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Generative artificial intelligence (GenAI) revolution: A deep dive into GenAI adoption☆

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A R T I C L E I N F O

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A B S T R A C T

This study examines key reasons (for and against) that influence business-to-business (B2B) managers' intention to adopt generative artificial intelligence (GenAI). We also investigate how GenAI adoption influences firm performance, along with the moderating effect of ethical leadership. Study 1 undertakes a series of in-depth interviews, yielding a set of hypotheses that are tested in Study 2. A total of 277 responses was collected from respondents in the USA, the UK, Canada, India, Australia, Malaysia, and Japan to test the proposed model using structural equation modeling. The findings highlight that need for uniqueness, information completeness, convenience, and deceptiveness significantly impact GenAI adoption. The results also highlight that GenAI adoption boosts firm performance. Finally, ethical leadership was found to moderate the effect of GenAI adoption on firm performance. This study enriches the GenAI, technology adoption, and behavioral reasoning theory literatures while also providing pertinent insights for firms intending to adopt GenAI.

1. Introduction

Artificial intelligence (AI) has significantly evolved over the years and one of its remarkable advancements lies in the development of Generative AI (GenAI) (Chakraborty et al., 2024). While early AI applications were based on algorithms that mimic human intelligence and perform tasks that typically require human cognitive abilities (Hollebeek et al., 2021; Mariani et al., 2023; Zirar et al., 2023), GenAI extends beyond these capabilities (Lim et al., 2023). Specifically, GenAI, which represents a natural extension of deep learning (Hermann & Puntoni, 2024; Chang & Park, 2024), is able to create original (e.g., textual or musical) content (Baidoo-Anu & Ansah, 2023), including, for instance, realistic images or lifelike characters in video-games (Eysenbach, 2023; Martinelli, 2022). Owing to these capabilities, GenAI has found applications across fields including art, entertainment, and education, among others (Castelli & Manzoni, 2022; Kirk & Givi, 2025). Pushing the boundaries of AI and inspiring new possibilities for human–machine collaboration (Chen et al., 2024), GenAI has captivated researchers and enthusiasts alike.

A recent report by Goldman Sachs (2023) reveals GenAI's potential to drive global GDP by 7 % (i.e., US$7 trillion) in the next decade, with its market size reaching a total forecast value of $51.8 billion by 2028 (Markets and Markets, 2023). Moreover, users' GenAI adoption has risen dramatically, with ChatGPT gaining 5 million users in its first 5

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days and DALL-E attracting 1 million users in just 2.5 months (Dialpad, 2023), highlighting the relevance of GenAI to multiple stakeholders.

Though the literature suggests that firms will undergo a radical transformation in the years to come (Dwivedi et al., 2022), understanding of the ethical and societal impact of GenAI technologies remains tenuous to date (Dwivedi et al., 2023), exposing an important gap in the literature. For example, to what extent can or should GenAI users attribute credit for their work to the technology? While prior researchers have examined the adoption of different disruptive technologies, including (traditional) AI (Baabdullah et al., 2021), AI-based customer and partner relationship management (Chatterjee et al., 2021, 2023), blockchain (Paul et al., 2022), big data (Wright et al., 2019), e-commerce (Hussein et al., 2019), marketing automation (Mero et al., 2020), and social media (Hollebeek, 2019), among others, acumen of GenAI adoption and its ethical implications, especially among business-to-business (B2B) firms, which tend to be overshadowed by business-to-consumer (B2C) firms in business research, remains tenuous to date, as therefore explored further in this article.

Ethical leadership is critical for firms that plan to integrate new technology, which may carry specific benefits and risks (Lin et al., 2020). Specifically, ethical leaders consider the broader implications of the firm's technological advancement and the impact on its users (Dwivedi et al., 2023). Making decisions with a strong ethical foundation ensures that the adopted technology aligns with the firm's objectives and values while minimizing any negative consequences (Lin et al., 2020). Drawing on behavioral reasoning theory, we consider the moderating role of ethical leadership in the association of B2B managers' GenAI adoption and firm performance, augmenting understanding of the key determinants of GenAI adoption in B2B firms. Addressing these issues, this study seeks answers to the following questions:

RQ1. What are the key drivers of B2B managers' adoption of GenAI?

RQ2. Does GenAI adoption exert a substantial impact on B2B firm performance?

RQ3. How does ethical leadership impact GenAI adoption?

This study makes important contributions to the literature. Collectively, Studies 1 and 2 advance understanding of the drivers, dynamics, and outcomes characterizing B2B managers' adoption of GenAI, yielding pertinent insight into these emerging issues. First, we explore the reasons (for and against) underlying B2B managers' adoption of GenAI to boost firm performance, reflecting their GenAI mindset and decision-making. While a handful of authors have addressed GenAI's impact on firm performance (e.g., Khan et al., 2024), these have not specifically focused on B2B firms, like this research.

Second, we explore the moderating role of the firm's ethical leadership in the association of B2B managers' GenAI adoption and firm performance, such that those firms featuring high (vs. low) ethical leadership are predicted to see a stronger effect. We find that firms led by ethical, moral principles are better equipped to responsibly manage the firm's GenAI adoption and its required organizational transition (e.g., by ensuring the equitable, inclusive use of GenAI; Islam & Greenwood, 2024). Advancing insight into the role of ethical leadership on the performance of GenAI-implementing firms is therefore of elevated practical relevance.

