

The Role of Accuracy and Validation Effectiveness in Conversational Business Analytics

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Abstract

This study examines conversational business analytics, an approach that utilizes AI to address the technical competency gaps that hindered end users from effectively using traditional self-service analytics. By facilitating natural language interactions, conversational business analytics aims to enable end users to independently retrieve data and generate insights. The analysis focuses on Text-to-SQL as a representative technology for translating natural language requests into SQL statements. Using models grounded in expected utility theory, the study identifies conditions under which conversational business analytics, through partial or full support, can outperform delegation to human experts. The results indicate that partial support, which focuses solely on information generation by AI, is viable when the accuracy of AI-generated SQL queries exceeds a defined threshold. In contrast, full support includes not only information generation but also validation through explanations provided by the AI, and requires sufficiently high validation effectiveness to be reliable. However, user-based validation presents challenges, such as misjudgment and rejection of valid SQL queries, which may limit the effectiveness of conversational business analytics. These challenges underscore the need for robust validation mechanisms, including improved user support, automated processes, and methods for assessing quality independently of end users' technical competencies.

1 Introduction

Business analytics aims to generate actionable insights that support data-driven decision-making across diverse organizational contexts. Self-service analytics, a significant development in this domain, empowers end users to independently fulfill their information needs without relying on experts such as data engineers or data scientists. By providing tools for retrieving, preparing, analyzing, and visualizing data, self-service analytics enhances flexibility and agility in addressing dynamic business demands.

Despite these advantages, self-service analytics has notable limitations. While end users are often domain experts, they frequently lack the technical skills required for advanced analytics tasks, such as navigating complex data structures, writing

program code, or utilizing machine learning techniques. This skills gap can result in errors and a continued dependency on technical experts, undermining the autonomy and effectiveness of self-service analytics.

Recent advancements in generative AI, particularly the development of large language models, provide a transformative solution to these challenges. These models enable natural language interaction with analytics systems, removing the necessity for technical expertise. Building on this foundation, conversational business analytics is emerging as an innovative paradigm that redefines how users interact with business analytics systems. By leveraging large language models, conversational business analytics allows users to delegate tasks such as data retrieval, analysis, and visualization to AI capable of understanding and generating natural language outputs. This approach bridges the skills gap and extends access to sophisticated analytics tools across a broader spectrum of organizational roles.

There is a growing number of initiatives to extend self-service analytics by a AI-powered natural language interface. In response, software vendors are expanding their product portfolios to leverage individual data analysis. These solutions are designed to empower end users to interact with data seamlessly, generate reports, and perform a wide range of analytical tasks independently.

This study develops models, grounded in expected utility theory, to identify the conditions under which conversational business analytics using Text-to-SQL outperforms delegation to human experts. Central to this analysis is the interplay between accuracy (the ability of AI to generate correct information) and validation effectiveness (the performance in correctly distinguishing between true and false information). The models examine two levels of AI support: partial support, where the AI generates information without additional validation, and full support, which includes a validation process to enhance trustworthiness. The conditions under which conversational business analytics surpasses delegation to human experts are identified, with a particular focus on scenarios where validation should be performed to enhance trustworthiness and those where it should be omitted to avoid a degradation in decision quality. These insights provide a structured framework for determining when and how AI-driven insight generation, combined with validation, can increase utility while maintaining reliability, offering practical guidance for implementing conversational business analytics in diverse business contexts.

The structure of this study is as follows: Chapter 2 provides an overview of traditional self-service analytics, highlighting its limitations. Chapter 3 introduces conversational business analytics, exploring its transformative potential with a focus on large language models. This chapter also illustrates the challenges of information generation and subsequent validation using Text-to-SQL as an example. Chapter 4 presents the models that examine the dynamics of partial and full support strategies, focusing on their implications for both information generation and validation. Finally, Chapter 5 concludes with a summary of the key findings, an acknowledgment of the study's limitations, and a discussion of directions for future research.

2 Traditional Self-Service Analytics

Business analytics focuses on generating actionable insights to support data-driven decision-making within business contexts [10, 17, 28, 78]. To achieve these goals, analytics ecosystems consist of components [30, 83, 63, 54] that automate four core interconnected tasks for generating insights: retrieving data, preparing data, generating information, and visualizing information (see Figure 1). In addition to these core tasks, there are complementary tasks such as ensuring data and information quality and establishing governance mechanisms [84]. Although these complementary tasks are important for achieving the goals associated with business analytics, they are not discussed further in this study.

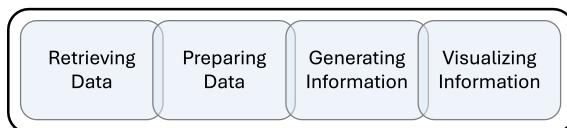


Figure 1: Core insight generation tasks of business analytics.

