The research follows a mixed-methods approach and includes the following: (i) a targeted literature review to contextualize the use of AI in sales process management, (ii) a survey across different sales roles in the international IT industry, and (iii) a pilot experiment on the application of GenAI for the creation of a presentation and other sales-related materials. The research integrates the different approaches and creates a simple model for prioritization. Although the research was conducted in the IT industry, the activities are similar across other industries and can be applied universally.

Keywords: Generative artificial intelligence, Knowledge management, Content creation, Personalization, B2B, Sales.

1. INTRODUCTION

However, in modern digital commerce, marketing and sales processes have become more and more knowledge-intensive and, at the same time, fragmented and dispersed over disparate information systems. This leads to increased search costs and delays in searching relevant information [1]. The search process in modern organizations relies largely on the historical and contextual knowledge accumulated during previous tasks and projects, which is difficult to capture in traditional indexing models [1]. Documentation in Customer Relationship Management (CRM) systems is another area that contributes to organizational waste in terms of time. Nevertheless, when embedded in the workflow, e.g., in the form of mobile CRM, collaboration and sales performance improve, suggesting that alignment with the process and a low administrative burden are key factors [2].

The second category of commercial knowledge work involves the creation of customer-facing artefacts, including presentations, briefs, and emails. Marketing research has predicted that Generative AI (GenAI) has the potential to revolutionize content creation and customer engagement in the near

Citation: Luca Braun. How Generative AI impacts B2B-Sales and Content Creation. **Advances in Artificial Intelligence and Machine Learning**. 2026. (Ahead of Print). https://dx.doi.org/10.54364/AAIML.2026.62298

future [3, 4]. Experimental and field studies have validated the productivity benefits of GenAI in structured knowledge work. For instance, in customer support, GenAI has been shown to increase throughput by approximately 15% [5]. Similarly, in a study conducted in the field, GenAI has been shown to help professionals complete writing tasks 40% faster with higher quality in the first pass [6]. Process management literature has generalized these findings at the task level to propose the integration of foundation models and process knowledge, including the new concept of Large Process Models [7, 8]. However, it must be noted that these benefits do not apply evenly to GenAI or digital sales technologies as a whole. Rather, their applicability is highly dependent on task characteristics and contextual appropriateness. Contemporary research on contingency theory has highlighted the importance of identifying specific time and quality bottlenecks before engaging in automation technologies, as indiscriminate adoption may not necessarily yield performance benefits [9]. The research presented here addresses three pain points that are most commonly cited by practitioners of sales and marketing functions. These pain points are related to slow and context-dependent internal search processes that undermine timely response capabilities [1], time-consuming documentation processes that utilize customer relationship management tools and result in poor quality when these processes are not contextual to actual business processes [2], and time-consuming content generation processes that GenAI can help alleviate, provided that the underlying knowledge is accurate and accessible to practitioners [3, 4, 10].

Knowledge-intensive B2B sales environments are increasingly faced with the challenge of having to improve internal processes while also providing sales teams with improved capabilities to operate efficiently throughout the sales cycle. Inconsistent documentation processes, fragmented information systems, and limited reuse of institutional knowledge are all factors that undermine time management and increase inefficiency in critical processes such as research, customer relationship management documentation, and content generation. The research presented here addresses these pain points by seeking to achieve three interrelated research objectives. The first research objective involves providing insight into where time and inefficiency are most concentrated during knowledge work processes, thereby providing empirical evidence on time and inefficiency during critical processes (Objective 1). The second research objective involves providing quantification on perceived task-level automatability and GenAI benefits, which can be used to establish a prioritization framework (Objective 2). Third, it validates the viability and performance impact of knowledge-grounded AI assistance via prompts using a within-subject pilot design with three exemplary sales-related tasks: (a) linking customer anecdotes to CRM fields, (b) retrieving reference stories and slides from a predefined content repository, and (c) designing customer-specific presentation decks (Objective 3).

The current work's contribution is threefold: (i) an empirically informed hotspot map of time and process drag in sales roles and activities, (ii) a task-level prioritization model based on normalized assessments of time burden, friction, and perceived suitability of AI, and (iii) a knowledge asset pattern that combines prompt-based generation with contextual delivery, which is aligned with current BPM research on AI-enhanced lifecycle models [7, 8] and marketing studies on the potential of GenAI in facilitating personalized content creation and customer engagement at scale [3, 4].