Third, our analyses advance acumen of behavioral reasoning theory, which explains the motivations underlying human behavior (Westaby, 2005). The theory posits that individuals' salient motives predict behavioral intentions and behavior (Sahu et al., 2022), as explored in the context of B2B managers' GenAI adoption in this research. The theory suggests that reasons for (vs. against) a particular behavior may concurrently explain an individual's motives (Kumar et al., 2024a, 2024b), fitting with our research objectives. While a few prior authors have adopted behavioral reasoning theory in the GenAI context (e.g., Wang et al., 2024), these have tended to assess the effect of specific GenAI technology on user-based dependent variables (e.g., information retrieval/processing). However, we examine its effect on firm performance, shedding new light on GenAI performance and facilitating managerial GenAI decision-making.

2. Literature review

2.1. Generative artificial intelligence

GenAI stands as a unique AI sub-category that has gained significant attention through platforms like ChatGPT (Lim et al., 2023). Specifically, the launch of OpenAI's "Chat Generative Pre-trained Transformer" (ChatGPT) in Q4, 2022, marked a milestone in spotlighting AI's capabilities (Lo, 2023; Baidoo-Anu & Ansah, 2023). Overall, GenAI stands out as a prime instance of exceptionally promising unsupervised machine learning (Fui-Hoon Nah et al., 2023).

Human-AI collaboration emerges as the linchpin in tackling challenges and capitalizing on the opportunities stemming from GenAI (Ooi et al., 2023; Hollebeek et al., 2024). With the continuous evolution of GenAI algorithms, there has been a notable rise in chatbot research (Zhang et al., 2024; Jeon et al., 2023). Traditionally, chatbots relied on Natural Language Processing (NLP) to interpret user queries and match them to the most suitable response sets within the system (Kecht et al., 2023). However, chatbots have further advanced by integrating language models and deep learning techniques to offer users instantaneous responses, enhancing their ability to handle NLP challenges in real-time while engaging with customers (Fitria et al., 2023).

GenAI has applications across sectors, including education (Baidoo-Anu & Ansah, 2023), marketing (Kshetri et al., 2023), hospitality (Dogru et al., 2023), healthcare (Zhang & Kamel Boulos, 2023), fashion (Harreis et al., 2023), and banking (Sleiman, 2023), among others. However, despite the rapid advancement of GenAI, prior studies have tended to focus on the customer's GenAI perspective, largely leaving scholars in the dark regarding the drivers, dynamics, and outcomes characterizing *managerial* GenAI adoption, particularly in B2B firms, as therefore addressed in this research.

2.2. Behavioral reasoning theory

Behavioral reasoning theory can be used to predict human decision-making processes (Westaby, 2005; Westaby & Fishbein, 1996). The theory suggests that motivations underlying human behavior stem from individuals' ability to rationalize and support their decision-making (Hajiheydari et al., 2021). It posits that reasons for and against a particular behavior can concurrently explain an individual's motives (Kumar et al., 2024a, 2024b; Sahu et al., 2022). Specifically, individuals employ specific reasons to rationalize their actions and decisions, driven by the desire to achieve specific goals and using those reasons to pursue these (Behl et al., 2023; Shankar et al., 2022).

Prior researchers have applied behavioral reasoning theory in contexts including binge drinking (Norman et al., 2012), adoption intention (Sivathanu, 2018), resistance intention (Hajiheydari et al., 2021), fake news sharing (Kumar et al., 2023), patronage intention (Tan et al., 2021), and food consumption (Kumar et al., 2021), among others, underscoring its versatility.

As managers are likely to have specific reasons for *and* against GenAI adoption in their firm, behavioral reasoning theory offers a suitable theoretical framework to examine these issues. However, despite its relevance, understanding of managers' GenAI-related decision-making processes from a behavioral reasoning theory perspective remains limited to date (Wang et al., 2024). This gap is significant because understanding the specific reasons that motivate or deter B2B firms from adopting GenAI can offer deeper insight into their decision-making processes and assist the development of more targeted adoption strategies. Therefore, this study is expected to enrich the behavioral reasoning theory literature in the GenAI context.

3. Research approach

We deployed a mixed-methods (qualitative/quantitative) approach to gather comprehensive insight into our research objectives (Venkatesh et al., 2013; Campbell & Fiske, 1959). Amalgamating qualitative and quantitative analyses, mixed-methods research aims for triangulation, complementarity, initiation, development, expansion, and diversity to draw *meta*-inferences (Venkatesh et al., 2013). Using a mixed-methods design offers advantages in addressing confirmatory or explanatory research questions while extracting valuable insight from existing theories and practical observations. We began with a qualitative study (Study 1) that aimed to uncover B2B managers' reasons for and against GenAI adoption. The findings were used to design Study 2, which formulates testable hypotheses, as derived from Study 1.

4. Study 1

Study 1 qualitatively explored B2B managers' reasons (for and against) GenAI adoption. To attain the required insight, we conducted a series of semi-structured interviews that lasted 30–40 min each during September-October 2023, which were continued until theoretical saturation was reached (Glaser & Strauss, 1967).

Data were collected from participants across seven countries, including the USA, the UK, Canada, India, Australia, Malaysia, and Japan. They were recruited through professional networks, industry conferences, and online platforms focused on AI and technology, ensuring that the respondents were individuals with first-hand experience in the implementation and use of GenAI in their firm. All the participants were working professionals who reported having a good understanding of GenAI usage.

Theoretical saturation was reached after completing 21 interviews. However, to ensure we had not missed any important insight, we conducted a small number of additional interviews, yielding a final sample of 27 participants (aged 18–51). Participants were assured of their anonymity in the research process and of the confidentiality of their responses. We commenced each interview by collecting basic information and then discussed the interviewee's reasons (for and against) for adopting GenAI in their firm. The interviews were audio-recorded and transcribed, after which we content-analyzed the interview transcripts using a blend of deductive and inductive reasoning (Lincoln & Guba, 1985), allowing us to situate our findings within the existing literature while also leaving room to uncover novel, emerging themes.

