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Integrating Generative AI in Business Intelligence: A Practical Framework for Enhancing Augmented Analytics

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Abstract
Business Intelligence (BI) workflows benefit from the improved access to insights that Generative Artificial Intelligence (GenAI) can bring, allowing for swifter democratization of data access and improved decision-making across various domains such as finance, retail, life sciences, education technology (EdTech), etc. Although existing literature discusses theoretical models or particular case studies, it does not provide a practical framework to integrate GenAI into BI. This study fills the gap by devising a pragmatic framework employing the qualitative research method featuring semi-structured interviews with professionals in varied disciplines. The results show that GenAI can improve the effectiveness of the interaction between technical experts and business users. Successful adoption, however, hinges on clarity of the organizational goals, effectiveness of the data management, user training, and system integration. Organizations can apply the proposed framework to integrate GenAI into BI systems to focus on operational excellence and support for real-time, data-driven decisions. These insights serve to advance BI practices, and act as a precursor to the future research in the domain of AI-integrated BI workflows.

Keywords- Generative AI, Augmented analytics, Business intelligence, Data democratization, Business value.

1. Introduction

Business intelligence (BI) and analytics are essential in making organizations data-driven. Global investments in BI markets are expected to rise from $29.42 billion in 2023 to $54.27 billion by 2030 (Fortune Business Insights, 2023), emphasizing the growing importance of data-driven decision-making. However, one of the ongoing problems is the disconnect between technical experts who create the analytics content and business users who consume it. Organizations are introducing self-service and augmented analytics solutions that enable business people to access and analyze data independently to bridge this gap (Passlick et al., 2023, Sallam et al., 2017). Despite improvements in accessibility, these tools face limitations due to the complexity of data environments, undermining the potential of an organization’s data assets and business value (John et al., 2023). The primary challenge is the divide between technical experts, who excel in data design and operations but often lack business context, and business users, who possess contextual knowledge and awareness of business priorities but find modern data environments too complex. This disconnect hinders efficient data utilization, delays actionable insights, and creates operational bottlenecks. Therefore, creative solutions are necessary to fill the gap.

The objective of this research is to develop a practical framework for implementing generative artificial intelligence (GenAI) in BI workflows. In particular, it answers the following research questions: (1) How can GenAI bridge the gap between the technical experts and business users in BI? (2) What are the main challenges and opportunities in using GenAI across various domains? (3) What should organizations do to adopt and integrate GenAI into their BI systems?

GenAI, specifically Large Language Models (LLMs) like Generative Pre-trained Transformer (GPT), provides easier ways to democratize data, especially aiding in improving data accessibility and self-serviceability for non-technical users. GenAI is a class of AI models that can autonomously create new content, such as text, images, music, and simulations, based on the large-scale data they were trained on. These models, including GPT-enabled tools can produce human-like responses to create extraordinary user experience (UX). They allow non-technical users to intuitively engage with data through easier interfaces like natural language interactions. This allows business stakeholders to ask questions in everyday language, explore data independently, and obtain real-time insights without relying heavily on technical teams, thereby enhancing decision-making agility (John et al., 2023). This research analyzes the implications of GenAI across different use cases and frameworks, such as the Cross-Industry Standard Process for Data Mining (CRISP-DM), to identify best practices and optimize its application.

Traditional BI models and workflows have analytics pipelines built by technical experts to address predefined questions by implementing business rules provided by business users. Business users often remain passive consumers of information and dependent on technical experts for refinements in data and pipelines as business contexts evolve and business rules and strategies change. These models often struggle to provide accurate, timely and actionable insights as business demands and complexities grow and shift frequently. In fast-paced environments, communication gaps often arise between business users and technical teams, preventing them from updating models with up-to-date business rules and quality data. This leads to BI models failing to meet business expectations, thereby breaking trust in insights they generate. This study examines how GenAI, particularly GPT-enabled BI tools, can enable business users to interactively engage with data, promote data democratization-making data accessible to non-technical users and allowing them to generate insights independently-and enhance decision-making agility.

To ground this study in existing knowledge, the following literature review examines prior work in GenAI, augmented analytics, and data democratization, highlighting the research gaps this study intends to address.

2. Literature Review and Research Gaps

GenAI systems can automatically create different kinds of content, including text, images, music and simulations. A subset of this technology is LLMs, which generate and analyze text in context using neural networks that have been trained on huge quantities of unstructured text (Linkon et al., 2024). Neural networks are algorithms with the main purpose to recognize patterns and relationships in data, similar to how the human brain does it too. They are the most important part of modern AI and are used in a wide range of tasks, including language processing and image recognition. Since its inception, Natural Language Processing (NLP)-teaching machines to understand and create text in a manner that is similar to how humans do, thus closing the gap between humans and machines-has grown from using rule-based systems to neural network-based models. These developments allowed for the technique of word embeddings which are real numbers that represent text in a continuous manner to capture the context of a text. Such techniques for obtaining vector representations of words (Word2Vec) enhanced the ability of understanding the relationships between words and thus provided a strong foundation for other sophisticated recurrent neural networks (RNNs) and long short-term memory (LSTM) networks.

The introduction of the transformer architecture by Vaswani et al. (2017) marked a key breakthrough for LLMs. Transformers make use of self-attention mechanisms to process input data in parallel, which makes training on large datasets more efficient compared to older, sequential data processing models like RNNs and LSTMs. Transformers handle long-range dependencies and large datasets effectively, leading to notable progress in language modeling. This architecture evolved into models like Bidirectional Encoder Representations from Transformers (BERT) by Devlin et al. (2018), which set new standards in tasks such as sentiment analysis, question answering, and named entity recognition. GPT models by OpenAI demonstrated the impact of scaling up model size and training data, revolutionizing language understanding and generation (Radford et al., 2019) across a wide range of different domains.

Research on GenAI and LLMs has expanded, exploring applications in fields like software development, marketing, supply chain management (SCM), customer relationship management (CRM), human resources (HR), finance, and life sciences (Cámara et al., 2023; Gozalo-Brizuela and Garrido-Merchán, 2023). Advancements in these models have largely improved text interpretation and generation, creating new possibilities for data analysis, BI, and human-AI collaboration across industries (Kaisler et al., 2023). However, limited research has explicitly examined the potential of GenAI and LLMs for BI, strategic decision-making, and data democratization.

By efficiently analyzing large volumes of structured and unstructured data, models like LLMs and GenAI have been transforming various business operations, such as SCM, CRM, HR, and strategic decision-making. With enhanced understanding of unstructured data, these models offer understanding of the market dynamics, consumers' behavior and the efficiency of the operations (O'Leary, 2023). For example, in SCM, GenAI enhances demand forecasting, inventory management, and logistics through forecasting changes, optimizing the delivery process, and effective resource management. It also allows for the modelling of supply chain disruptions which assists organizations in fine-tuning their strategies and minimizing risks (Muller et al., 2023). In CRM, these models perform tasks such as sentiment analysis, customer segmentation and predictive modelling-statistical and machine learning (ML) methods and techniques on current and past information to generate information about future events, to enable efficient and effective targeted marketing, personalized recommendations and customer service (Verma and Kumari, 2023). These capabilities result in targeted services and precise insights, which, if incorporated in a company will enhance the customers' satisfaction and the general performance of the business. Similarly, in HR, GenAI simplifies processes of talent acquisition, employee engagement, and workforce planning. It helps with recruitment, provides retention insights, and forecasts staffing needs, boosting organizational performance.

In finance, GenAI supports tasks like risk assessment, fraud detection, and algorithmic trading by analyzing data from various sources, such as market reports and social media. These models enhance financial forecasting (Nie et al., 2024) and allow for simulations of market conditions, which help in stress-testing trading strategies (Lee et al., 2020). Many investment banks and hedge funds utilize GenAI-driven models to improve trading decisions by analyzing sentiment from news articles and social media in real time, providing traders with a competitive edge in high-frequency trading environments. However, integrating these models for real-time financial data analysis by attaining desired scalability and robustness, still requires further exploration.