To guide the empirical investigation, the study addresses the following research questions:

- RQ1: Where do time and perceived process drag concentrate across sales-cycle stages and roles (e.g., account research, discovery documentation, preparation of customer-facing materials)?
- RQ2: To what extent does knowledge-grounded, prompt-based generation reduce task time and improve first-pass quality for common artefacts (e.g., CRM entries, personalized materials)?
- RQ3: Under which boundary conditions (e.g., role, task type, data availability, governance maturity) do these effects materialize or vary?

While the empirical evidence is drawn from the international IT sector, the conceptual framework and observed effects are intended to generalize across B2B sales contexts with comparable process structures and content demands.

2. THEORETICAL BACKGROUND AND RESEARCH POSITIONING

Generative Artificial Intelligence (GenAI) is viewed as having a transformative impact on marketing and sales processes. The current marketing and sales process literature argues that GenAI changes the process of knowledge creation in the context of value creation for all business processes [3]. While GenAI systems have been used for automating tasks, it is now seen as having an impact on the process of strategic communication and information creation. At the same time, innovation and governance studies highlight the need for GenAI outputs to be included in organizational capabilities and governance systems for it to be viewed as knowledge, as opposed to content pieces or information fragments [4, 11]. The BPM literature focuses on process augmentation, as opposed to tool augmentation. The phenomenon of "AI Drifts" indicates the interrelatedness of these constructs, especially when it comes to augmented systems and processes. The emerging concept of Large Process Models indicates the integration of foundation models and process knowledge for context-aware and adaptive support in business processes. The overall body of literature indicates that GenAI must be viewed as an integral component within end-to-end business processes, as opposed to standalone systems.

These literature streams are of great significance for marketing and sales organizations where knowledge-based activities like content development, internal search processes, and CRM documentation are major business processes. Research has pointed out that search processes are major business processes in enterprise search systems; however, these processes are dependent on knowledge and context. Fragmented knowledge repositories result in increased search times and re-works for users [1]. CRM documentation is another major business process for sales teams; however, these processes are known to take up significant time for sales teams. Research has pointed out that when these processes are integrated with in-process workflows like mobile CRM systems, these processes result in increased collaborative effectiveness [2].

In terms of digital sales technology literature, research has pointed out that performance effects are dependent on context variables like types of tasks, types of offers being made, and sales stages [9]. Thus, GenAI augmentation is not expected to have uniform effects on different business processes and users.

2.1 Empirical Evidence on GenAI Productivity Effects

However, existing empirical research has shown significant productivity benefits from GenAI in structured knowledge activities. GenAI has been shown to be capable of creating emails, proposals, presentations, and briefs, all of which are significant to marketing and sales activities [3]. Productivity has been shown to increase by 14-15% in customer support settings, with more significant benefits for less experienced employees [5]. Experiments conducted to investigate GenAI in professional writing activities have shown significant benefits in reducing completion times and enhancing first-pass quality for well-structured assignments with pertinent input sources [6]. However, these studies are conducted in a narrow task environment. There is no quantification of time concentration for activities in commercial settings, nor is there any integration of GenAI in multi-stage sales processes such as CRM document production and knowledge retrieval. To synthesize the current state of research, TABLE 1 presents an overview of the principal streams of academic research pertinent to GenAI in marketing and sales.

Table 1: Principal streams of academic research pertinent to GenAI in marketing and sales

Research Stream	**Core Contribution**	**Empirical Basis**	Identified Limitation
Marketing & Innovation [3, 4, 11]	GenAI reshapes content creation and customer engagement; governance is critical	Conceptual and case-based	Limited activity-level quantification
BPM & AI Augmentation [7, 8]	Process-aware integration; AI drifts; Large Process Models	Conceptual frameworks	No empirical sales-task validation
Enterprise Search & CRM [1, 2]	Contextual knowledge and embedded CRM reduce friction	Field studies	Not linked to GenAI artefact generation
Digital Sales Contingency [9]	Performance effects depend on task and role context	Large-scale quantitative	No focus on GenAI
GenAI Productivity Studies [5, 6]	Time reduction and quality gains in structured tasks	Field and experimental	Not embedded in sales-cycle workflows

The literature therefore provides strong conceptual foundations and initial empirical evidence yet remains fragmented across theoretical and empirical domains.