Retrieving data involves gathering raw data from various source systems, such as structured data from relational databases, semi-structured data like JSON or XML, and unstructured data such as text or images. The next step, preparing data, includes cleansing, transformation, and enrichment processes to ensure quality and usability. Prepared data is stored in data warehouses and data marts for structured analysis, while semi-structured or unstructured data is stored in data lakes [44] or variants, prepared when needed.

Generating information applies the three main methods of business analytics [16]: descriptive, predictive, and prescriptive analytics. Descriptive analytics summarizes historical and real-time data, providing insights into past and current performance using key performance indicators (KPIs), trend analysis, and target-versus-actual comparisons [17]. Predictive analytics uses statistical models and machine learning techniques to forecast future developments, such as predicting customer churn or market trends. Prescriptive analytics recommends actions based on forecasts, utilizing planning, simulation, and optimization methods to identify effective decisions. These methods are complementary, with prescriptive analytics relying on both descriptive and predictive results.

Finally, visualizing information transforms analytical results into intuitive formats that support decision-making [69]. Effective visualizations, such as dashboards, simplify complex insights, enabling to explore trends, identify opportunities, and act quickly.

Day-to-day information needs are typically met through predefined reports provided by analytics ecosystems. However, when new information needs arise, self-service analytics [29, 1, 46] enables end users to fulfill information needs independently, providing a viable alternative to the traditional reliance on expert (e.g. data engineers and data scientists) intervention. In this context, an end user refers to any organizational member who uses information to make decisions – whether to inform their own decisions or to prepare information for others, such as supervisors.

These individuals are typically domain experts with extensive knowledge in their respective fields, distributed across various departments within the organization.

The implementation of self-service analytics provides significant benefits [29, 1, 59]. It enables flexible and timely information generation, supporting early identification of opportunities and risks. This allows for faster decision making, both to capitalize on positive outcomes and to mitigate negative impacts. Self-service analytics also falls under the umbrella of "end-user computing" [57], where tasks traditionally managed by specialized departments are now performed by members of the organization. By eliminating the need to delegate information retrieval tasks to experts, self-service analytics removes dependencies and delays, thereby streamlining processes. In addition, it reduces the agency costs associated with delegation [26] by minimizing the exposure to hidden actions, which in turn reduces the need for incentives or oversight.

Self-service analytics for descriptive purposes has traditionally relied on the data mart approach, enabling users to access predefined information and perform OLAP operations [13, 9] like drill-down and roll-up. However, much of the data—customer, product, or process-related—exists outside data marts, in warehouses, lakes, or source systems. While real-time OLAP and in-memory computing have improved responsiveness, generating actionable insights often still requires expert assistance, leading to delays. To address this, greater flexibility is needed [1], allowing to independently retrieve and prepare data, perform analytics, and visualize results. This autonomy enhances decision-making and supports agile responses to changing business needs.

Effective utilization of self-service analytics necessitates technical expertise [66], which many end users lack. While end users typically possess domain-specific knowledge, they often lack proficiency in critical areas such as data retrieval, modeling, machine learning, programming, and navigating complex data structures [60]. For instance, Microsoft's financial data warehouse, comprising 632 tables, over 4,000 columns, and 200 views, illustrates the significant challenges posed by navigating large and intricate databases [21]. This knowledge gap not only increases the likelihood of errors but also limits to independently generate actionable insights.

Several studies underscore the importance of technical skills for the effective application of self-service analytics [29, 37, 5]. Imhoff and White highlight the necessity of user-friendly tools, noting that "sophisticated analytics are often too intricate, complex, or difficult to construct for many information workers." Similarly, Lennerholt, Laere, and Söderström emphasize the dual importance of intuitive tool design and comprehensive training programs to address the technical knowledge gap among non-technical users [37]. In an empirical study, Alparslan and Hügens examine the challenges small and medium-sized enterprises face in leveraging analytic ecosystems [3]. Their findings reveal that for approximately 70% of respondents, inadequate technical skills represent a primary obstacle to transforming raw data into actionable insights.



Figure 2: CBA facilitating natural language requests and generating insights [2]

3 Conversational Business Analytics

3.1 Overview

Business analytics is undergoing significant development with the emergence of generative AI, giving rise to a new approach termed “Conversational Business Analytics” (CBA). This new paradigm leverages natural language processing to address persistent challenges in traditional self-service analytics, particularly the technical skill gap among end users. CBA enables natural language interactions for tasks such as data processing, analysis, and insight generation, presenting the potential to enhance the accessibility and efficiency of business analytics.

CBA shifts the focus from traditional graphical user interfaces to natural language-driven interactions, supported by advancements in large language models (LLMs) [77, 18, 7]. These models process natural language by tokenizing text and employing self-attention mechanisms to interpret contextual relationships. This architecture allows for context-aware and relevant outputs, with responses generated token by token based on probabilistic modeling. Trained on extensive text corpora, LLMs optimize billions of parameters to achieve high performance in natural language understanding and generation. As depicted in Figure 2, CBA facilitates the transformation of natural language inputs into actionable outputs, such as structured reports or visualizations.