In retail, GenAI helps manage inventory better, personalize recommendations for customers, and predict demand by analyzing customer data and purchasing patterns. Many large retailers, like Amazon, use machine learning to optimize warehouse stock levels and improve delivery efficiency based on customer behavior. Insights that are generated from AI-based models guide pricing strategies more efficiently by anticipating demand changes, to improve operational efficiency (Muller et al., 2023). Despite these advances, the complete integration of GenAI into real-time retail systems and BI workflows still remains a challenge.

In life sciences, GenAI plays an important role in drug discovery, clinical trials, and personalized medicine. LLMs help interpret complex biomedical literature with less efforts, providing clinicians with updated insights on treatments and latest medical breakthroughs (Thirunavukarasu et al., 2023). Pharmaceutical companies use AI models to create synthetic medical data and to simulate molecular interactions. Their aim is to cut down the research time it takes for new drug discovery. Efficient data analysis using AI helps find viable drug candidates by speeding up the identification of potential drug compounds faster than the traditional methods (Smith et al., 2023). Hospitals are also using AI integrations into processes like hospital management systems (HMS) to improve administrative efficiency by optimizing resource allocation, patient scheduling, and treatment planning. There are still sizable gaps, however, in integrating AI models into real-time clinical workflows and biopharmaceutical research pipelines. Further investigations and research are required to increase efficiencies of these models and for improved decision-making to enhance patient outcomes (Smith et al., 2023), and to establish more trust on AI-based decisions.

GenAI has `considerable potential in education technology (EdTech) too. LLMs can help in creating learning content that is more focused on individual student needs, improving engagement and learning outcomes (Salemi et al., 2023) using power of personalization. Several EdTech platforms now leverage AI to tailor lessons and exercises based on student's progress and needs in real-time by constantly monitoring student's behavior and actions, and based on that dynamically varying the complexity and pace of the content delivery to help them stay more focused and motivated. Additionally, virtual tutors, interactive simulations, and gamifications, all that is made easier by AI-driven tools, can offer very immersive learning experiences overall. Still, a lot of further research is needed to understand the long-term implications of these technologies on student equity in education and their integration into EdTech analytics workflows (Saaida, 2023). Gaps also remain in understanding how GenAI addresses ethical concerns, including biases in AI-driven recommendations (Dwivedi et al., 2023). One common example of bias involves language and cultural differences. Many GenAI models are trained largely on English-language datasets. As a result, when these models are used in EdTech platforms for students from non-English-speaking backgrounds, they may deliver recommendations or generate learning content that is less relevant or can even be culturally inappropriate.

2.1 Related Work

Significant progress has been made in the fields of augmented analytics (Alghamdi and Al-Baity, 2022), self-service BI (Michalczyk et al., 2020), and hybrid human-AI methods (Allen et al., 2023). However, there is limited empirical research on how generative AI can be practically integrated into analytics workflows to democratize data access across industries (Hassani & Silva, 2023). Data democratization is crucial for closing the gap between technical experts and business users (Davenport & Alavi, 2023). While theoretical discussions exist about the potential of generative AI in BI, empirical validation of its real-world application remains scarce (John et al., 2023).

Allen et al. (2023) discusses the potential of GenAI to improve analytics workflows, particularly in enabling effective human-AI collaboration. However, their work primarily focuses on theoretical applications, leaving questions about how these models scale and integrate into real-world settings unanswered. Similarly, John et al. (2023) offer practical guidance on implementing GPT-enabled BI tools but do not deeply examine the specific challenges businesses encounter when deploying these tools across various domains. While research has started to investigate GenAI's ability to bridge the gap between technical and business perspectives (Beheshti et al., 2023), few studies address the practical difficulties organizations face when scaling these technologies. There is a clear need for identifying these challenges and creating frameworks that provide actionable strategies for successful implementation of such technologies in domains such as finance, retail, life sciences, and EdTech.

2.2 Research Gaps
Key research gaps identified in the current literature include:

- Lack of Empirical Evidence: There is very little empirical evidence regarding the practical application and effectiveness of GenAI-enabled BI tools across various domains like finance, retail, life sciences, and EdTech. Their impact on business functions such as SCM, CRM, and HR remains underexplored too.
- Challenges in Data Democratization: Few studies explore how GenAI can democratize data and empower non-technical users to generate actionable insights across domains such as finance, retail, life sciences, and EdTech, and across business functions such as SCM, CRM, and HR.
- Need for Comprehensive Frameworks: Existing research lacks frameworks that address integration challenges of GenAI in analytics workflows, especially in bridging the gap between technical and business teams within domains such as finance, retail, life sciences, and EdTech, and across business functions such as SCM, CRM, and HR.

The literature reveals noticeable key gaps in integrating GenAI into BI, including the need for empirical research, comprehensive integration frameworks, and the democratization of data for non-technical users. Addressing these gaps is important for advancing AI-driven decision-making and increasing business value. To address these gaps, this study introduces a practical framework aimed at GenAI integration into BI tools to democratize data access and enhance real-time decision-making.

In summary, while prior scholarly research has examined the potential of GenAI and LLMs, a considerable lack of understanding still remains about their practical application in BI workflows, particularly in the areas of data democratization, business model innovations, and GenAI integration across different domains. This study seeks to fill these gaps by presenting a framework designed to improve the adoption of GenAI in BI. That could help organizations tackle the challenges emphasized in existing research.

The following section provides the conceptual foundation, explaining the theoretical principles that support the development of this framework.

3. Conceptual Foundation
This section draws on theoretical insights from research on use of LLMs and GenAI in data management, augmented analytics, and BI. The analysis of these insights helps identify broader themes about how these emerging technologies enhance data-driven decision-making across industries and as a result improve business outcomes.

3.1 Generative AI: A Catalyst for Augmented Analytics
GenAI uses many advanced algorithms-such as GPT, BERT, and GANs-to autonomously produce various forms of content such as text, images, audio, and even simulations (McKinsey & Company, 2023). It can also create videos, synthetic data, and interactive user experience. These capabilities are impressive, though they still face challenges in some contexts. What makes these algorithms remarkable is their ability to produce realistic outputs autonomously, based on user prompts. That has transformed how industries nowadays tackle tasks like creative design, customer interaction, and content generation. For example, models like transformers can generate human-like text, while GANs are known for producing lifelike images, enabling applications from art creation to deepfakes. Interestingly, when paired with advanced analytics tools, GenAI is reshaping business analytics by making it generate actionable business insights from available data, almost effortless. It helps businesses make sense of data quickly, even for people without a technical background. Szumilo and Wiegelmann (2024) illustrate this in the retail domain, where with just a small amount of data, GenAI can help predict trends and make smarter pricing decisions, saving

time and resources. AI also demonstrates its potential in interpreting large and complex datasets, in real-time. For instance, an inventory manager of a retail company could use GenAI to analyze customer behavior and trends, say from social media reviews or sales data, at the moment they happen. This allows them to adjust inventory, making quicker, smarter decisions every day.

A key advantage of GenAI lies in its ability to democratize data access. Using intuitive, conversational interfaces, it enables non-technical users to directly interact with large and complex data. This helps bring business users and technical teams closer together to collaborate. By simplifying how they interact with data, it lets team members at all levels easily access and use insights in real-time, while also aligning insights with strategic objectives of the business (Davenport & Ronanki, 2018). Models like GPT empower teams to automatically generate insights from large data sets, automate natural language insights, and offer personalized recommendations. For example, a marketing team could use GPT models to quickly analyze customer feedback and adjust their campaigns in real-time to accommodate shifting trends. These capabilities enable self-service analytics, allowing business users to analyze data independently and reducing reliance on data scientists (Gupta et al., 2023). The heart of this framework is data democratization-making data easier to access for everyone, through GenAI tools, which helps companies make faster data-driven decisions.