2.2 Proactivity and Contextual Alignment

Empirical research into context-aware recommendation systems has shown that the inclusion of contextual features such as “task type,” “urgency,” and “user role” has a substantial impact on relevance and performance outcomes [12]. Proactive information delivery mechanisms within mobile and rule-based systems have also been shown to reinforce the importance of timely and appropriate support based on user role [13].

Similarly, research into BPM has reinforced the need for digital assistants to intervene at the execution rather than the completion of tasks [8]. Conversely, research into digital sales has shown that technological interventions need to be "consonant with the context" of the task in order for performance gains to be observed [9], which implies that the performance outcomes of GenAI are likely to be subject to a range of factors such as "user role," "task complexity," and "data availability". TABLE 2 summarizes the empirical research regarding the impact on GenAI and productivity outcomes.

Table 2: Empirical research in the context of GenAI and its impact on productivity

Study Context	**Reported Effects**	**Boundary Conditions**	**Transferability to Sales**
Customer Support Field Study [5]	$+14-15\%$ productivity	Structured environment	Limited complexity
Professional Writing Experiment [6]	~40% time reduction; ~18% quality increase	Structured, grounded tasks	Not multi-stage sales tasks
Governance & Capability Research [4, 11]	Emphasis on accountability	Organizational readiness required	No task-level measurement

While the evidence confirms that GenAI can enhance structured knowledge work, systematic evaluation within integrated commercial workflows remains limited.

2.3 Identified Research Gap

Collectively, these studies show that GenAI has the potential to improve knowledge-intensive work processes and that its effectiveness is dependent on context and governance structures. Nevertheless, there are still three major gaps in GenAI studies. Firstly, little development has been made in activity-level quantification of time concentration and perceived process friction in sales activities. Secondly, GenAI studies conducted through experiments rarely investigate knowledge-grounded artefact generation in customer relationship management (CRM) and retrieval processes. Thirdly, although contingency theory predicts GenAI effectiveness in different roles and tasks, empirical studies of these factors in business processes are still limited.

In addressing these gaps in knowledge, this study proposes an integrated approach that combines a cross-role survey and a pilot experiment design. Research Question 1 is addressed through a survey aimed at identifying time and friction hotspots in sales activities. Research Questions 2 and 3 are addressed through a pilot study aimed at evaluating knowledge-grounded GenAI assistance in CRM documentation processes and asset retrieval and presentation development processes.

The study aims to bridge these gaps in knowledge and provide empirical support for GenAI integration in business-to-business (B2B) sales processes.

3. RESEARCH DESIGN AND METHODOLOGY

3.1 Context of the Pilot Experiment

In this study, the focus is on B2B sales in the global IT domain. In traditional work flows, a mainstream customer relationship management system, as well as traditional office software, is used. In such a setting, meeting notes and discovery phase results are documented in the CRM, while customer-facing content, such as briefs and decks, is produced as needed from disparate sources. This represents the traditional frictions associated with search systems, in which the application of past and present knowledge is critical, and fragmentation entails a greater time investment. While CRMs take time, the integration into the existing workflow promises benefits in terms of collaborative and performance benefits, as described in the literature. Recent research in business process management and marketing suggests the potential for generative AI tools as content creation tools, especially when used within a process-aware environment as opposed to standalone tools, as described in the literature [3, 4, 7, 8]. Research suggests that such tools have the potential for efficiency and quality benefits for knowledge work in general, as described in the literature [5, 6]. However, benefits for sales teams depend on various factors, such as role, task, and structure, as described in the literature [9]. The current pilot study explores a simple augmentation strategy based on knowledge groundings, focusing on the most critical sales tasks, such as CRM field mapping, asset retrieval, and the creation of presentation materials, with and without AI.

3.2 Overview of Empirical Components

The study has three parts: literature review, cross-role survey, and within-subject pilot experiment. For the literature review, the study made use of the Scopus and Web of Science databases to collect peer-reviewed articles published between 2019 and 2025. The articles were about generative AI, sales, business process management (BPM), customer relationship management (CRM), and enterprise search. After the appropriate procedures, relevant and recent articles were obtained [1–9, 11–13].