Using content-analytical procedures, we coded the data into prominent themes (i.e., reasons for and against GenAI adoption). The researchers individually validated the emerging themes to ensure their accuracy, striving for inter-coder agreement to establish external validity. This process yielded 78 % agreement among the researchers. We applied open, axial, and selective coding to analyze the data (Hollebeek, 2011; Lim, 2025). Guided by behavioral reasoning theory, we grouped the open codes into subcategories, consolidating conceptually related codes. Overall, Study 1 identified three main reasons for adopting GenAI (i.e., need for uniqueness, information completeness, and convenience), and two reasons against its adoption (i.e., deceptiveness and information overload), as shown in Fig. 1 (also see Study 2).

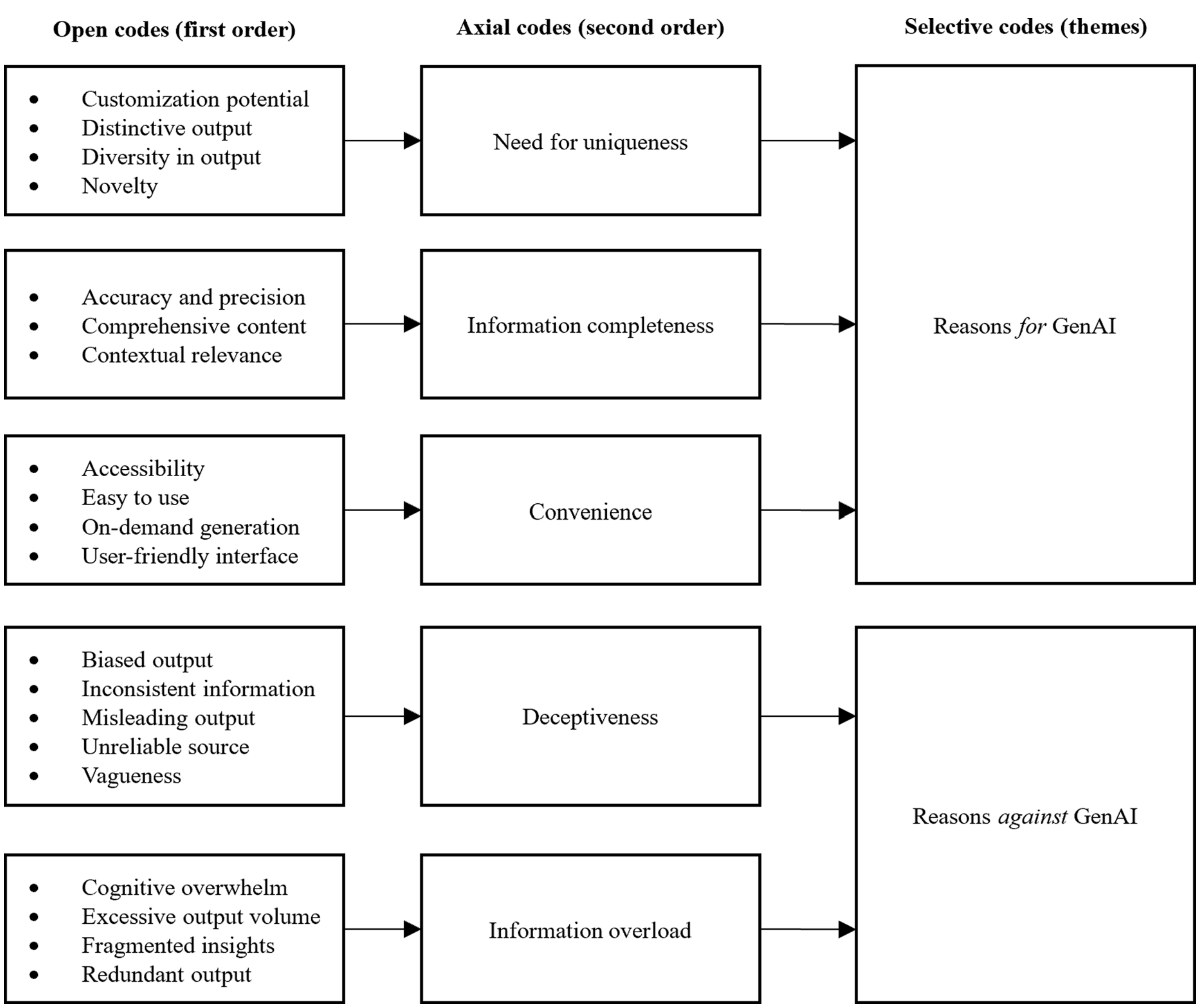

Fig. 1. Study 1 findings.

5. Qualitative data analysis and hypothesis development

5.1. Need for uniqueness

Need for uniqueness reflects an individual's aspiration to stand out from the crowd (Sharma et al., 2018; Park et al., 2013). To pursue their individuality, individuals may be motivated to use emerging technologies (e.g., that enable personalization; Lang & Armstrong, 2018). Users' desire to stand out from the crowd can thus motivate their adoption of innovative technologies like GenAI, elevating their self-perception or perceived uniqueness (Hajiheydari et al., 2021).