3.2 GenAI Bridging the Gap Between Technical Experts and Business Users

A common hurdle to BI adoption is the gap between technical experts, such as data scientists, and non-technical decision-makers, like business users, who drive the business outcomes. GenAI helps close this gap by providing self-serviceability, user-friendly interfaces, and automating complex analytics, to enable business users to access and interpret data without advanced technical expertise (John et al., 2023). Natural language interfaces and conversational AI make analytics easier to understand, allowing non-technical users to generate actionable insights (Davenport & Alavi, 2023). These features help reduce the time required to derive insights, enabling quicker business responses and fostering a culture of data-driven decision-making strategies within organizations by making data more accessible (Beheshti et al., 2023). For example, in large consumer goods companies, GenAI-enabled BI tools allowed marketing managers to query large datasets using plain language commands. This reduced their dependency on data teams and enabled them to quickly tailor promotional strategies based on emerging trends.

GenAI also takes care of routine tasks by automating them such as predictive modeling, report generation, and data visualization. This allows data scientists to focus on strategic initiatives while making data more and directly accessible to business users. The combined effect improves data-driven decision-making and smoothly integrates BI into everyday operations of the business.

3.3 Role of Generative AI in Data Mining Frameworks

GenAI shows a lot of promise, but there are still challenges when it comes to turning its potential into practical applications and real-world results. Mazumder (2023) emphasizes GenAI's key role in advancing data visualization and improving data-driven decision-making for businesses around the world. By automating tasks like NLP, domain-specific analytics, and image processing, GenAI helps companies to respond swiftly to market changes, reveal hidden insights, and refine strategies (Samuel et al., 2024). For example, a retail chain might use GenAI to automatically analyze customer feedback across social media platforms, allowing them to quickly identify emerging trends and adjust their inventory to meet demand before it spikes.

Alghamdi and Al-Baity (2022) emphasize the value of augmented analytics in data preparation and modeling to guide data mining processes from business understanding to deployment. They also explain how that fit within the CRISP-DM framework, a widely used methodology to guide data projects from start to end. GenAI extends these capabilities by going beyond basic CRISP-DM phases, including business understanding, deployment, and feedback loops. This evolution demands updates to traditional data mining frameworks to maximize the benefits of AI-driven analytics. The proposed framework incorporates these advancements, outlining how GenAI supports every stage of the BI process, from initial business understanding to real-time decision-making.

Even with all these advances, the way GenAI works can still feel like a 'black box,' making it hard to see exactly how it adds value to the business. Black box nature-where the underlying processes and reasoning behind AI-generated insights are not always transparent, can create trust issues among business users, who may struggle to rely on insights they do not fully understand. This study aims to clear up this mystery by looking at how GenAI and LLMs can improve business intelligence workflows, turning data into a powerful tool that drives real results.

3.4 Generative AI's Impact Across Data Mining Phases

GenAI has been making a real difference on data mining processes, like in individual phases of the CRISP-DM. Even though we don't yet have a fully developed CRISP-DM framework built around AI, it's clear that there's a big opportunity waiting to leverage AI's full potential to transform traditional data mining. As an example, automating key data mining steps, such as data preparation, predictive modeling, and feedback loops, can improve the overall efficiency and adaptability of CRISP-DM. This means it might be time to rethink such traditional data mining approaches, to make them more adaptable and efficient using GenAI. Three key areas of CRISM-DM framework where AI's influence is most evident are: business understanding, data deployment, and feedback loops.

During the business understanding phase of CRISP-DM, GenAI, particularly LLMs, makes it easier to interact with data in natural language, enabling non-technical users to identify analytical needs and critical business questions more efficiently (Musazade et al., 2024). For example, companies like Tableau and Microsoft Power BI are integrating GenAI-driven NLP tools, to let business decision-makers ask data-related questions in everyday language. It reduces dependence on technical experts and ensures that data analysis closely aligns with business' strategic goals. In the deployment phase of CRISP-DM, GenAI helps automate the implementation of predictive models. According to Musazade et al. (2024), GenAI adapts these models to ever-changing business contexts, providing real-time insights that enhance data-driven decision-making. Ride-sharing technology platforms, for example, use AI to continuously deploy and fine-tune models that predict rider demand and optimize pricing in real time based on location-specific conditions. GenAI also strengthens feedback loops by learning from user interactions, real-time data, and shifting business conditions. This continuous learning ensures that models remain relevant and effective. de Castro and Balaniuk (2024) emphasize the value of maintaining a documented trail of actions, which supports ongoing model refinement and knowledge sharing. Large online retailers like Amazon, use feedback-driven AI systems to fine-tune and personalize product recommendations by constantly learning from user behavior and purchases, ensuring their algorithms stay up-to-date with flexible customer preferences. This feedback mechanism supports effective, smarter decision-making driven by data.

By making data more and easily accessible, facilitating non-technical users with improved self-serviceable tools, and enabling AI-augmented real-time decision-making processes, the proposed framework shows how organizations can leverage GenAI to drive better business outcomes. These foundations for the framework guide organizations in operationalizing AI to meet their strategic objectives. With this conceptual foundation in place, the study now details the methodology used to test and validate how this framework can be practically implemented in real-world scenarios.

This conceptual foundation emphasizes the strategic benefits of integrating GenAI into BI workflows, but putting it into practice requires turning these core principles into actionable strategies tailored to specific domains. The following sections show how these ideas can be applied in different domains and functions by offering concrete examples and solutions to address the real-world challenges of AI adoption.

4. Methodology

This section describes the research design, data collection methods, sampling strategy, and data analysis techniques used in this study. This methodology adopts grounded theory, an inductive approach developed by Glaser and Strauss (1967) and later refined by Tie et al. (2019) to build on the conceptual foundation and the gaps identified in the literature review sections. Grounded theory works very well for this study because it supports the development of a framework grounded in the complex, often messy, real-world experiences of integrating GenAI into BI workflows. This approach provides a deeper look at how these processes actually play out when put into practice, instead of just theoretical ideas (Charmaz, 2006).

This approach takes the study through an iterative cycle of data collection and analysis, allowing key themes to emerge organically. These themes directly shape the proposed framework, ensuring it addresses practical challenges identified in the research, such as data quality, user adoption, and system integration. The framework zeroes in on these challenges and aims to provide actionable solutions that help businesses get the most out of GenAI in their BI workflows. Grounded theory is a great fit for examining the real-world's practical strategies and challenges involved in integrating GenAI into BI workflows. The study also takes measures to make sure everything is valid, reliable, and ethically sound.

4.1 Research Design

This research employs a qualitative design guided by grounded theory principles; prioritizing insights drawn directly from data rather than relying on a predefined theoretical framework. This approach is important for understanding complexities and challenges of bringing GenAI-enabled BI tools within augmented analytics workflows. By constructing theory from empirical data, the study captures the real-world challenges and opportunities organizations encounter when deploying these technologies.

To maintain methodological rigor, theoretical references were intentionally limited to preserve the openness required for the grounded theory process. Drawing heavily on existing literature could potentially constrain the emergent nature of this approach. Instead, this research relies on empirical observations, referencing existing literature only when it directly enhances or contextualizes the findings.

4.2 Data Collection

Semi-structured interviews were conducted with 11 participants from SCM, CRM, HR, finance, retail, life sciences, and EdTech. We selected participants based on their data analytics expertise, familiarity with GPT-enabled BI tools, and their active roles in organizations using these technologies. The interviews were conducted over four weeks in person or via secure video conferencing, lasting 45 to 60 minutes each. They were recorded with participant consent, and transcripts were reviewed for accuracy. Such semi-structured interviews align with grounded theory, providing flexibility to explore emerging themes while focusing on key areas.

The interviews were centered around key questions that were designed to identify the practical challenges, opportunities, and potential strategies in integrating GenAI into BI workflow systems: (1) What challenges did you encounter in implementing GenAI within BI workflows? (2) How do you perceive the role of GenAI in bridging the gap between technical experts and business users? (3) What strategies have been most effective in adopting GenAI tools in your domain and business function?

4.3 Sampling Strategy

A purposive sampling strategy was used to select participants with relevant expertise, ensuring they could provide valuable insights into the study's core themes. Participants in senior or technical roles within organizations that have implemented or are considering to implement GenAI-enabled BI tools were chosen. The sample size of 11 was sufficient to reach theoretical saturation, a grounded theory concept where no new themes emerge from further interviews.