For the cross-role survey, the study involved four roles in sales: Account Executives, Solution Sellers, Sales Engineers, and Sales Development Representatives (SDRs). The participants were asked to assess the importance of ten common sales activities in three aspects: time share, process drag, and perceived automatability. Each of the aspects was evaluated with a seven-point Likert scale. The responses were randomized with an attention check. There were about 70 participants in the study. Informed consent was obtained.

For the pilot experiment, the study involved 18 participants with the same roles as the study above. Each of the participants had at least six months of work experience. Each of the participants was

asked to complete three tasks: CRM entry, retrieval, and presentation. Each of the tasks was done with and without the support of GenAI. In the case of the use of GenAI, the participants were asked to complete the three tasks with the use of the following tools:

- In the GenAI condition, CRM entries were supported via voice summaries, retrieval via Atlassian Rovo, and presentations via Gamma.

3.3 Measurement Instruments and Analysis Approach

For survey-based prioritisation, we computed an activity-level opportunity score combining time share, process drag, and perceived automatability. For each respondent r and activity a, each dimension $x_{r,a}$ was min–max normalised across the ten activities: $x'_{r,a} = (x_{r,a} - \min_a x_{r,a})/(\max_a x_{r,a} - \min_a x_{r,a})$. The opportunity score was then defined as $\mathrm{OS}_{r,a} = \mathrm{Time}'_{r,a} \times \mathrm{Drag}'_{r,a} \times \mathrm{Auto}'_{r,a}$; activity scores were averaged across respondents to rank target activities. This multiplicative form prioritises activities that are simultaneously time-intensive, high-drag, and perceived as automatable, consistent with contingency-oriented targeting in digital sales technology research [9]. For the pilot, the measurement strategies included:

Task duration in terms of minutes. First-pass quality was also included, which was measured using a 7-point scale. Completeness was conceptually included but not analyzed owing to data inconsistency. The participants performed all the tasks under both conditions. Δ time and Δ quality were analyzed using a paired t-test. Normality was checked using the Shapiro-Wilk test. Additionally, the Wilcoxon test was conducted to ensure robustness. Visualization was performed to understand the results. Subgroup analyses of the role-specific effects were carried out via ANOVA or Kruskal-Wallis tests, respectively. While these analyses are exploratory in nature, they offer directionally relevant insights into the areas in which GenAI is likely to have its most significant effect. Planned but unused moderator constructs for RQ3 comprised a six-item data availability index (e.g., accessibility, findability, timeliness, reusability) and a governance maturity index (e.g., approved tools, permissions, review protocols). Both were conceptualised as composite means intended for interaction analyses in future work [17, 18] but were not used here due to the absence of respondent-level linkage between survey and pilot data. All study participants provided informed consent to participate in the study. One task time outlier, due to technical issues, was winsorised at 3 standard deviations.

Consistent with the principles of exploratory research, the findings emphasize effect sizes, confidence intervals, and task/role effects over statistical significance. The dual-method approach allows for prioritization of knowledge-grounded GenAI support in digital sales, as well as its testability, via the pilot study approach.

4. RESULTS

4.1 Outcomes of RQ1

Mixed effects analysis of variance (between/within: Role x Activity) reveals that the distribution of perceived time share and process drag in the sales process is not uniform, with some stages and roles experiencing significantly more drag than others. Two stages in the sales process, Offer Design (Proposal/Quote) and Sales Governance (Forecasting), are the main hotspots for process drag, where the effects of role are particularly pronounced. For these stages, both Account Executives and

Solution Sellers experienced significantly more drag than Solution Engineers/Pre-Sales, while all roles reported high levels of perceived automatability. This analysis is further supported by robust results from the ART ANOVA analysis, as described below.

4.1.1 Data foundation and operationalization

N = 75 B2B sales professionals participated in the study: 16 Account Executives (AE), 22 Solution Sellers (SS), 27 Solution Engineers/Pre-Sales (SE), and 10 Sales Development Representatives (SDR). Ten sales process activities were included in the analysis: Lead Research, Outbound, Discovery, CRM/Documentation, Proposal, Quote, Follow-up, Forecasting, Preparation, and Customer-facing. Each activity was operationalized using three 7-point Likert-type scales: Perceived Time Share, Perceived Process Drag, and Perceived Automatability (10 items per scale, aggregated to the scale means).