For example, using GenAI for problem-solving tasks may encourage users' creative thinking or ideas. In other words, GenAI may facilitate the development of individuals' unique solutions to complex ideas, reinforcing their sense of uniqueness (Hajiheydari et al., 2021). The qualitative findings support these arguments. For example, several of the participants illustrated how they use GenAI to create uniqueness or competitive advantage in their jobs:

> *"Well, the AI's ability to generate distinct outputs is quite fascinating. We've noticed it's not just about churning out content; it's about creating something that feels tailor-made. It's like having a writer who can adapt to different styles and tones, providing us with a variety of options that truly stand out."* [P7, Male, 24 years, Education]
> *"We were exploring new marketing angles, and the AI produced a set of ad copies, each with a distinct tone and approach. It gave us fresh ideas we hadn't considered before. That uniqueness helped us stand out in a crowded market."* [P16, Female, 28 years, Marketing]
> *"Sure, there was a campaign where the AI produced video snippets combining our product information with pop-culture references. It was unexpected yet resonated so well with our audience, creating a buzz we hadn't anticipated."* [P20, Female, 25 years, Content Creation]

We hypothesize:
***H1:** The need for uniqueness positively influences GenAI adoption in B2B firms.*

5.2. Information completeness

Users anticipate receiving up-to-date, comprehensive information about their topics of interest (Cheng et al., 2020). Completeness of information reflects users' judgment of the breadth, depth, and coverage of the information they have received (Liu et al., 2020). Data completeness, a crucial facet of data quality, assesses the availability of all necessary data to execute a particular task (Hajiheydari et al., 2021). If information is deemed to be incomplete, this can cause significant issues or repercussions (e.g., inaccurate decision-making; Wei et al., 2019), as supported by the findings of Study 1, For example, several of the participants illustrated their perception of GenAI's provision of comprehensive, complete information, as follows:

> *"The completeness of AI-generated content has elevated the quality of our research outcomes. It's enabled us to produce more detailed reports, adding significant value to our stakeholders and clients."* [P3, Male, age 31, Research]
> *"In our line of work, precision matters. The GenAI's strength lies in its potential to provide detailed insights. But it's not just about quantity; accuracy is non-negotiable. It needs to cover all aspects while ensuring every piece of information is on point."* [P9, Male, age 25, Media]
> *"Occasionally, I have noticed the Generative AI missing out on details or alternative viewpoints. While it provides a broad overview, sometimes it overlooks specific angles that could add depth to the information."* [P17, Female, age 21, Finance]

We posit:
***H2:** Information completeness positively influences GenAI adoption in B2B firms.*

5.3. Convenience

Convenience refers to the ability to efficiently complete a task with minimal human effort, significantly boosting engagement (Boden et al., 2020). For example, convenient services tend to save users time and minimize their effort. In line with prominent theoretical perspectives like the technology acceptance model (Davis, 1989), a technology's perceived convenience stands out as a pivotal determinant of its adoption (Shankar & Rishi, 2020). When users perceive a technology to be convenient, they believe it to be able to facilitate task completion, enhancing its appeal (Lai & Liew, 2021). Moreover, users who perceive a technology as convenient are more likely to consider it useful and easy to use.

B2B managers are more likely to adopt GenAI tools if these are perceived to offer a more streamlined or convenient workflow, as supported by the findings of Study 1. For example, several of the respondents illustrated their perceived convenience of GenAI:

> *"GenAI has streamlined our processes. With just a few prompts, we can get quality content within minutes. It is like having a content creator at our beck and call, available whenever we need it."* [P10, Female, age 36, Content Creation]
> *"It has been a time-saver. Instead of brainstorming sessions for content creation, we now rely on prompt-based inputs for the Generative AI. This streamlined process has freed our creative team to focus on strategy and innovation."* [P5, Male, age 28, Sales]
> *"The interface is intuitive. Even team members without technical expertise can navigate it effortlessly. It is like having a content generator with a user-friendly manual."* [P23, Female, age 31, Advertising]

We propose:
***H3:** Convenience positively influences GenAI adoption in B2B firms.*

5.4. Deceptiveness

Deceptiveness reflects a technology's presentation of inaccurate or erroneous information that gives the impression that it falls short of meeting expectations or of executing its tasks (Zhang et al., 2018). For example, if users come across deceptive or manipulative data produced by the technology, its perceived credibility, precision, and impartiality will be undermined (Hajiheydari et al., 2021).

As deceit diminishes users' perceived credibility and authenticity of the technology, perceived deceptive technology will typically not be relied upon in decision-making tasks (Cenfetelli & Schwarz, 2011). Consequently, scepticism will be instilled among its users, lowering their intent to adopt it (Ansari & Gupta, 2021), as supported by the findings of Study 1. For example, several participants illustrated feeling like they were being deceived by the information produced by GenAI:

> *"Sometimes the content generated might lack context or inadvertently create ambiguity. We've had to ensure our prompts are fine-tuned to prevent any misleading outputs. It's about balancing the AI's creative capacity while ensuring the information stays authentic and factual."* [P13, Male, age 30, Media]
> *"There have been instances where the GenAI pulls references that do not seem to exist in reality. It cites authors or sources that could not be found anywhere upon verification."* [P6, Male, age 27, Research]
> *"Sure, there was an instance where the [Gen]AI misunderstood a statistical trend, leading to a potentially misleading conclusion in a report. It required human intervention to rectify and clarify the data's actual implications."* [P25, Male, age 31, Finance]

We theorize:
***H4:** Deceptiveness negatively influences GenAI adoption in B2B firms.*

5.5. Information overload

Information overload occurs when individuals feel they are being inundated with an excessive amount of information, surpassing their ability to process it effectively (Swar et al., 2017; Edmunds & Morris, 2000). This mental overload tends to generate adverse outcomes such as stress, anxiety, or declining in decision-making quality (Wang et al., 2023). In computer-mediated environments, information overload manifests when individuals encounter an overwhelming volume of data on virtual platforms that they feel unable to handle, process, or manage effectively (Pang & Ruan, 2023).