4.4 Qualitative Analysis Method

The data analysis followed grounded theory principles, where data collection and analysis occurred simultaneously to allow theories to emerge naturally. Thematic analysis, based on Braun and Clarke (2006) approach was used to identify and interpret patterns within the qualitative data. This iterative process ensured that themes developed organically and have provided important insights for constructing the framework. To gain deeper understanding of the content and to avoid potential misinterpretation of the data, we carefully reviewed the interview transcripts. Using NVivo software, we performed initial coding to focus on key themes related to the research questions. We then applied the constant comparison method from grounded theory to grouped these initial codes into broader themes. Next, we reviewed the themes to make sure they accurately represented the data and aligned with the study’s goals. Each theme was clearly defined to maintain clarity and consistency throughout the analysis. Finally, we incorporated the themes into the findings, forming the basis-or the foundation, for the framework designed to integrate GenAI into augmented analytics workflows. For example, during the analysis of interviews with participants from the retail and finance sectors, a recurring theme emerged around user skepticism toward AI-generated insights. Business users expressed concerns about trusting automated recommendations, especially in high-stakes decision-making contexts, such as investment portfolio management. By identifying this theme through iterative coding and constant comparison, we were able to highlight the importance of incorporating transparency and explainability into GenAI-driven BI tools. This insight directly influenced the design of the framework, ensuring that the proposed solution emphasizes clear communication of how AI models generate insights.

4.5 Validity, Reliability, and Ethical Considerations

We took several measures to ensure the credibility and trustworthiness of the findings. Triangulation was used by comparing data across participants from various domains and business functions to identify recurring themes, thereby strengthening the robustness of the analysis. Member checking was conducted, allowing participants to review their interview transcripts and preliminary findings to verify accuracy and offer validation. To minimize potential biases, we also conducted peer debriefing sessions to discuss the findings of the study. This was to make sure that any potential biases were minimized and that the results derived were as accurate as possible. Methodological procedures like keeping audit trail were also adhered to in this study; this involved the detailed documentation of all the procedures that were followed in data collection and analysis to make the study replicable and transparent.

All ethical considerations were observed in the course of the research. These include the protection of participants’ confidentiality and maintenance of anonymity along with other ethical measures to make sure that the participants’ rights were not violated in any way. All the data was stored securely and the study was conducted in a manner that would adhere to ethical and professional practices in order to protect the participants and maintain the integrity of the research.

This data analysis phase outlined in the next section involves examining the collected data to identify key insights and patterns, which guide the development of the GenAI framework presented in this study.

5. Data Analysis

A few key themes were observed when a systematic qualitative analysis of participant experiences was conducted to identify themes related to the integration of GenAI into BI workflows.

5.1 Findings and Thematic Content Analysis

The analysis identified the strategies teams usually implement, skills they rely on, and challenges the organizations face while implementing GenAI into BI workflows. In particular, the challenges in addressing the divide between technical experts and business users. One participant observed, "The biggest challenge we face is not the AI itself or technical complexities but getting our business teams to easily understand and confident trust the insights generated by AI tools." For example, a large pharmaceutical company faced low adoption rates of its GenAI-driven BI tool due to the steep learning curve for business users and skepticism about the insights generated by systems they did not fully understand. This sentiment frequently came up during the interviews, emphasizing that user adoption is a significant challenge in successfully integrating GenAI. These insights played a key role in shaping a conceptual framework that provides a structured perspective on what factors generally affect GenAI adoption in BI workflows.

Table 1. Thematic content analysis.

Theme	**General insights**	**Domain and business function specific insights**	**Challenges overcome**	**What GenAI adds**
Empowering Business Users	GenAI democratizes data, enabling non-technical users to access powerful BI tools, but user adoption remains slow due to learning curves and AI literacy gaps.	•SCM: Managers use AI for inventory control but still face challenges with real-time demand forecasting. •CRM: Customer support teams use AI for sentiment analysis but find it challenging to interpret outputs. •HR: HR teams use AI for talent acquisition but find retention prediction challenging. •Finance: Non-technical users access complex models but struggle to interpret outputs and trust the result. •Retail: Store managers optimize inventory but cannot fully use AI for advanced purposes. •Life Sciences: Healthcare professionals face hurdles in using AI insights and trusting the outcome. •EdTech: AI tools for educators face low adoption rates.	Slow user adoption due to complex tools, AI literacy gaps, and inferior support frameworks.	Simplifies complex data analysis and interpretation for non-technical users, making data more accessible without the need for deep technical expertise.
Cross-Functional AI Integration	GenAI fosters collaboration between technical and business teams, but a lack of comprehensive frameworks limits seamless integration.	•SCM: AI integrates logistics and inventory management but faces alignment issues, and challenges in integration with other functions. •CRM: AI improves customer segmentation but needs better alignment with sales strategies. •HR: AI integrates workforce planning but requires better alignment with HR policies and compliance processes. •Finance: AI integrates risk, compliance, and operations but faces issues with smoother alignment. •Retail: AI links sales and supply chain but lacks cohesive frameworks to incorporate other business functions. •Life Sciences: AI spans research and clinical functions but needs stronger integration between technical and medical teams to leverage data capabilities more effectively. •EdTech: AI supports administrators and educators but needs standardized frameworks across the enterprise.	AI integration struggles to align technical capabilities with business strategies, leading to limitations and low adoption.	Improves cross-functional collaboration, allowing smoother data-driven insights to flow between teams, ultimately improving decision-making processes.

Table 1 continued…

Enhancing Data Analytics	GenAI automates data analysis, streamlines workflows, and enhances decision-making, improving data quality and accessibility.	•SCM: Automates demand forecasting and inventory management. •CRM: Enables real-time customer insights and predictive analytics, helping proactive outreach. •HR: Enhances talent acquisition, retention, and workforce analytics. •Finance: Automates risk and market forecasting. •Retail: Helps optimizing inventory management. •Life Sciences: Enhances drug discovery and diagnostics. •EdTech: Provides personalized learning experiences.	Challenges like data silos and improvements in real-time data analysis and decision-making.	Automates complex data preparation and data analysis, allowing organizations to focus on strategic decisions and real-time operations.
Improving Decision-Making	GenAI delivers real-time, actionable insights for more strategic decision-making.	•SCM: Optimizes inventory control and logistics decision-making. •CRM: Improves customer satisfaction with real-time operational support. •HR: Enhances workforce planning and retention strategies. •Finance: Improves risk mitigation and portfolio management. •Retail: Provides real-time price management decisions. •Life Sciences: Enhances clinical and research decision-making. •EdTech: Informs teaching strategies.	Human error, improved decision-making alignment with real-time data, and enhanced overall strategic thinking.	Provides real-time insights that help organizations respond dynamically to market changes, patient needs, or consumer behavior.
Navigating Goal Clarity	GenAI must align with organizational goals to realize its full potential, but a lack of clarity often hinders AI success.	•SCM: Aligns AI strategies with supply chain optimization. •CRM: Aligns with customer engagement priorities. •HR: Ensures AI-driven workforce analytics align with HR policies. •Finance: Aligns AI strategies with regulatory requirements. •Retail: AI aligns with customer satisfaction and business bottom lines. •Life Sciences: Ensures AI insights align with clinical outcomes. •EdTech: Aligns with educational outcomes.	Misalignment between AI initiatives and strategic business goals leading to hurdles like underperformance and low adoption.	Aligns AI-driven insights with organizational goals, ensuring that businesses achieve targeted outcomes through better-informed, data-driven decision-making and strategies.
Domain Competence	Tailored AI solutions for specific industries drive operational efficiencies, but domain-specific models are essential.	•SCM: Combines AI with logistics expertise and just-in-time inventory management practices. •CRM: Integrates AI for personalized customer interactions. •HR: Uses AI to predict workforce needs and to support retention practices. •Finance: Merges AI with financial acumen for market predictions. •Retail: Uses AI for dynamic pricing and inventory control. •Life Sciences: Integrates AI in diagnostics and personalized medicine. •EdTech: Uses AI for adaptive learning and content personalization.	Lack of domain-specific models leading to suboptimal AI implementation and less actionable insights.	Customizes AI models to fit domain-specific needs, enhancing operational efficiencies and strategic impact.
Data and Tech Competence	Advanced data architectures and technological capabilities are critical for effective AI adoption.	•SCM: Requires real-time data integration for inventory management and logistics. •CRM: Needs advanced data handling for customer interactions. •HR: Needs AI-driven analytics for employee performance tracking. •Finance: Demands robust data processing for risk assessment. •Retail: Requires real-time inventory data and customer behavior analytics. •Life Sciences: Needs smooth integration of AI and big data into clinical workflows. •EdTech: Incorporates adaptive learning algorithms and student data analytics.	Handling large datasets, ensuring privacy, and integrating advanced AI systems pose significant challenges.	Ensures scalable AI systems that efficiently manage large datasets while maintaining privacy and regulatory compliance.