4.1.2 Measurement quality and descriptive role means

Scale reliabilities were acceptable to good: Automatability $\alpha = .68$ (standardised $\alpha = .71$, 95% CI [.56, .78], average inter-item $r = .20$), Process Drag $\alpha = .82$ (standardised $\alpha = .79$, 95% CI [.75, .87], $r = .28$), and Time Share $\alpha = .76$ (standardised $\alpha = .69$, 95% CI [.67, .83], $r = .18$). TABLE 3 reports the means (M) and standard deviations (SD) for the role-specific scale scores.

Table 3: Role means (M) and SD (1–7 scale) for Automatability, Process Drag, and Time Share (N per role).

Role	**N**	**Automatability M (SD)**	**Process Drag M (SD)**	**Time Share M (SD)**
Account Executive	16	6.13 (0.324)	5.22 (0.647)	5.19 (0.343)
Solution Seller	22	5.97 (0.358)	5.30 (0.567)	5.20 (0.564)
Solution Engineer/Pre-Sales	27	5.61 (0.311)	3.99 (0.644)	3.95 (0.429)
Sales Development Rep	10	5.92 (0.471)	5.42 (0.651)	5.21 (0.586)
Overall	75	5.87 (0.401)	4.83 (0.883)	4.75 (0.764)

Solution Engineers/Pre-Sales showed significantly lower drag and time share relative to the other roles. All roles showed high levels of automatability (around 5.6 to 6.1 out of 7).

The second research question centered on the effect of GenAI support on task performance, including the time taken to complete the task and the quality of the work done. In the experiment, the participants were required to perform representative work tasks. These tasks were done twice: once without the support of GenAI and once with the support of GenAI. We recorded the time taken to complete the tasks. Additionally, we evaluated the quality of the work done without any revisions. FIGURE 1 illustrates the performance differences between the two conditions of the experiment with respect to a specific task.

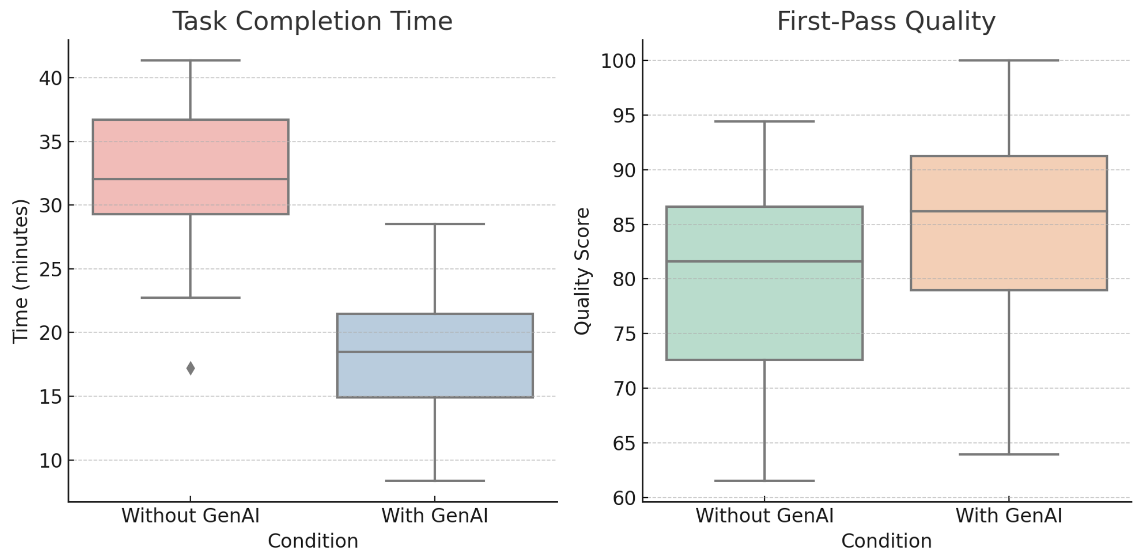

Figure 1: Comparison of task performance with and without GenAI support. The left panel shows a boxplot of task completion times (in minutes), and the right panel shows a boxplot of first-pass quality scores (on a 0–100 scale). Each pair of distributions reflects the same participants (paired) completing the task manually versus with AI assistance. Lower times and higher quality scores indicate better performance.