Prior literature has examined the role of information overload in contexts including social media platforms or online communities, among others (Pang & Ruan, 2023). However, while the effect of GenAI on perceived information overload has been examined in other contexts (e.g., education; Halvorson, 2024), acumen of its impact in the context of B2B managers' decision-making remains limited to date. However, several of the Study 1 respondents reported feeling overloaded by the information produced by GenAI, as follows:

> *"GenAI is incredibly efficient, but there is a fine line. Sometimes, it provides more than is needed, flooding us with data. So, managing the output volume without compromising quality and relevance is crucial."* [P11, Male, age 25, Sales]
> *"Yes, especially during peak project times. The Generative AI generates so much content so quickly that it can be overwhelming. We've had to fine-tune our processes to manage the influx better."* [P22, Female, age 22, Marketing]
> *"We emphasize training team members to use AI outputs judiciously. It's crucial not to consume all generated content but to focus on what's essential for decision-making."* [P27, Female, age 39, Research]

We posit:

***H5:** Information overload negatively influences GenAI adoption in B2B firms.*

5.6. GenAI adoption and firm performance

GenAI has been heralded to offer substantial advantage to its adopters (Prasad Agrawal, 2023). Specifically, its implementation boosts operational efficiency, unlocking potential benefits (Chatterjee et al., 2021b). Likewise, prior studies have shown how (other) technological innovations may be used to streamline business processes or boost firm performance (Chatterjee et al., 2021c). As GenAI increasingly permeates firms, it promises to revolutionize the marketing function (Chui et al., 2022) while improving firm performance (Ooi et al., 2023). Early GenAI adoption is thus thought to offer a competitive edge to firms (Prasad Agrawal, 2023). Those that are able to effectively harness its potential are likely to differentiate themselves in the market (e.g., adapting faster to emerging trends or staying ahead of competitors; Saivasan & Lokhande, 2023). We hypothesize:

***H6:** GenAI adoption in B2B firms positively impacts firm performance.*

5.7. Moderating role of ethical leadership

It is crucial for leaders to prioritize ethical conduct in their firms, particularly as they integrate advanced technologies like GenAI (Lin et al., 2020). Ethical leaders typically establish clear, consistent, ethical benchmarks for their stakeholders (e.g., employees), communicate these values, provide rewards for ethical behavior, and implement consequences for unethical actions (Hameed et al., 2023).

Ethical leadership also plays a critical role in safeguarding the company's reputation and credibility, emphasizing its ethical conduct and decision-making, particularly in terms of its stakeholder relationships while it navigates new technological investments (Al Halbusi et al., 2023). Companies guided by strong ethical leadership in their technological innovation endeavors tend to foster trust-based relationships with stakeholders (Ye et al., 2023; Lin et al., 2020). The extent to which leaders demonstrate trustworthiness in embracing new technological advancements emerges as a pivotal factor in determining the effectiveness of these innovation pursuits (Lin et al., 2020).

The active involvement and personal commitment of ethical leaders in the company's long-term commitment to technological innovation and excellence significantly impact whether the technology yields tangible firm performance (Kalra et al., 2023; Lin et al., 2020). We suggest that those industrial companies that display high (vs. low) ethical leadership will see a stronger effect of their managers' GenAI adoption on the firm's ensuing performance, exposing the proposed moderating role of ethical leadership. We posit:

***H7:** Ethical leadership significantly moderates the association between GenAI adoption and firm performance in B2B firms.*

6. Study 2

6.1. Measures and data collection

The proposed framework, which summarizes the hypotheses, is shown in Fig. 2. The questionnaire was developed using measurement scales from prior literature (see Appendix A). The draft questionnaire was shared with subject matter experts to verify the content and framing of the items. Moreover, a pilot study was conducted using 40 respondents who were selected to represent a diverse cross-section of B2B firms with differing levels of familiarity with and exposure to GenAI technologies. Minor revisions were made to the questionnaire based on the feedback received from the pilot study and subject-matter experts.

To test the model, we conducted a cross-sectional survey. We gathered data from managers across the globe who were using or were aware of GenAI applications in their firm. We deployed Prolific to gather the data (https://www.prolific.com/), which represents a widely used data collection platform (Kumar et al., 2024a/b). Prior literature suggests that a sample size of over 200 generally suffices to conduct covariance-based structural equation modeling (CB-SEM) (Hair et al., 2017). To ensure an adequate sample size for CB-SEM, it is also widely recommended to maintain a minimum ratio of 1:5 between the number of measurement items and the sample size (Hair et al., 2017). Adhering to this item-to-sample ratio, we aimed to strengthen the robustness and validity of our results. Of 301 potential responses, 277 successfully passed the attention and screening questions. Notably, 53.4 % of respondents identified as male, with 45.1 % falling within the 25–35 age bracket and 50.5 % reporting an average personal GenAI usage of four hours daily.

6.2. Common method bias assessment

To mitigate the potential existence of common method bias (CMB), we applied procedural measures and statistical controls. Furthermore, we executed Harman's single-factor test to evaluate CMB in Study 2. The results revealed that CMB accounted for 41.26 % of the observed variance, remaining below the 50 % threshold (Podsakoff et al., 2003) and indicating that CMB is not an issue in our data. We thus infer that the participants engaged attentively and responded considerately to the survey questions.