Table 1 continued…

Ethical Considerations	Ethical AI use, data privacy, and bias management are critical for responsible adoption.	•SCM: Addresses ethical concerns in supplier data handling. •CRM: Manages customer data privacy and compliance. •HR: Uses AI ethically for employee monitoring. •Finance: Balances innovation with regulatory compliance. •Retail: Safeguards customer data in personalized marketing. •Life Sciences: Ensures regulations and patient data confidentiality. •EdTech: Prioritizes fairness and privacy in student data analytics.	Navigating ethical concerns is essential to foster trust and ensure responsible AI use.	Promotes responsible AI practices, ensuring compliance with privacy and ethical standards.
Human Oversight	Human expertise is crucial to ensure AI-driven insights align with business goals and ethical standards.	•SCM: Validates AI-driven logistics optimizations. •CRM: Aligns AI insights with customer engagement strategies. •HR: Guides AI-driven workforce analytics. •Finance: Monitors AI for accurate market assessments and risk oversights. •Retail: Adjusts AI recommendations for market dynamics. •Life Sciences: Ensures AI-enhanced diagnostics meet clinical standards and research outcomes. •EdTech: Aligns AI-driven learning insights with educational objectives.	Need of human oversight to contextualize AI results and ensure they meet organizational goals.	Combines AI automation with human validation, ensuring ethical practices and long-term strategic alignment.
AI-Driven Personalization	GenAI enables hyper-personalization by analyzing large datasets to deliver tailored insights.	•SCM: Adapts to demand fluctuations and business shifts. •CRM: Customizes customer experiences, often based on geographic location. •HR: Implements personalized employee engagement strategies. •Finance: Customizes financial product offerings. •Retail: Enhances personalized shopping experiences. •Life Sciences: Devices customized treatment plans. •EdTech: Adapts learning content to student needs.	Balancing personalization with privacy and regulatory requirements.	Improves customer satisfaction and operational efficiency through hyper-personalized services.
Scaling AI in Diverse Environments	GenAI scales across organizations and geographies, enabling global AI adoption.	•SCM: Scales global logistics optimization. •CRM: Expands customer segmentation strategies. •HR: Applies workforce analytics across global regions. •Finance: Scales risk assessment tools. •Retail: Adapts AI based inventory and pricing strategy management globally. •Life Sciences: Expands AI-enhanced diagnostics to global healthcare adhering to global regulations. •EdTech: Implements adaptive learning in different educational systems, globally.	Scaling AI globally requires adaptation to local regulations while maintaining core capabilities.	Expands AI solutions worldwide, optimizing operations across diverse markets.
Real-Time AI Adaptation	GenAI adapts to real-time changes in operational and market conditions, offering dynamic decision-making.	•SCM: Adjusts logistics in real-time and just-in-time inventory management. •CRM: Responds to customer interactions on the fly, with minimal manual intervention. •HR: Modifies engagement strategies based on real-time workforce and behavior data, and feedback. •Finance: Adapts to market fluctuations, real-time. •Retail: Adjusts ongoing pricing based on supply and demand. •Life Sciences: Updates treatment plans with real-time data and feedback. •EdTech: Adapts content in response to student performance, and feedback.	Real-time adaptation requires seamless data integration and constant model updates.	Provides dynamic responses, enabling swift, data-driven decisions.

Table 1 continued…

Long-Term AI Sustainability	GenAI offers long-term value by building sustainable AI systems that evolve with business needs.	•SCM: Ensures sustainable logistics optimization. •CRM: Maintains adaptable customer engagement strategies. •HR: Supports evolving workforce planning by aligning with business' long-term strategies. •Finance: Builds enduring AI-driven financial models. •Retail: Sustains AI relevance in changing market conditions. •Life Sciences: Evolves AI for patient care advancements. •EdTech: Develops sustainable AI-driven learning systems.	Ensuring long-term adaptability requires regular updates and alignment with market trends.	Builds enduring AI solutions that evolve, maintaining relevance and effectiveness over time.
AI Governance and Risk Management	AI governance is crucial for establishing guidelines, ethical considerations, and accountability mechanisms in the deployment of GenAI models within BI workflows.	•SCM: Requires risk management policies for AI-driven logistics optimization and supplier data handling. •CRM: Needs customer data protection policies and management of AI-driven marketing strategies. •HR: Involves the ethical use of AI in workforce analytics, including managing biases in talent acquisition. •Finance: Must comply with regulatory requirements and mitigate risks in AI-driven financial decision-making. •Retail: Addresses data privacy for AI-driven personalization and dynamic pricing strategies. •Life Sciences: Manages patient data security and ethical considerations in AI-driven diagnostics. •EdTech: Ensures privacy and fairness in student data analytics and AI-generated learning content.	Developing and implementing AI governance frameworks to manage biases, ensure data privacy, and establish accountability across all domains and business functions.	Provides automated compliance monitoring, enables risk assessment through predictive analytics, and ensures that AI-driven decisions align with ethical and legal standards.

In summary, the thematic content analysis, as outlined in **Table 1**, shows that GenAI has considerable potential for bridging the gap between technical experts and business users. However, its success depends on clear goal definition, effective data management, comprehensive user training, smooth system integration, and transparent processes. These findings serve as the basis for the proposed framework, which aims to address the core challenges that are identified in this research. For instance, a hedge fund company might use this framework to improve collaboration between their data modelers and business decision-makers by setting up cross-functional teams, where data modelers can provide real-time market insights while decision-makers align these insights with trading strategies.

5.2 Insights and Conceptual Framework Development

The findings from the data analysis were utilized to propose a conceptual framework that outlines the competencies needed across different phases of integrating GenAI-enabled BI tools within augmented analytics workflows. The exploration of generative AI's impact across domains such as finance, retail, life sciences, and EdTech, and across business functions such as SCM, CRM, and HR highlights both universal and domain-specific opportunities and challenges. A common theme is AI's ability to enhance data analytics workflows, empower business users, and improve decision-making processes. These commonalities were synthesized into a conceptual framework that serves as a foundational step toward unpacking the role of GenAI in driving business value and operational impact.

Building on these insights, the next section elaborates on the emerging framework, detailing its components and how they address the identified challenges.

6. Emerging Framework

Based on the analysis of data from multiple domains, a conceptual framework was developed to identify key competencies to integrate GenAI in augmented analytics workflows. A prototype application was designed to represent the framework, demonstrating its practical implementation in creating AI-driven workflows. The framework provides a comprehensive strategy for integrating GenAI-enabled tools into augmented analytics workflows across different domains. By emphasizing the interaction between organizational goals, data democratization, and cross-functional teamwork, the framework provides a practical guide for adopting AI to enhance data-driven decision-making and improve operational performance. For instance, in the life sciences domain, GenAI can help researchers automate data preparation and analysis for clinical trials, reducing the time needed to process large datasets for accelerating the development of new treatments.