As illustrated above in FIGURE 1, the time taken to complete the task was significantly less when the participants were aided by the support of GenAI. When the participants were not aided by the support of GenAI, the time taken to complete the task varied widely. In most cases, the time taken was between 25 and 40 minutes. However, the median time taken was about 30 minutes. In contrast, the time taken was less when the participants were aided by the support of GenAI. In most cases, the time taken was between 15 and 22 minutes. However, the median time taken was about 18 minutes. This indicates that the support of GenAI resulted in a significant reduction in the time taken to complete the task. This reduction was statistically significant since the t-test showed that the reduction was significant at approximately $t \sim 9.50$ and $p < 0.0001$. In addition, the effect size of the improvement was very large with a value of Cohen's $d \sim 1.7$. This indicates that the support of GenAI resulted in a consistent improvement in the time taken to complete the task. In all cases, the time taken with the support of GenAI was less than the time taken without the support of GenAI. In most cases, the time taken with the support of GenAI was less than the median time taken without the support of GenAI.

Besides the speed benefit, the participants also achieved better quality in the first pass with the help of GenAI. The right side of FIGURE 1, illustrates the range of quality without GenAI assistance ranging from 60 to 85 with a median at 80, while the quality with GenAI assistance ranges from 70 to 95 with a median in the mid-80s. The assisted condition not only increased the quality with a higher mean value (around 85 with GenAI and around 80 without GenAI) but also reduced the number of low-quality results. The quality improvement was also statistically significant according to the results of the paired t-test carried out on the data (t ~ -6.46, $p < 0.001$). Although the improvement in the quality is not very high (around 5 on the 100-point quality metric), it is consistent across all the participants (Cohen's d ~1.2), which is a very high value indeed. This means the quality of the first pass with the help of AI is already close to the overall quality with the help of GenAI. The overall trends of the results indicate that the majority of the participants have benefited from the GenAI condition with either an improvement in quality or comparable quality to the results of the manual condition. Only a few results showed no improvement or a slight decrease in quality when GenAI is used. This is mostly because of minor errors in the GenAI results that the participants were not able to detect during the first pass. The results clearly indicate the benefits of using GenAI assistance: faster completion of the task with no decrease in quality and an improvement in the quality of the first pass itself.

The third research question was about how GenAI support effects vary by task type and participant role, and whether performance gains are robust. We delved deeper into the results by breaking down performance improvements in different task scenarios. We also looked at whether participant roles affected GenAI support effects. FIGURE 2 shows the variation in the effects of AI on performance for three representative task types in the experiment. Below is a summary of the results in relation to task types and participant roles.

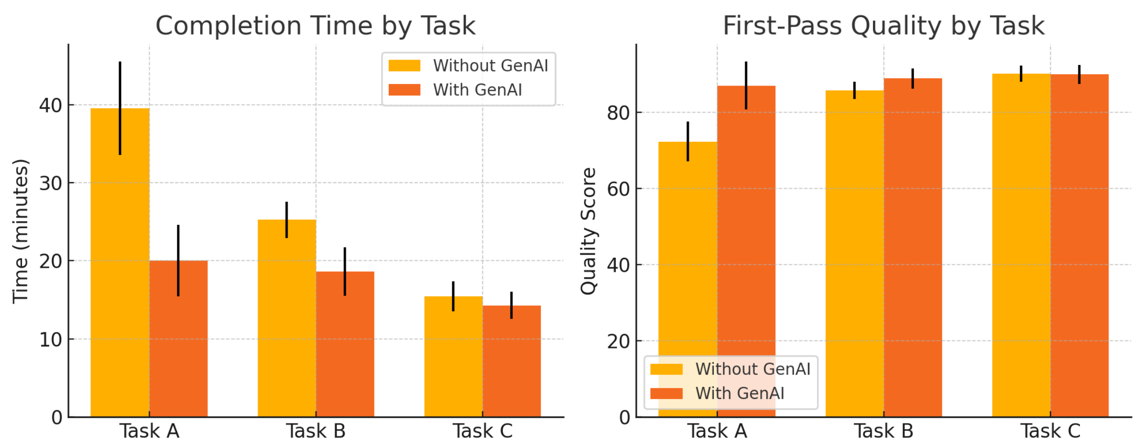

Figure 2: GenAI performance impact by task type. Left: Mean completion time (minutes) for three tasks of varying complexity, with and without GenAI. Right: Mean first-pass quality scores for the same tasks, with error bars indicating ±1 SD. Task A focused on creating a tailored, customer-specific presentation deck. Task B consisted of using customer insights to identify and retrieve internally available information assets, such as presentations, reference stories, or materials with a similar thematic focus. Task C involved extracting insights from a discovery vignette and completing the relevant CRM fields. The benefits of GenAI assistance, measured in terms of time reduction and quality improvement, were substantially larger for Task A than for Task C, illustrating that the impact of AI varies markedly with task characteristics.