6.3. Measurement model results

Following Hair et al. (2017), we assessed the measurement model by evaluating the reliability, convergent validity, and discriminant validity of the latent constructs. Confirmatory factor analysis (CFA) using the AMOS v.26 software was conducted to scrutinize the reliability and validity of the studied constructs. To assess reliability, Cronbach's alpha values were computed for each construct, each surpassing the critical value of 0.7, affirming their respective reliability (Hair et al., 2017). Convergent and discriminant validity were established by examining the average variance extracted (AVE) values (all > 0.5) and composite reliability (CR) values (all > 0.7). We also compared the square root of the AVE for each variable with the correlation coefficients among

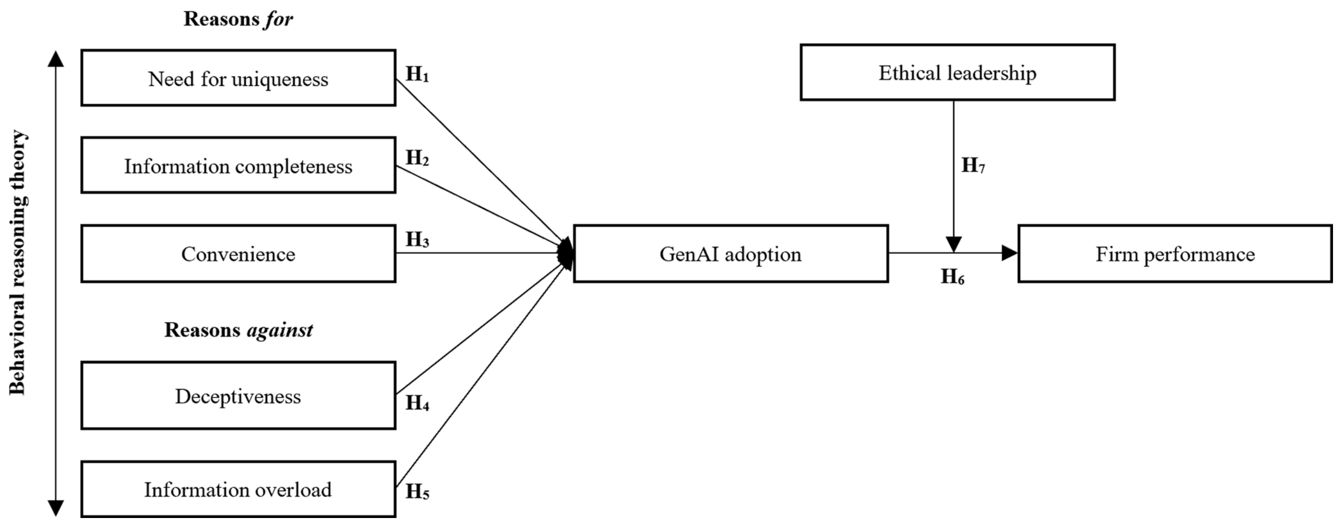

Fig. 2. Conceptual framework.

constructs, confirming discriminant validity, as the square roots exceeded the values of their respective correlation coefficients (see Tables 1 and 2; Fornell & Larcker, 1981).

Table 1
Measurement model results.

Variables and items	Factor Loading	Cronbach's alpha	Composite reliability	Average variance extracted
Need for uniqueness		0.944	0.945	0.810
NFU1	0.863			
NFU2	0.943			
NFU3	0.885			
NFU4	0.907			
Information completeness		0.886	0.900	0.746
IC1	0.692			
IC2	0.927			
IC3	0.941			
Convenience		0.756	0.754	0.492
COV1	0.750			
COV2	0.664			
COV3	0.725			
Deceptiveness		0.826	0.849	0.628
DEC1	0.642			
DEC2	0.813			
DEC3	0.904			
Information overload		0.864	0.859	0.645
IO1	0.751			
IO2	0.795			
IO3	0.932			
GenAI adoption		0.920	0.926	0.803
ADP1	0.808			
ADP2	0.943			
ADP3	0.926			
Firm performance		0.873	0.899	0.749
FP1	0.961			
FP2	0.984			
FP3	0.587			
Ethical leadership		0.930	0.945	0.766
EL1	0.865			
EL2	0.969			
EL3	0.954			
EL4	0.956			
EL5	0.548			

6.4. Hypothesis testing results

The findings of the path analysis (see Table 3) suggest that the need for uniqueness (β = 0.379***), information completeness (β = 0.370***), and convenience (β = 0.294**) are positively associated with GenAI adoption in B2B firms. Hence, H1, H2, and H3 are supported. Furthermore, the findings suggest that deceptiveness (β = -0.552***) is negatively associated with GenAI adoption in B2B firms, supporting H4. Moreover, GenAI adoption (β = 0.769***) is positively associated with firm performance in B2B firms, supporting H6. However, information overload did not have a significant effect on GenAI adoption in B2B firms. Therefore, H5 is rejected. The R^2 values for GenAI adoption and firm performance are 0.87 and 0.77, respectively.

6.5. Moderation analysis results

Model 1 in the Process Macro was used to assess the moderation hypothesis (Hayes, 2013). The results presented in Tables 4 and 5 illustrate that the impact of GenAI adoption on firm performance in B2B firms is significantly moderated by ethical leadership, supporting H7. This finding shows that B2B firms that exhibit high (vs. low) ethical leadership see a stronger effect of GenAI adoption on firm performance.

7. Discussion

The results reveal that the need for uniqueness, information completeness, and convenience is significantly associated with GenAI adoption in B2B firms, corroborating earlier findings in other technology adoption contexts (Hajiheydari et al., 2021; Lai & Liew, 2021).