CBA extends the capabilities of business analytics by automating core tasks for insight generation, including data retrieval, preparation, analytics, and visualization.

Task	References
Data Retrieval	[75], [71], [33], [32], [24]
Data Preparation	[90], [67], [34], [11], [56]
Information Extraction and Generation	[52], [70], [39]
Information Visualization	[86], [68], [45], [49], [15]

Table 1: Selected advancements in CBA regarding the core tasks of business analytics. These advancements are categorized based on their focus on specific core tasks of business analytics. It is important to note that many of these advancements affect multiple tasks simultaneously, highlighting the interconnected nature of tasks such as data retrieval, preparation, analysis, and insight generation.

It supports structured data (e.g., from data warehouses), semi-structured data (e.g., from data lakes), and unstructured data (e.g., textual documents). For structured and semi-structured data, semantic parsing techniques are used to convert natural language queries into executable code. For unstructured data, LLMs extract insights through advanced text processing methods. The Table 1 below summarizes core tasks and their corresponding references for recent advancements.

CBA also introduces interactive exchanges between users and AI, enabling refinement of requests, validation of outputs, and clarification of insights. Such interaction underscores its user-centric and adaptive design, as exemplified by tools like OpenAI’s ChatGPT Advanced Data Analysis, which guide users through tasks such as analytical modeling and workflow optimization [70].

By integrating natural language processing, interactive communication, and support for diverse tasks and data types, CBA introduces a novel form of delegation in business analytics (see Figure 3). Through CBA, complex tasks such as data processing and information generation can be assigned to AI, enabling the autonomous generation of insights on behalf of the end user. This delegation has the potential to reduce dependence on human experts while addressing the limitations associated with traditional self-service analytics.

Given the dynamic nature of CBA, this study focuses on Text-to-SQL as a key semantic parsing technology [33, 6, 4, 19, 87]. Text-to-SQL, a component of natural language interfaces to databases [41], translates natural language prompts into Structured Query Language (SQL) queries, enabling the retrieval and transformation of data from relational databases. This technology supports both data retrieval and the preparation of comprehensive workflows for generating actionable insights.

The origins of Text-to-SQL can be traced back to Codd’s vision in the 1970s, which proposed natural language interfaces for “casual users” to interact with relational databases [12]. Early implementations, such as rule-based systems [82], were limited in flexibility, but subsequent advancements, including Long Short-Term Memory (LSTM) networks [91], improved the handling of sequential inputs. More recently, transformer-based architectures have replaced LSTM networks, demonstrating superior performance for complex natural language processing tasks. Modern Text-to-SQL systems leverage large language models (LLMs) for both training and inference, significantly improving accuracy and capability.

The primary focus of this study is on the accuracy of Text-to-SQL, defined as

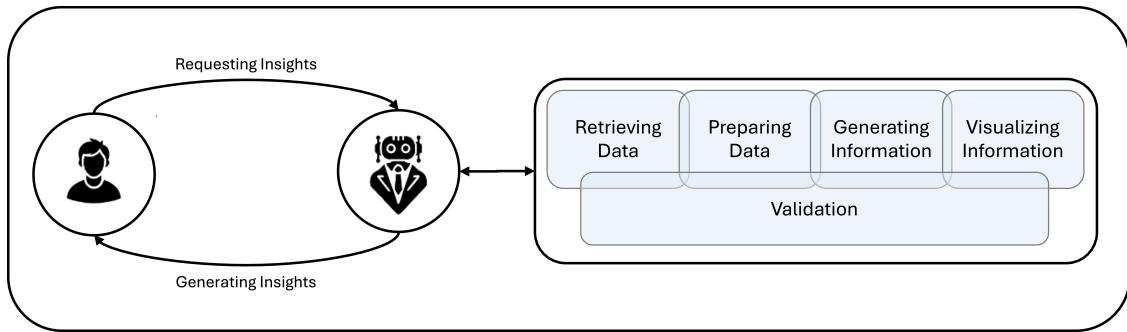


Figure 3: Delegation of core tasks to AI.

its effectiveness in generating correct SQL queries. Ensuring accuracy is crucial, as errors in query generation can lead to incorrect insights and suboptimal decisions. Additionally, the study examines validation effectiveness, which reflects the ability to correctly distinguish between accurate and inaccurate outputs. Validation effectiveness plays a key role in verifying the reliability of generated information, particularly in high-stakes scenarios where flawed data can have significant consequences. The dual challenges of ensuring effectiveness in information generation and validation are explored in detail in the following sections.