As depicted in FIGURE 2, the effect of GenAI assistance differed significantly across task types. For Task A (tailored presentation development), the longest completion times under manual conditions were recorded alongside the lowest first-pass quality scores, reflecting the task's synthesis and narrative demands. GenAI assistance reduced completion time substantially and increased output quality into the mid-80s (approximately +15 points). Task C (discovery-to-CRM documentation) showed the smallest incremental benefit from GenAI, consistent with its more constrained and rule-based structure; both time savings and quality gains were comparatively modest. Task B (asset retrieval) exhibited intermediate effects, with GenAI reducing completion time by approximately one quarter and improving first-pass quality slightly (approximately +3 points). Overall, the pattern supports the interpretation that GenAI creates the greatest performance uplift in synthesis-intensive artefact generation, while gains are attenuated for already structured documentation tasks.

Notably, these enhancements (or lack thereof) were consistent across the various participant role groups. Our results did not indicate a significant interaction between Role and AI Condition with respect to completion time or quality outcomes, i.e., there were no notable differences in the effectiveness of the AI tool between role groups, such as between managers and support staff. For example, similar proportional benefits in terms of time saved were observed between junior support staff and senior account managers on Task A completion time, although the actual task completion time differed between the two groups. The results indicate that the benefits of the GenAI tool are not limited to any specific subgroup of users, including those who are more experienced or have more expertise in the domain. We also noted a role-related difference in how the AI tool was utilized by the participants (qualitatively, managers tended to use the AI tool more for text creation, whereas analysts used it more for brainstorming ideas), although these differences did not result in role-related differences in the outcomes.

Lastly, the boundary conditions that are relevant to the GenAI support are considered. The availability of data, for instance, was a condition that affected the GenAI's utility. Specifically, tasks that necessitated the availability of specific internal data, such as information about clients or proprietary data such as figures, had limited GenAI utility in the event that such data was not made available to the GenAI. Indeed, in the experiment, the participants occasionally had to contend with such limitations, such as in the analytical task, whereby the GenAI's utility was limited to the availability of real business data. As such, in the event that the data was not available or was considered sensitive to the extent that it could not be shared with the GenAI, the participants had to work manually. Indeed, in the experiment, the participants were subjected to strict conditions that affected the GenAI's utility, whereby in the event that the GenAI was fed certain data, the output of the GenAI was considered to be of little utility. As such, the GenAI's utility was limited to the availability of data. Additionally, tasks that necessitated the GenAI to have specific expertise in the specific domain, such as tasks that had to adhere to specific regulations, had limited GenAI utility. Indeed, in the experiment, the GenAI's utility was limited in the event that the GenAI was not considered to have the requisite expertise in the specific domain. As such, the GenAI utility was limited to the availability of data. However, despite the limitations, the GenAI's utility was consistent in all the roles and task scenarios.

In addition to the main research question, the data collected revealed a number of interesting associations that add to the general understanding of the findings. A high positive correlation was found between the degree of 'drag' associated with a task or activity and its perceived automatability. Essentially, tasks that are highly tedious or 'drag' on an individual are those that are perceived to be highly automatable. Quantitatively, a significant correlation was found across the range of tasks surveyed. More specifically, a high positive correlation was found to exist between the mean drag rating of tasks and the mean automatability rating of tasks. This indicates that individuals are looking to automate tasks that are most burdensome or 'drag' on their productivity, which is in alignment with the high-drag tasks being targeted for GenAI or other forms of automation. A certain degree of alignment was found to exist between tasks that are burdensome in nature, as observed in RQ1, and those tasks that have observed the greatest gains in performance using AI in RQ2. More specifically, the greatest time savings were observed in Task A, which was also rated as being burdensome in nature. Conversely, Task C was not observed to be a 'pain point' in the survey, yet it was not observed to have a high degree of improvement using AI. A scatter plot of the average drag rating of each task vs. the average time reduction observed in each task using AI was conducted. A high positive correlation was observed to exist, indicating that tasks that are more 'drag-prone' are those tasks in which the greatest efficiency gains are observed. While the range of tasks was small, it was observed that GenAI was able to identify those tasks in which employees are looking to improve their processes.