First, need for uniqueness drives individuals to seek innovative, one-of-a-kind solutions. GenAI has the capacity to create novel, unique, or differentiated content or solutions. Second, information completeness is essential to create accurate, reliable outputs. The surveyed managers in B2B firms were found to value GenAI for its potential to produce comprehensive information or content, contributing to high-quality business outcomes. Third, based on the results, convenience raises GenAI adoption in B2B firms (e.g., by saving users time or by providing higher-quality outputs). If these tools are user-friendly, accessible, and integrate seamlessly into existing workflows, managers in these firms are more likely to adopt them.

Consistent with authors including Hajiheydari et al. (2021) and Cenfetelli and Schwarz (2011), the findings also reveal that perceived deceptiveness reduces GenAI adoption among managers in B2B firms. A plausible reason for this finding is that perceived deceptiveness of GenAI

Table 2
Discriminant validity testing results.

Variables	1	2	3	4	5	6	7	8
1. GenAI adoption	0.896							
2. Convenience	0.596	0.702						
3. Deceptiveness	−0.294	−0.614	0.793					
4. Information completeness	0.143	0.585	−0.548	0.863				
5. Firm performance	0.364	0.660	−0.535	0.754	0.866			
6. Ethical leadership	0.229	0.590	−0.300	0.210	0.297	0.875		
7. Information overload	−0.497	−0.177	0.695	−0.759	−0.631	−0.743	0.803	
8. Need for uniqueness	0.162	0.272	−0.423	0.861	0.782	0.165	−0.693	0.900

Notes – Diagonal value indicates the square root of AVE of individual latent construct.

Table 3
Path analysis results.

Path	Beta	SE	T-value
Need for uniqueness → GenAI adoption	0.379***	0.065	3.83
Information completeness → GenAI adoption	0.370***	0.075	4.09
Convenience → GenAI adoption	0.294**	0.09	2.96
Deceptiveness → GenAI adoption	−0.552***	0.119	5.12
Information overload → GenAI adoption	−0.022 ns	0.049	0.35
GenAI adoption → Firm performance	0.769***	0.057	18.50

Notes – *** implies $p < 0.001$; ** implies $p < 0.01$; ns: not significant.

Table 4
Moderation analysis results.

Moderating role of ethical leadership	Effect	SE	p-value	Moderation
GenAI adoption → Firm performance	0.18	0.025	0.000	Yes

Table 5
Moderation (low vs. high levels).

Moderating role of ethical leadership	Level	Effect	SE	p-value
GenAI adoption → Firm performance	Low	−0.007	0.066	0.917
	Medium	0.213	0.062	0.001
	High	0.434	0.072	0.000

output might stem from concerns about its trustworthiness, accuracy, or reliability. The results also highlight that GenAI adoption is positively associated with firm performance in B2B firms, extending prior exploratory findings (Chatterjee et al., 2023). GenAI adoption is expected to lower operational costs (e.g., by automating repetitive tasks, minimizing errors, and by optimizing resource allocation), directly impacting firm performance in these firms.

However, contrary to prior literature in other (technology adoption) contexts (Wang et al., 2023; Pang & Ruan, 2023), information overload was not found to exert a significant effect on GenAI adoption in B2B firms. GenAI tools typically allow their users to customize or personalize the information they receive. This customization or personalization might enable users to more effectively manage information, reducing perceived information overload. Therefore, users may develop strategies to filter through the vast amount of information (e.g., by focusing on their trusted sources or those most relevant to their needs), thus mitigating the negative effects of information overload. Moreover, in line with the extant literature (Lin et al., 2020), the results reveal that the impact of GenAI adoption on firm performance in B2B firms is significantly moderated by ethical leadership, which influences how GenAI is used in these firms. Notably, leaders who prioritize ethical considerations guide the responsible adoption and utilization of AI, ensuring its implementation aligns with ethical standards that boost firm performance.

8. Implications

8.1. Theoretical implications

This study raises important issues for further theory development. First, our analyses advance acumen of the drivers, dynamics, and outcomes characterizing GenAI adoption in B2B firms. Drawing on behavioral reasoning theory, we assessed the role of specific determinants for (vs. against) GenAI adoption in B2B firms (Norman et al., 2012). Here, need for uniqueness, information completeness, and convenience emerged as key reasons for adopting GenAI while deceptiveness and information overload arose as important reasons against. These findings yield pertinent issues for further theory development, including: What is the relative strength or importance of the respective factors for (vs. against) identified in Study 1? To what extent may specific factors support one another to strengthen GenAI adoption (vs. collide to lower their adoption in this regard)?

Second, the findings of Study 2 showed that ethical leadership moderates the effect of GenAI adoption and firm performance in B2B firms, thus offering important new insight. Specifically, the results suggest that B2B firms that display high (vs. low) ethical leadership are likely to see heightened firm performance, indicating the importance of ethical leadership to unlock GenAI's true potential. This finding likewise raises important questions for further theory development, including: Does the moderating effect of the firm's ethical leadership offer a linear effect, or increasing or decreasing effects? Therefore, what is the optimal ethical leadership level to optimize the impact of GenAI adoption on firm performance? To what extent does GenAI adoption in B2B firms impact different stakeholders' perceived benefits?

8.2. Practical implications

This study yields several implications for managers adopting, or seeking to adopt, GenAI. First, Study 1 pinpointed B2B managers' rationale for and against adopting GenAI, offering insight into their GenAI decision-making. The results also show that need for uniqueness, information completeness, and convenience raise GenAI adoption in B2B firms. To leverage the identified drivers, managers are advised to (a) adopt an organizational culture that values and nurtures uniqueness and creativity, which GenAI is expected to facilitate, (b) train their employees to engage in decision-making based on complete information as much as possible, which GenAI can likewise assist with (e.g., by ensuring the use of high-quality training data), and (c) invest in high-quality GenAI tools that boost convenient task execution.