3.2 Accuracy

Delegating tasks to human experts is grounded in their ability to accurately interpret and respond to information needs, as well as to build a shared understanding of the underlying goals and requirements [22, 31]. A similar dynamic exists when interacting with AI: the AI must understand the user’s request to generate the desired outcome. However, while natural language is flexible and often ambiguous, SQL is highly structured and formal. For instance, the key figure “material availability” may be interpreted differently by the logistics and maintenance departments within the same organization due to the coexistence of multiple terminological systems [50, 85, 27]. Beyond terminological differences, ambiguities may also arise from the linguistic complexity of the request itself, such as context dependencies or vague formulations. To translate such requests into correct SQL queries, the AI must map the terms used in the request to the corresponding tables and columns within the data model (schema mapping). This requires a deep understanding of the semantics of the data model, including the specific meaning of fields and the relationships between tables. Thus, the AI must not only understand the request but also identify the relevant tables and columns that match the user’s inquiry.

The AI’s ability to interpret a natural language request and translate it into correct SQL code is referred to as its accuracy. Several distinct types of accuracy can be identified to assess different aspects of AI performance [33, 89, 74, 32]. Syntactic accuracy examines whether the SQL statements generated by the AI are executable. Execution accuracy evaluates whether the SQL query generated by the AI produces the expected result, even if the query’s structure differs from a reference SQL statement (often referred to as the “gold standard”). In contrast, exact match accuracy is more stringent, as it requires not only the correct result but also that

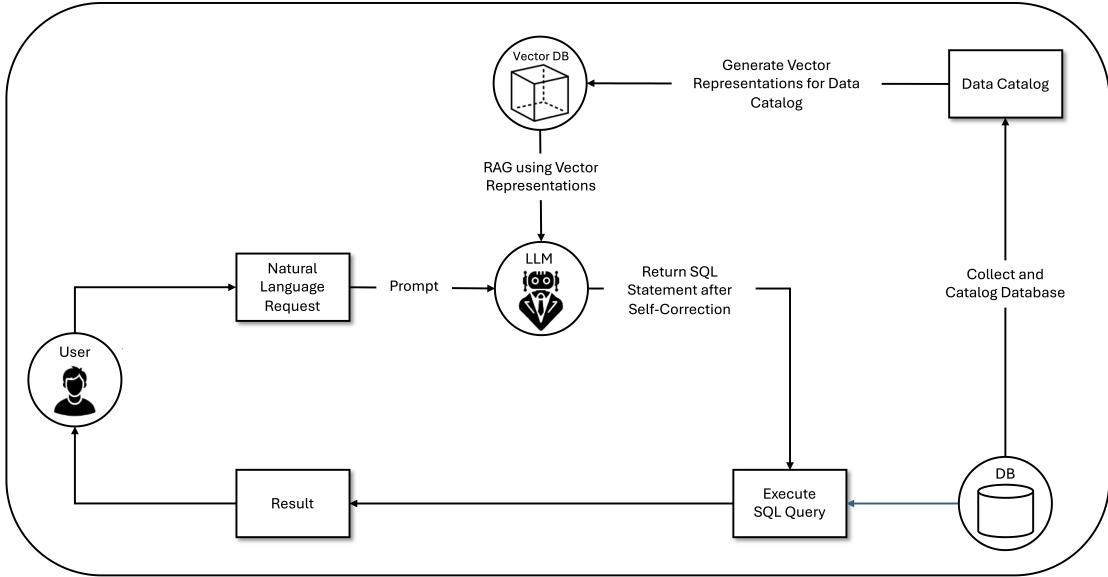


Figure 4: Integration of LLM and Retrieval-Augmented Generation for Text-to-SQL; based on [24, 20, 6, 72].

the generated SQL query exactly matches the gold standard.

Two main strategies have been proposed to enhance the accuracy of Text-to-SQL: fine-tuning and prompt design. Each of these methods addresses different aspects: fine-tuning focuses on adjusting the model parameters of the LLMs, while prompt design involves crafting the input to the LLM.

1. Fine-tuning: Training an LLM from scratch is resource-intensive, requiring vast amounts of data and computational power [64, 62, 72, 24]. As an alternative, organizations can leverage transfer learning, wherein a pre-trained LLM, which has already learned general language representations, is refined with domain-specific data. Fine-tuning involves adjusting the parameters of a pre-trained LLM to better align with specific organizational needs and domains. In the context of Text-to-SQL, fine-tuning involves training the model on labeled datasets consisting of pairs of natural language requests and corresponding SQL queries. This process helps the model understand the organization’s specific data models, schema, and terminology, enabling it to generate accurate SQL queries based on user input.

One major downside of fine-tuning is the potential for overfitting. This occurs when the model becomes overly specialized in domain-specific data and is less capable of adapting to other queries, making it harder to generalize to different contexts. Moreover, ongoing maintenance poses challenges: as data repositories such as data warehouses or marts evolve, schemas frequently change. Therefore, the fine-tuned LLM may require periodic updates to remain effective, increasing operational complexity and costs. Fine-tuning is not a one-time task; it requires continuous updates to avoid becoming outdated as the organizational data landscape evolves.