To summarize, the findings show that the current process pain points are significant but manageable, that there are a few key processes that, being low-level administrative in nature, take up disproportionate time and energy, and that these processes represent exactly the area in which significant improvement is possible with the help of automation tools like GenAI. The experiment showed that there is significant, robust benefit to be had from GenAI assistance in general, that the maximum benefit is to be had in complex, tedious processes, and that there is consistency across user types given the right conditions. This chapter, therefore, provides evidence to support the implementation of GenAI to help address known pain points, while also showing the need to ensure that there is adequate data access and policy in place to ensure that the full potential of the GenAI is being utilized.

5. DISCUSSION AND PRACTICAL IMPLICATIONS

Based on the integrated results of the survey and pilot study, there appears to be evidence that the application of generative AI (GenAI) provides real-world value within sales processes when focused on tasks that have high levels of time expenditure, high levels of perceived process inefficiencies, and high levels of automatability. In particular, the survey results indicate that governance and documentation-related tasks appear to have high levels of inefficiencies, and there exists a positive correlation between perceptions of automatability and inefficiencies. Moreover, the results of the pilot study confirm the findings of the survey, showing that knowledge-based and prompt-based support can significantly reduce time spent and improve first-pass quality. Further, task-level results show that the amount of improvement is related to the amount of synthesis and storytelling required in the task, where customized presentation development (Task A) showed the highest levels of improvement, asset retrieval (Task B) showed intermediate levels of improvement, and discovery to CRM documentation (Task C) showed the lowest levels of improvement.

With respect to organizational implementation, the results suggest the following with respect to staged implementation: First, activity-level data should be measured to establish baseline levels of time share, process inefficiency, and perceived automatability to establish a small set of "hotspots" that are empirically valid. Second, the opportunity score framework provides a way to stage intervention activities based on activities that score well on dimensions of time intensity, process inefficiency, and perceived automatability. Third, knowledge-grounded design patterns should be followed to ensure that discovery and account context are well-supported, the assistant is integrated with approved internal sources to support information retrieval, and generation is constrained through role- and task-specific prompt scaffolding and review points. Fourth, governance maturity should be operationally defined through controls such as approved tool environments, rules around data handling, human review of customer-facing artifacts, and quality gates so that speed does not come at the cost of compliance and trust.

With respect to limitations of the research, minor revisions to the pilot sample were not designed to test moderation effects but were instead designed to support estimates of effect size. Future research should seek to balance task order effects, use multiple raters to quantify inter-rater reliability, and relate survey-based measures of readiness (data availability, governance maturity) to task-level deltas to more conclusively establish boundary conditions.

6. CONCLUSION

This paper fills a particular niche in the developing literature on Gen AI in commercial environments by bringing together quantification of knowledge-intensive sales activities at the activity level with experimental results on their impact on sales performance in integrated sales environments. Prior productivity results on writing and support activities have rarely been connected to multi-step B2B sales pipelines, cross-role heterogeneity, or CRM systems for artefact generation. This paper makes a significant contribution to this emerging literature by providing a survey (cross-role N = 75) and pilot experimental results (within-subject N = 18) to advance this literature from conceptual potential to empirically grounded prioritization.

First, this paper demonstrates that quantification of knowledge-intensive sales activities at the activity level revealed a differentiated topology for hotspots in terms of time share and process drag. Governance-intensive and documentation-intensive activities are structurally persistent sources of process drag. The relationship between perceived automatability and process drag is empirically supported, providing support for a contingency-based targeting strategy instead of automation.

Second, this paper demonstrates that a within-subject pilot experiment revealed causal results for knowledge-grounded Gen AI assistance in terms of task duration and first-pass quality. Effect size varied systematically by task type. Synthesis-intensive artefact generation (Task A) benefited most from Gen AI assistance, asset retrieval (Task B) had intermediate effects, and CRM documentation (Task C) had the smallest incremental effects. Practically, this paper suggests that organizations could use this opportunity score to focus on a limited number of hotspot activities, use knowledge-grounded Gen AI with governance controls and human review for customer-facing artefacts, and track task-level delta in terms of time share and first-pass quality as adoption scales.

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