Furthermore, the results suggest that deceptiveness is negatively associated with GenAI adoption in B2B firms. To mitigate these risks, managers are advised to cultivate the development of a critical mindset in their employees, enabling them to critically judge any perceived deceptiveness of the information provided by GenAI and allowing them to take corrective action, as needed. We also recommend firms to develop methodologies to assess the authenticity and reliability of GenAI outputs before they are disseminated in or outside the firm (e.g., by cross-checking a GenAI's output with that of other technology).

Second, Study 2 found that GenAI adoption boosts firm performance in B2B firms, as moderated by the firm's ethical leadership, thus offering pertinent information for managers. Specifically, the attained positive effect of GenAI adoption on firm performance can be used to instil managerial confidence in GenAI adoption. Relatedly, the moderating effect of ethical leadership shows that to capitalize on GenAI's potential value, firms should adopt ethical, responsible leadership. We thus recommend GenAI-adopting firms to carefully consider their key hiring and management decision-making, which should be geared toward ethical leadership.

9. Conclusion, limitations, and further research

GenAI has emerged as a transformative technology with profound implications for firms. Despite its transformative potential, understanding of the drivers, dynamics, and outcomes of GenAI adoption, especially among B2B firms, remains limited, exposing a pertinent gap in the literature. Addressing this gap, we drew on behavioral reasoning theory to conduct Studies 1–2 to uncover B2B managers' key reasons for and against GenAI adoption in their firm.

The findings of Study 1 contribute that the need for uniqueness, information completeness, and convenience emerge as key reasons for adopting GenAI while deceptiveness and information overload arise as major reasons against. The results in Study 2 further highlight that GenAI adoption boosts firm performance and that ethical leadership acts as a significant moderator in the association of GenAI adoption and firm performance. Overall, this research advances the literature on GenAI, B2B marketing, ethical leadership, and behavioral reasoning theory while also providing core practical implications for GenAI adopting firms.

Despite its contribution, this research also has limitations. First, our work relies on cross-sectional data, thus failing to offer insight into the evolving nature of the modeled variables over time. Future researchers could thus adopt longitudinal data to facilitate the development of more comprehensive acumen of GenAI adoption. Second, while we explored the effect of GenAI adoption on firm performance, we only considered this from a perceptual and intentional perspective in terms of measurement. Future researchers may thus examine actual GenAI adoption using field data. Third, given the relatively recent launch of GenAI, it has limited adoption rates to date, as reflected in our relatively small samples. Therefore, future scholars are advised to validate the reported findings with larger samples that may also feature additional (e.g., cultural/organizational) variables. Finally, while this research outlines key determinants of GenAI adoption in B2B firms, we examined GenAI generically (vs. focusing on any specific GenAI technology). Though this approach allows us to identify broad GenAI patterns, the attained insight may be refined by addressing the drivers and effects of specific GenAI tools (e.g., large language models, image generators, or code generation tools).

CRediT authorship contribution statement

Aman Kumar: Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Amit Shankar:** Writing – original draft, Supervision, Software, Methodology, Funding acquisition, Data curation, Conceptualization. **Linda D. Hollebeek:** Writing – original draft, Supervision, Resources, Investigation. **Abhishek Behl:** Writing – original draft, Validation, Software, Project administration, Methodology, Conceptualization. **Weng Marc Lim:** Writing – original draft, Supervision, Resources, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Measurement items

	Variables and items
	Deceptiveness (Hajiheydari et al., 2021)
DEC1:	Information provided by Generative AI is sometimes misleading
DEC2:	Generative AI does not always provide the information that it should be
DEC3:	Information provided by Generative AI is sometimes distorted
	Information overload (Hajiheydari et al., 2021)
IO1:	Generative AI provides too much information
IO2:	Finding the relevant information is hard in Generative AI outputs
IO3:	The amount of information outputs is overwhelming
	Need for uniqueness (Hajiheydari et al., 2021)
NFU1:	Using Generative AI helps me to establish a distinctive image
NFU2:	Using Generative AI is in line with improving my personal uniqueness
NFU3:	Using Generative AI helps me to shape a more unusual personal image
NFU4:	I actively seek to develop my personal uniqueness by using Generative AI
	Information completeness (Hajiheydari et al., 2021)
IC1:	Generative AI provides me with a complete set of information
IC2:	Generative AI produces comprehensive information
IC3:	Generative AI provides me with all relevant information I need
	Convenience (Hajiheydari et al., 2021)
COV1:	Using Generative AI makes doing my job easier
COV2:	Using Generative AI allows me to save time, when doing my job
COV3:	Using Generative AI enables me to do my jobs quickly
	GenAI adoption (Jebarajakirthy & Shankar, 2021)
ADP1:	I intend to use Generative AI in future
ADP2:	I plan to use Generative AI
ADP3:	I expect that I would use Generative AI in future
	Firm performance (Chatterjee et al., 2021c)
FP1:	Using Generative AI helps the firm to earn better business profit
FP2:	Using Generative AI help the firm to become more competitive
FP3:	Usage of Generative AI in cocreation activities makes the firm become more innovative
	Ethical leadership (Al Halbusi et al., 2023)
EL1:	My supervisor listens to what employees have to say
EL2:	My supervisor disciplines employees who violate ethical standards.

(*continued on next page*)

(*continued*)

EL3:	My supervisor conducts his/her work in an ethical manner
EL4:	My supervisor has the best interests of employees in mind
EL5:	My supervisor discusses business ethics or values with employees

Data availability

Data will be made available upon reasonable request.

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