2. Prompt Design: Unlike fine-tuning, prompt design [24, 43, 62] does not alter

the underlying parameters of the LLM. Instead, it leverages the model’s generalization capabilities by crafting prompts that guide the LLM toward accurate SQL query generation. In few-shot learning [7, 43], for example, a user’s request is enriched with additional contextual information, such as data model details or examples of analogous SQL queries. The LLM processes the enriched prompt to infer the appropriate SQL query. Here, the LLM does not acquire new knowledge; rather, it uses its existing understanding along with the provided context to generate SQL queries that it has not previously encountered. Retrieval-Augmented Generation (RAG) further enhances prompt design by retrieving relevant contextual information, such as metadata stored in a vector database. Upon receiving user input, RAG integrates this context into the prompt, enabling the LLM to generate SQL queries. These queries undergo automated checks for syntax, schema alignment, and compliance with user requirements. If discrepancies are detected, the LLM’s self-correction mechanism refines the query. Once validated, the query is executed, and the information is presented to the user. Figure 4 illustrates the integration of LLMs with RAG, highlighting seamless context retrieval and query refinement.

Prompt design has the advantage of eliminating the need for continuous fine-tuning, saving both time and computational resources. However, as more contextual information is added, the number of tokens increases, pushing against the limits of the LLM’s context window—the maximum number of tokens it can process in a single instance. Although modern LLMs have extended context windows, this limitation can still lead to information loss in very complex or lengthy prompts, potentially impacting the overall accuracy of the generated query.

The integration of LLMs has significantly advanced the performance of Text-to-SQL. On the SPIDER benchmark [89], which assesses the generalization capabilities of Text-to-SQL models across a wide variety of database schemas, the performance of leading models has markedly improved, with execution accuracy increasing from approximately 54% to 91%. Exact match accuracy, which was around 5% initially, has risen to 82%. By comparison, the BIRD benchmark [40], which presents even greater complexity, reveals that current LLM-based Text-to-SQL models achieve execution accuracy of around 73%, underscoring the challenges posed by this benchmark.

3.3 Validation Effectiveness

When delegating information production to human experts, there is a challenge of “hidden action,” where the actions of experts are not fully observable or assessable, potentially leading to misalignment of interests [26]. Similarly, when delegated to AI, the issue shifts also to the transparency and reliability of outputs. While human experts may act in self-interest, leading to agency costs through false information or requiring additional incentives, AI systems present the challenge of output opacity. End users cannot evaluate the correctness of SQL queries and resulting KPIs until after implementation, risking decisions based on false information with economic consequences. Ensuring the reliability of AI-generated information is crucial, particularly in high-stakes decision-making scenarios where false information can result

in significant negative business outcomes. The requirement for reliability is further intensified by the inherent tendency of LLMs to produce hallucinations [42, 61], resulting in fabricated or erroneous SQL queries that may appear credible. Consequently, robust techniques are essential to ensure the validation of these generated SQL queries.

The techniques for validating automatically generated SQL queries fall within the broader field of explainable AI [14, 65, 48, 36, 23]. Since the advent of expert systems, researchers have emphasized the pivotal role of explanations in enhancing the interpretability of AI-generated results [80, 53]. In recent years, the growing demand for transparency in machine learning has prompted significant advances in the field of explainable AI, leading to an expansion in both the scope and sophistication of explanation techniques. The primary objective of explainable AI is to provide explanations that elucidate the underlying processes behind AI outputs, thereby facilitating tasks such as debugging, regulatory compliance, the establishment of user trust, and the effective utilization of AI.

In the specific context of Text-to-SQL, validation necessitates the provision of explanations that help to comprehend and verify AI-generated SQL queries. These explanations must detail the structure of the queries, including the involved tables, fields, and operations (e.g., filtering, grouping, or joining). Such detailed information enables users to critically evaluate the logical coherence of the query and its alignment with their intended objectives, thereby supporting an independent validation process. Effective validation ensures that users can reliably differentiate between correct and incorrect SQL queries. However, ineffective validation—where erroneous queries are mistakenly validated or accurate ones are erroneously dismissed—compromises the reliability of the process and may result in suboptimal decision-making.

Validation in Text-to-SQL extend beyond mere explanation, often encompassing also techniques for error correction. These techniques reflect the interactive nature of CBA and aim to support users in both identifying and rectifying errors in SQL queries. In this study, the interpretability of AI outputs and their correction are treated separately, with a focus on validation effectiveness as the primary metric. Validation serves as the foundation for reliable decision-making, as correct validation is essential for subsequent error correction.

Current literature identifies three different techniques for validating and explaining SQL queries (see [58] for an overview). Decomposition techniques (see Figure 5) break SQL queries into components such as tables, fields, and operations, presenting intermediate results to trace each element’s contribution to the final output, aiding error detection [55]. Visualization techniques use graphical representations to map relationships among query components, enhancing clarity and navigation in complex query structures [38, 47, 51]. Dialogue techniques employ LLMs to provide natural language explanations, enabling users to interactively explore and refine queries by addressing specific components or the underlying data model [73, 19, 35, 25, 81, 88].