In comparison to established BI frameworks like CRISP-DM and other traditional self-service BI models and tools currently available in the market-like Microsoft's Power BI, the proposed framework addresses critical limitations identified in the literature review. It introduces an innovative approach integrating GenAI, helping to effectively close the gap between technical experts and business users. While CRISP-DM focuses mainly on processing and modeling structured data, the new framework extends these capabilities to include unstructured data, NLP, and real-time data accessibility. This enhancement with AI-driven analytics provides a more intuitive user experience through self-service features, making it well-suited for flexible, cross-domain applications where traditional BI methods may fall short. For instance, in retail, GenAI can process unstructured data from customer reviews, social media posts, and customer support chat logs to identify product issues. By analyzing this data in real time, product and marketing teams can respond quickly to customer feedback, adjust product offerings, and improve overall customer satisfaction.

To achieve this, the framework leverages the expanded capabilities of GenAI, supporting all phases of the BI process-from business understanding to real-time decision-making, as detailed in Section 3.4. By aligning GenAI with the CRISP-DM methodology, it demonstrates the evolution of traditional data mining processes to fully use AI-driven analytics capabilities across the phases. The framework emphasizes not only data preparation and data modeling but also other critical elements for the successful process like business understanding, automated deployment, and feedback loops, all improved through GenAI. As an example, in financial services, automated deployment of GenAI models can streamline fraud detection processes by continuously updating models based on new transactional data, ensuring that fraud patterns are detected as they evolve.

Table 2 outlines the proposed modifications to the traditional CRISP-DM framework for BI workflows, incorporating AI-driven tools and techniques. These changes demonstrate how AI can enhance each phase of CRISP-DM, from business understanding to feedback loops, while addressing prevalent challenges like goal misalignment, technical obstacles, and data quality concerns. The table also includes examples of AI tools or techniques applicable at each phase of CRISP-DM, along with the expected benefits of these enhancements. The objective of these enhancements is to make data analytics more accessible and actionable for both technical experts and business users alike by improving data democratization through self-serviceability.

GenAI's impact and implementation vary across domains such as finance, retail, life sciences, and EdTech, and across business functions such as SCM, CRM, and HR, each revealing distinct opportunities and challenges. However, GenAI is considered crucial in enhancing data analytics workflows, empowering business users, and improving decision-making.

Table 2. Enhancements to the CRISP-DM with AI integration.

CRISP-DM phase	Proposed changes	Expected benefits	Example AI tools/techniques	Challenges addressed
Business Understanding	Integrate AI tools to interpret business language and requirements using natural language interfaces for goal clarity.	Enhanced goal clarity and alignment with business needs.	NLP-based chatbots, GPT models	Misalignment of goals, communication barriers
Data Preparation	Use AI-driven automation for data cleansing, transformation, and integration, making data preparation accessible to business users.	Reduced technical barriers and faster data preparation.	AutoML, DataRobot, AI-based ETL	Manual data handling, data quality issues
Modeling	Incorporate AI-powered tools for model selection and analysis through natural language queries, enabling business user participation.	Democratized model selection and improved decision-making.	AI model selection tools, AutoML	Complex model selection, technical knowledge gap
Deployment	Streamline deployment with AI tools that provide real-time analytics dashboards and maintain automatic feedback loops.	Real-time insights and continuous model refinement.	AI-powered dashboards (e.g., Tableau AI), ML Ops	Slow deployment, lack of real-time insights
Feedback Loops	Employ AI-driven dynamic feedback mechanisms that adjust analytics based on data and user interactions.	More responsive BI system aligned with user preferences.	Reinforcement learning, A/B testing platforms	Slow adaptation, feedback integration issues
People, Process, and Technology Alignment	Include AI literacy and training programs to facilitate the alignment of people, processes, and technology.	Improved collaboration and AI adoption within the organization.	AI literacy programs, interactive AI tutorials	Technical-user divide, low AI adoption rates

6.1 Navigating Goal Clarity: Deciphering Transformation vs. Refinement

The initial step in integrating GenAI into BI workflows involves clarifying organizational goals, a finding underscored in Section 5. Understanding whether AI adoption aims for transformation or refinement is critical for strategic alignment. A clear distinction must be made between transformation and refinement. If you're completely changing how the business works, that's transformation. Refinement, on the other hand, just means improving what's already there. Organizations need to carefully decide which approach to GenAI adoption-whether acting as a taker, shaper, or maker, as described by Baig et al. (2023)-best fits their own strategic challenges. The study emphasizes that most organizations go toward taker or shaper approaches without critical analysis of their strategy. When goals aren't clear, people often end up working at cross purposes, which leads to missed expectations. While taking a transformative approach, GenAI can become a driving force for innovation, enabling the creation of new business opportunities and enabling the exploration of strategic questions that might otherwise remain unexplored. This proactive mindset allows organizations to navigate diverse business paths while promoting data democratization and building a culture centered around data-driven decision-making. On the refinement side, GPT-enabled tools can enhance traditional analytics frameworks like CRISP-DM by automating tasks such as data preparation, data visualization, and data modeling. Both approaches, using GenAI can make it easier for technical experts and business users to collaborate and achieve the common goals of the organization.

Along with efficient data accessibility, quality of data is also very important for data-drive processes and decision-making. Whether the focus is on transformation or on refinement, GenAI also plays a key role in advancing automation in data quality assessments and improvements. That helps organizations maintain high-quality data with minimal manual efforts by relying on enhanced processes and advance technology.

6.2 Domain Competence: Bridging Business and Data Understanding

Domain competence was observed as a critical factor in data analysis (Section 5), reflecting its importance in effectively integrating GenAI with augmented analytics tools. By focusing on domain-specific needs, organizations can ensure that AI-driven solutions truly address their own challenges. That helps improve business's top-line growth and bottom-line efficiency both with better customer experiences, informed decision-making, and operational performance. On the flip side, lack of domain competence can leave organizations data-rich but insight-poor and limit their ability to convert available data into actionable strategies.

A common issue many organizations face is the gap between technical teams and business users. While business users often bring deep domain knowledge, they often have to rely on easy-to-use tools like spreadsheets. That limit their ability to perform deeper data analysis. In contrast, data scientists and engineers often require more advanced tools, needing coding skills, that many business users lack. GPT-powered augmented analytics tools help close this gap by offering user-friendly interfaces, allowing non-technical users to directly interact with complex data and advanced AI models. Although these tools can deliver actionable insights, strong domain competence remains crucial for tasks like identifying root cause and understanding the factors that drive performance.

Making data more accessible and introducing self-service to analytics requires AI tools that are not only intuitive but can also smoothly fit into business processes. To facilitate widespread adoption of such tools, effective change management is also very important. Together, that helps organizations fully leverage the potential of AI in empowering their workforce in becoming data-driven.

6.3 Data and Tech Competence: Innovating Through Architecture

Being skilled with data and technology, as explained in the conceptual foundation (Section 3), are essential for maximizing AI's impact on advanced analytic. For example, General Electric uses AI models to analyze the vast quantities of data generated by turbine sensors. However, skilled technical engineers play a crucial role in defining threshold values and performance parameters for the AI models. These parameters ensure that the models generate accurate and actionable insights for data-driven decision-making. As data scientists and AI engineers of the organization refine their data and technology architectures for more efficiency and ease of use, they can start using AI models like GPT-based LLMs that can turn plain language into specific analytics tasks. LLMs also support a method known as 'few-shot learning,' where they can quickly identify patterns with minimal labeled data. That allows these models to deliver analytics solutions with minimal data input. These capabilities can make things a lot simpler for non-technical business users, who might not need as much technical expertise anymore, to derive insight from data and use that for decision-making.

Participants in this study frequently emphasized the importance of modular and flexible architecture designs. These modular systems let organizations update AI models quickly, replacing pre-trained or fine-tuned models as needed to adapt to advancing technologies. Investing in these flexible architectures make sure that augmented analytics workflows remain agile and able to response quickly to constantly changing business environments, promoting continuous innovation.

By embracing modular architectures, organizations can stay flexible in their augmented analytics workflows, helping them stay competitive in an AI-driven environment. This approach is critical for businesses want to stay ahead in a rapidly advancing technological environment.