Empirical studies on validation techniques for Text-to-SQL reveal varying levels of effectiveness in supporting SQL comprehension and error correction. Ning et al., through a user study, observed that decomposition, visualization, and dialogue techniques achieved an effectiveness rate of approximately 56% [58]. In contrast,

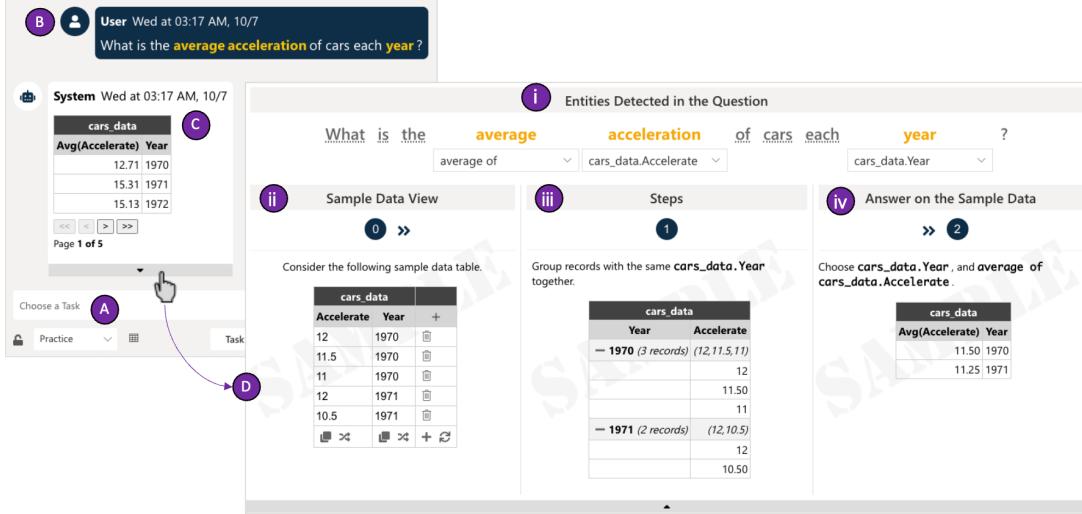


Figure 5: Decomposition technique for explaining SQL queries [55].

Tian et al. demonstrated that their technique, which combines decomposition and dialogue techniques, significantly outperformed existing techniques, achieving a validation and error correction effectiveness of approximately 85% [73]. These findings underscore substantial progress in user-based validation and error correction, showcasing their transformative potential to enhance the reliability of AI-generated SQL queries. However, the results also highlight persistent challenges, particularly in real-world scenarios involving large-scale, highly complex SQL queries and extensive data models, where existing techniques may prove inadequate.

A critical factor influencing the success of validation is the interplay between the competence of the end user and the quality of the explanations provided. While Tian et al. demonstrated that their technique consistently achieved high effectiveness regardless of users' technical expertise [73], the intricacies of SQL queries in complex business environments such as data warehouses with hundreds of interconnected tables and fields necessitate a more nuanced evaluation.

The end user's background and domain experience significantly affect their ability to assess the correctness of SQL queries, and this capability is further shaped by the clarity, detail, and comprehensiveness of the explanations generated. Additionally, the complexity of the underlying data model [8] and the resulting SQL query plays a pivotal role in the validation outcome. Complex data models with numerous interdependencies and abstract schema structures can obscure the logic of even well-constructed SQL queries, making validation tasks challenging for end users.

4 Models of CBA

4.1 Basic Assumptions

This study introduces models based on rational choice theory, with an emphasis on expected utility theory [79, 76], to evaluate the effective use of CBA. The analysis focuses on the example of Text-to-SQL. Two primary influencing factors are

considered:

- accuracy, defined as the AI's ability to generate correct SQL queries.
- validation effectiveness, defined as the ability to distinguish between correct and incorrect SQL queries.

It is assumed that the end user knows the levels of these factors determining the performance of the delegation of insight-generating tasks to AI at hand and can judge the suitability accordingly. Delegation to a data engineer is considered as an alternative to using AI for insight generation.

In an ideal scenario, both accuracy and validation effectiveness would be perfect, ensuring the generation of reliable and actionable information. However, these factors are inherently probabilistic and subject to imperfections. The models examine how the interaction between accuracy and validation effectiveness influences the effectiveness of Text-to-SQL and its potential advantages over delegation to a human expert. Specifically, the models evaluate how varying levels of these factors affect the relative advantage of delegating tasks to AI, with or without validation support. By exploring this interplay, the models aim to identify the conditions under which Text-to-SQL can serve as a viable alternative to human expertise, providing a structured framework for its adoption in CBA. This structured approach not only quantifies the trade-offs between accuracy and validation effectiveness but also highlights how CBA bridges the competency gaps that hinder traditional self-service analytics. By doing so, it underscores AI's role in empowering end users to make informed decisions without relying on advanced technical skills, thereby expanding the accessibility and effectiveness of analytics.

The models assume a risk-neutral perspective, where the end user has a linear utility function. This simplification allows for a focus on average outcomes (expected values) while ignoring the variability in potential gains and losses. By assuming linearity, the models quantify all values in monetary units.

The analysis begins with the end user's need for information that cannot be provided by standard reporting. The current value of a KPI is critical for making informed business decisions. While users may have access to data marts, the necessary data resides in data warehouses, requiring an SQL query for extraction. This query retrieves and prepares the data, ultimately generating the required KPI. A correctly formulated SQL query produces a valid KPI, enabling optimal decisions and yielding a net profit of $+1$. Conversely, an erroneous query generates a misleading KPI, resulting in suboptimal decision and a financial loss of -1 . The analysis assumes that the data warehouse contains high-quality, undistorted data, making the correctness of the SQL query the sole determinant of information quality. Despite possessing expertise in business processes, the end user lacks technical skills required to apply traditional self-service analytics effectively.

Currently, no data engineer is available to create the KPI, and such a resource will only be accessible at a later time. The delayed delivery of the KPI results in a reduced (net) profit v (where $0 < v < 1$). This profit is lower than the achievable maximum of $+1$, reflecting the adverse effects of delayed action. In extreme cases, v may even approach zero, rendering the KPI almost valueless. Additional

factors, such as the effort required to align requirements and potential motivational challenges that could negatively impact collaboration between end user and data engineer, are not considered in this analysis. Consequently, v serves as a measure of the urgency of KPI procurement, with lower values of v indicating greater urgency.

The process of KPI generation can be delegated to AI equipped with a natural language interface powered by LLMs. AI offers two levels of assistance: partial support (PS) and full support (FS). Under PS, the AI translates the natural language request into SQL code, which is executed on the data warehouse to calculate the KPI. The KPI is then used to inform decision-making, resulting in a business impact. FS includes an additional validation step to ensure the correctness of the SQL query. During this step, the end user is provided with explanations of the generated SQL query, enabling independent validation of its correctness. If the SQL query is deemed correct, the process concludes with confirmation, allowing to act on the KPI. If the query is identified as erroneous, it is rejected, and no action is taken, avoiding both gains and losses. In this process, AI acts as a collaborative partner, assisting in overcoming technical challenges while ensuring that the business decision is supported by a correct and validated KPI.

In contrast to the dynamic, iterative nature of CBA, this study adopts a static perspective in which KPI generation and validation occur in a single execution cycle. This idealized approach isolates the roles of information generation and validation, enabling a focused analysis of their individual impacts on the effectiveness of Text-to-SQL. The static perspective is also chosen, as iterative processes for information generation and validation within CBA are still under development.

It is further assumed that the end user incurs no direct costs (e.g., for data storage, processing, or the use of the LLM) when utilizing Text-to-SQL. This aligns with the prevailing practice in traditional self-service analytics, where no fees are charged for individual instances of information generation.

Since traditional self-service analytics is not feasible due to a lack of expertise, the end user evaluates whether the KPI should be generated via delegation to AI (either PS or FS), or whether it is more advantageous to wait for the data engineer to receive the KPI at a later time. The end user selects the option with the highest benefit. When CBA (either PS or FS) offers a higher expected value than the profit through the data engineer, it is preferred. Conversely, if the expected value from CBA is lower, human delegation is preferred. In such cases, CBA is deemed ineffective, as it fails to provide timely and decision-relevant information. By addressing the lack of technical skills required for traditional self-service analytics, CBA closes the competency gap that often hinders non-technical users from independently accessing and analyzing data.

The following table provides the mathematical symbols used in the following and their explanation.

4.2 Partial Support (PS)

The first stage involves the end user evaluating the feasibility of PS. PS addresses the competency gaps that prevent end users from utilizing traditional self-service analytics by automating the translation of natural language inputs into SQL queries.

Symbol	Explanation
α	accuracy
β	validation effectiveness
v	profit obtainable through data engineer
$E_{PS}(\alpha)$	expected value in PS
$E_{FS}(\alpha, \beta)$	expected value in FS
α_{PS}^*	accuracy threshold for PS to outperform data engineer
α_{FS}^*	accuracy threshold for FS to outperform data engineer
β^*	threshold for validation effectiveness to outperform data engineer
β^{**}	threshold for validation effectiveness to outperform PS

Table 2: Overview of the mathematical symbols used and their meaning.

This capability eliminates the need for technical proficiency in SQL syntax, allowing users to focus on decision-making rather than query formulation.

The success of this approach depends primarily on the accuracy of the AI in translating natural language requests into correct SQL queries. As outlined earlier, current advancements such as fine-tuning combined with prompt design are employed to enhance the AI’s information generation capabilities. Given the probabilistic nature of LLMs, the generation of SQL queries is treated as a discrete random variable. The probability of generating a correct SQL query, denoted as α (where $0 < \alpha < 1$), corresponds to execution accuracy. This probability is determined by the ratio of successfully generated SQL queries to the total number of natural language requests of a similar type.