However, organizations that don't have strong data and tech expertise often struggle in maintaining data quality, addressing privacy concerns, and staying up-to-date with technologically. Future-proofing architectures requires ongoing investment in both infrastructure and skilled talent capable of implementing and iterating on AI-driven solutions.

6.4 Inter-Domain Differences: Tailoring AI Integration to Domain-Specific Needs

Drawing on insights from the thematic analysis (Section 5.1), the integration of GenAI into BI workflows shares common principles across domains, yet the specific challenges, opportunities, and ethical considerations differ by domains. The framework emphasizes a structured, strategic approach tailored to the specific needs of each domain, ensuring that AI implementations align with organizational goals and user requirements:

- *SCM*: GenAI delivers real-time insights that help businesses optimize operations and anticipate potential disruptions.
- *CRM*: AI automates tasks like customer interactions, direct marketing, sentiment analysis, and predictive analytics, enhancing customer engagement to boost overall customer satisfaction.
- *HR*: AI plays a key role in talent acquisition, workforce planning, talent management, and employee engagement, enabling more efficient HR policies to improve overall organizational performance.
- *Finance*: AI supports data privacy and security measures, real-time risk assessment, fraud detection, and portfolio management to balance innovation while ensuring regulatory compliance.
- *Retail*: AI enhances customer behavior analysis, inventory management, and adaptive pricing decisions to allow retailers to quickly adapt to market trends and shifts.
- *Life Sciences*: AI accelerates advancements in drug discovery, improves diagnostic accuracy, and enables personalized medicine, while ensuring that ethical considerations stay a priority.
- *EdTech*: AI promotes personalized learning experiences and automates administrative tasks, while safeguarding student data privacy, while ensuring ethical practices remains a priority.

Across all sectors, known common challenges such as data privacy concerns, limited computational resources, and biases in AI models can hinder the ability to fully tap into GenAI's potential. The universal need for human oversight remains very important to make sure that AI-generated insights are contextualized, ethically sound, and aligned with business goals. By emphasizing the importance of human expertise, organizations can guide, validate, and refine AI-driven insights to deliver tangible business value.

6.5 People, Process, and Technology in Generative AI Integration

The successful integration of GenAI into BI workflows, as suggested in this framework, depends on the interdependence between people, processes, and technology. Building AI literacy, developing adaptable processes, and adopting scalable technologies form the foundation for translating GenAI capabilities into real-world organizational impact.

- *People*: The effectiveness of GenAI adoption relies on promoting collaboration between business users, data scientists, and IT professionals, a theme highlighted in our earlier findings (Section 5.1). Building AI literacy among business users, as identified in the thematic analysis, involves structured training programs, cross-functional workshops, and the development of 'translator' roles to improve communication between technical and non-technical teams.

- *Process*: Adaptability in processes, particularly within the CRISP-DM methodology, are key to integrating GenAI effectively. As an example, agile practices can be employed in data preparation, model deployment, and feedback loops to promote continuous refinement. This framework emphasizes the importance of establishing standardized workflows, including human oversight, governance and ethical guidelines, to address potential biases in AI outputs.
- *Technology*: The technological foundation of this framework extends beyond AI models, emphasizing the need for modular and extensible architectures as highlighted in section 6.3. Investing in cloud-based infrastructure, advanced databases, and automation tools is crucial for processing large datasets and supporting real-time analysis. These technologies enable smooth integration into existing BI systems, promoting effective data-driven decision-making capabilities across all domains.

Even while goal clarity, data competence, and domain competence are aligned, organizations can navigate the complexities of AI integration only by aligning people, processes, and technology within those competences to ensure the framework's effectiveness in driving data-driven decisions and innovation across the organization.

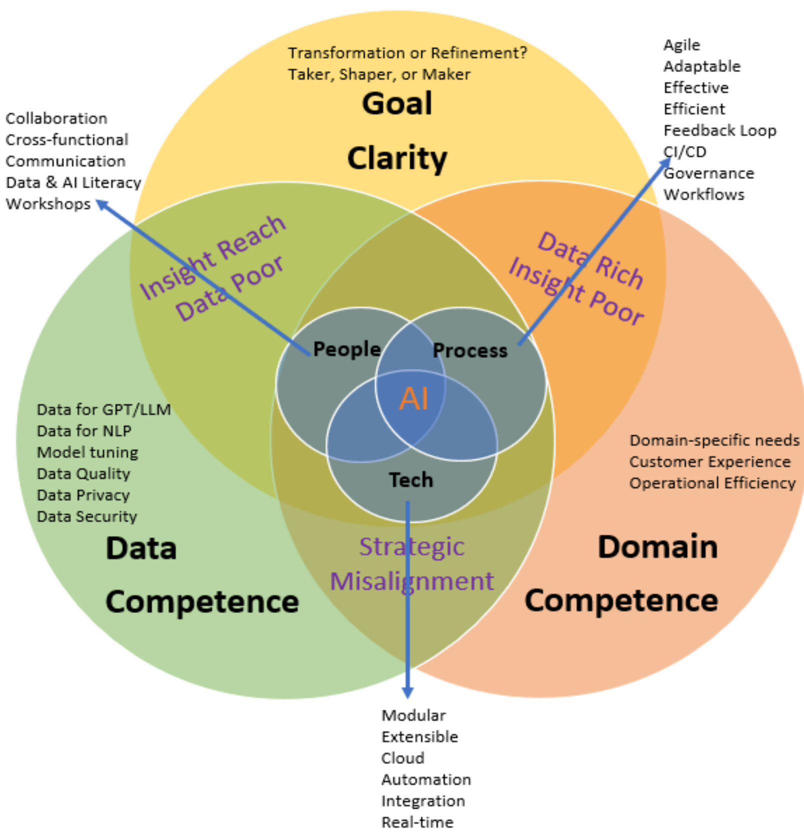

Figure 1. AI-Driven competency framework for strategic decision-making.

6.6 Enhancing Strategic Decision-Making with AI

Figure 1 depicts the interdependence of three core competencies: Goal Clarity, Data Competence, and Domain Competence. All three are equally important for implementing effective data-driven decision-making processes. The diagram emphasizes how strategically implemented AI bridges the critical connections between People, Process, and Technology. Alignment between all these competences addresses common organizational challenges: "Insight Rich but Data Poor," "Data Rich but Insight Poor," and dealing with "Strategic Misalignment." By aligning these competencies, organizations can use AI to enhance analytics capabilities, optimize decision-making processes, and democratize data.

The proposed integrative framework strengthens analytical capabilities while enhancing strategic decision-making processes. For example, IBM's Watson for Oncology illustrates "insight rich, but data poor" challenge. It was designed to provide personalized cancer treatment recommendations, however, over reliance on synthetic data and limited real-world patient data led to inaccuracies and unsafe treatment suggestions (Saviano et al., 2025). On the contrary, a Sydney Fintech, Rich Data company faced "data rich, insight poor" challenges while working on improving dynamic credit assessments, are leveraging AI to address this issue (The Australian, 2024). It provides a structured blueprint for incorporating AI and data analytics into operational and strategic workflows to ensure adaptability to advancing business environments. Aligning AI integration with domain-specific needs enables organizations to realize its full potential from being data-driven, driving innovation, delivering business value, and staying competitive in an AI-driven environment.

A prototype was developed to demonstrate the framework's practical application. The next section details the prototype development process, spotlighting how the framework's competencies can be operationalized to address the challenges identified by the study.

7. Prototype Development Process

For organizations across sectors, being data-driven and capable of extracting actionable insights through GenAI and augmented analytics is becoming increasingly important. Yet, many analytics tools fail to prioritize the alignment of goal clarity, data competence, and domain expertise, with people, process, and technology, often leading to suboptimal results and missed opportunities. To bridge these gaps, an augmented analytics prototype was developed to help organizations assess and address their competency gaps while designing effective strategies and workflows. Key stages from the conceptual framework were translated into features within the prototype, ensuring users could achieve their analytics objectives effectively. The prototype combines front-end technologies like HTML, CSS, and React.js to provide an interactive user-friendly interface, and uses back-end tools such as Node.js, Express.js, and MongoDB for data storing, processing and scalability. GenAI is coherently integrated into the workflow, offering user-centric solutions for identifying and addressing competency gaps. The prototype includes guided, intuitive interfaces designed for diverse user personas-Taker, Shaper, and Maker.

Insights from the development process reinforces the importance of guided workflows. Features like predefined templates and prompts helped users articulate their competency gaps and analytics goals while effectively defining relevant metrics and KPIs. Interactive visualizations and collaboration tools strengthened domain competence by enabling users to interpret and validate data insights. Also, tools for data import, quality assessment, and cleaning tools enhanced the data competence, making data preparation more efficient. Usability testing with five business analysts and data scientists evaluated the prototype's interface, functionality, and integration with existing BI workflows. Participants reported a 30% improvement in their ability to interact with BI tools using the prototype's user-friendly interface. They also praised its ability to bridge technical experts and business user gaps, allowing intuitive data insights.

These findings support the framework's capacity to address key challenges in GenAI integration. These evaluation results justify the prototype's alignment with the proposed framework, as it effectively demonstrated its capacity to address data management, user training, and system integration challenges identified in the study. The insights gained from this iterative development process not only demonstrate the prototype's alignment with BI workflow requirements but also provide valuable lessons and implications for the broader adoption of GenAI in BI. The following section discusses these implications and practical applications, and addresses potential limitations and future research directions.

8. Discussion

Integrating GenAI and GPT-enabled BI tools has become a game-changing strategy for organizations aiming to maximize the value of their data, offering new ways to bridge the gap between technical experts and business users. This study confirms that AI's use in BI platforms, through GenAI, ML, and NLP, enhances the entire analytics cycle, from data preparation to visualization and insight generation, aligning with prior work on augmented analytics (Alghamdi and Al-Baity, 2022). While GenAI makes data more accessible and automates insights remarkably well, it's clear from experience that technology alone can't solve every problem. Human involvement is still a key to making sure these insights are actionable, relevant, and contextually valid, as well as they make sense in real-world scenarios.

Emerging applications like Voice BI, which integrates voice data with BI workflows, open up exciting new possibilities for advancing BI. The conceptual framework proposed by Sattarapu et al. (2021) points out the importance of voice engagement through conversational AI, suggesting that tracking voice metrics can help build voice-driven BI systems. The adoption of GenAI tools, particularly when combined with voice data, marks a substantial shift in BI practices, emphasizing intuitive user interaction alongside data-driven automation. Imagine a scenario where a busy warehouse manager uses Voice BI to ask about stock levels on a particular shelf while on the move. Such real-time responses could significantly enhance productivity and decision-making speed.

The practical framework we developed through this research provides a structured help for organizations to integrating AI into BI workflows. What stood out most during the study was the critical need for aligning AI initiatives with business goals while including human oversight, and customizing solutions to domain-specific needs. By addressing challenges such as gaps between technical experts-business users alignment and need for ethical considerations, the framework provides actionable strategies for AI adoption across various domains and functions.

This study has several practical implications for AI integration in BI workflows:

- *Aligning AI with Organizational Objectives:* The proposed framework emphasizes the importance of clearly defining goals when implementing AI. Organizations should distinguish between transformational objectives, which drive innovation and new business models, and refinement objectives, which enhance existing processes. Focus on this distinction between objectives is very important for aligning AI adoption with business strategies and guiding investments in technology for desired outcome.
- *Bridging the Technical Experts-Business Users Gap*: A key finding is the need to bridge the understanding and operational gaps between business users and technical experts. Having a solid understanding of both business and data analytics is key to effectively using GenAI in BI workflows. The study advocates for cross-functional training and teamwork, helping business users like strategic decision-makers and technical experts like data scientists to understand each other's domains and functions. Developing 'translator' roles can further improve communication and teamwork, to bridge the gaps between teams for tighter integration.
- *Building Scalable Data Architecture*: Successful AI implementation requires a sturdy and sophisticated data and technology architecture. The study's findings show that scalable infrastructure is key for

handling increased data processing needs. Organizations should invest in cloud-based solutions, AI-friendly databases, and APIs to ensure flexibility and easy, real-time access to data. Using an agile architecture can allow smooth integration of new AI applications, supporting continuous innovation and making sure that technology keeps up with growing business needs.
- *Domain-Specific Customization*: Integrating GenAI into BI workflows looks different depending on the domain, so domain-specific strategies are required. For example, SCM the focus is on logistics and inventory control, while in CRM it helps with customer segmentation. In HR, AI supports talent acquisition, and in finance, it helps with maintaining security and compliance. Life sciences focus on ethical use and medical accuracy, retail uses AI for demand forecasting and personalization, and EdTech focuses on ethical AI in learning. Customizing AI integration to meet each sector's unique regulatory, operational, and ethical demands is a key.

The framework also emphasizes an important role of human oversight in ethical AI use. While GenAI can drive efficiency and automation, human expertise is still required for guiding, validating, and contextualizing AI outputs. Human oversight helps ensuring that AI adoption remains responsible and aligns with compliance and industry standards to make sure concerns such as data privacy, fairness, and transparency are being addressed.

While this study provides valuable insights into GenAI in augmented analytics, it has limitations. This research has focused only on specific domains, such as finance, retail, life sciences, and EdTech, and across business functions, such as SCM, CRM, and HR, which might not fully capture the challenges faced in other domains and functions. While this framework shows promise in variety of practical scenarios, it is also important to acknowledge its limitations to provide a holistic and balanced perspective.

This study provides a cross-sectional view of AI adoption, which might not reflect the advancing nature of technology integration within organizations. As AI rapidly advances, the organizational experiences with these technologies may change, bringing new complexity that a single research period cannot fully capture. Also, relying on semi-structured interviews as the primary data source can introduce potential biases, such as participants' personal perspectives and interviewer's way of forming questions that may influence their responses. While the study employs grounded theory to extract themes, the findings may still reflect the specific contexts and experiences of the interviewees, which could potentially limit how well the proposed framework applies to other BI settings. These limitations point out areas where future research can dive deeper, as discussed in the next section.

9. Conclusion and Future Research

In today's fast changing world of BI and analytics, the integration of GenAI and GPT-enabled tools is transforming how organizations connect the gap between technical experts and business users. These technologies make data more accessible through self-serviceability, empowering organizations to make faster, smarter data-driven decisions that drive real business value. For examples, finance teams to generate real-time cash flow projections or retail managers to independently analyze sales trends. The framework in this study offers a practical guide for aligning GenAI with organizational objectives. It emphasizes the importance of human oversight while addressing the specific needs of various domains and functions. The framework addresses gaps in the existing literature by offering actionable guidance for implementing GenAI in fields such as finance, retail, life sciences, and EdTech, along with functions like SCM, CRM, and HR. Although more empirical validation is needed, adopting this framework could help organizations enhance analytics capabilities, improve operations, and promote a more collaborative, data-driven culture.

Future research should focus on several key areas. Such studies would be valuable to explore the long-term effects of AI-enabled BI tools on data-driven decision-making and overall organizational performance. This kind of research would highlight what drives lasting success and throw light on new challenges as AI adoption progresses. Also, ongoing research to address ethical considerations such as data privacy, fairness, and biases in AI systems is very important to developing responsible AI practices and regulatory frameworks. Further exploration is also needed to encourage cross-domain learning, where mature AI applications in sectors like CRM and finance can share best practices with emerging areas such as retail and life sciences. Lastly, investigating human-machine collaboration within BI workflows will help to strike the optimal balance between automation and human oversight, ensuring AI's benefits are maximized without losing the value of human expertise.

To validate the proposed framework, future research should apply it in various organizational settings and a variety of industries. That can assess its adaptability, reveal any necessary adjustments that may be required, and can provide further evidence of its effectiveness in enhancing BI workflows through GenAI. Research advancements like that will contribute to a deeper understanding of AI’s progressing role in BI workflows and its long-term impact on a variety of business strategies and their performance.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

AI Disclosure

During the preparation of this work the author(s) used generative AI in order to improve the language of the article. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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