The expected value $E_{PS}(\alpha)$ under PS is calculated as the weighted sum of the possible outcomes. A correct SQL query yields a profit of $+1$, while an incorrect SQL query results in a loss of -1 . These outcomes are weighted by the probabilities of success (α) and failure ($1 - \alpha$), respectively. The expected value is therefore expressed as:

$$E_{PS}(\alpha) = \alpha \cdot (+1) + (1 - \alpha) \cdot (-1) = 2\alpha - 1.$$

Delegation to AI through PS is preferred over waiting for a data engineer when the expected value $E_{PS}(\alpha)$ exceeds the delayed profit (v). This condition can be formalized as the "AI delegation condition of PS":

$$E_{PS}(\alpha) > v \Leftrightarrow \alpha_{PS}^* > (1 + v)/2. \quad (1)$$

The threshold (1) represents the accuracy that must be exceeded for PS to be more advantageous than relying on a data engineer. When this condition is met ($\alpha > \alpha_{PS}^*$), PS is viable and enables effective KPI generation without relying on human expertise. This is particularly beneficial since traditional self-service analytics is constrained by the end user’s limited technical skills. Conversely, if this condition is not satisfied ($\alpha \leq \alpha_{PS}^*$), the expected value from PS falls below the profit achievable through delegation to a data engineer, rendering PS unsuitable for time-sensitive, decision-critical business analytics.

4.3 Full Support (FS)

The second stage involves assessing the viability of FS, which includes an additional validation process to enhance the reliability of AI-generated SQL queries. This evaluation determines whether validation meaningfully improves the quality of the generated queries, ensuring their correctness and relevance for decision-making. By incorporating validation, FS demonstrates AI's role as an active partner in ensuring reliability and correctness. The validation process not only identifies and mitigates errors but also enhances the end user's trust in the system by providing transparent explanations. This collaboration between AI and the end user enables decision-making that aligns more closely with organizational goals, even in scenarios with imperfect accuracy.

Various techniques such as decomposition, visualization, and dialog-based are used to enhance the interpretability and traceability of automatically generated SQL queries. The effectiveness of these validation techniques depends on several factors, including the clarity, comprehensiveness, and contextual relevance of the explanations provided, as well as the user's technical expertise in evaluating them. High-quality explanations can significantly aid users in identifying errors and verifying the correctness of SQL queries. However, the end user's ability to critically evaluate these explanations plays an equally crucial role in determining the success of the validation process.

Validation is inherently uncertain due to variability in user comprehension and the probabilistic nature of AI-generated explanations. These explanations are not guaranteed to be correct, as LLMs generate outputs based on probabilities rather than deterministic logic. Poor validation can amplify risks by failing to detect erroneous SQL queries or by incorrectly rejecting valid queries. This dual risk undermines decision-making and may reduce trust in the system. While user-based validation is intended to mitigate inaccuracies, its effectiveness heavily depends on the user's ability to interpret complex SQL logic and explanations. This reliance introduces variability, making validation inconsistent across users with differing expertise levels.

To quantify this uncertainty, validation effectiveness is modeled as a random variable, denoted as β (where $0 < \beta < 1$). This probability reflects the likelihood that a user can correctly assess the SQL query based on the explanations provided. It is defined as the ratio of successful validations to the total number of validation attempts. By adopting this probabilistic framework, the model accounts for the inherent uncertainties associated with validation processes.

The expected value $E_{FS}(\alpha, \beta)$ for FS is calculated as:

$$E_{FS}(\alpha, \beta) = \alpha\beta \cdot (+1) + (1 - \alpha)(1 - \beta) \cdot (-1) = \alpha + \beta - 1.$$

The expected value $E_{FS}(\alpha, \beta)$ is influenced by two key factors: accuracy and validation effectiveness. Higher values of α indicate improved accuracy in generating correct SQL queries, while higher values of β represent enhanced effectiveness in validating the correctness of those queries. The combined improvement in these factors increases the expected value of FS, making it more likely to yield reliable and actionable KPI. This relationship highlights the complementary roles of accuracy

and validation effectiveness in ensuring the success of FS in CBA.

4.4 Comparison of Full Support with Partial Support and Delegation to the Data Engineer

The end user will choose FS only if it provides a higher expected value than the profit achievable through delegation

$$E_{FS}(\alpha, \beta) > v$$

and offers a better outcome than PS

$$E_{FS}(\alpha, \beta) > E_{PS}(\alpha).$$

For FS to outperform delegation to a data engineer, the following condition, referred to as the "AI delegation condition for FS" must be satisfied:

$$E_{FS}(\alpha, \beta) > v \Leftrightarrow \beta^* > (1 - \alpha) + v. \quad (2)$$

This condition (2) requires the validation to be sufficiently effective and robust (e.g., against the shortcomings of the end user conducting the validation based on the provided explanation) to compensate for inaccuracies in AI-generated information ($(1 - \alpha)$) and to deliver an overall expected value exceeding the guaranteed, but delayed profit v . If the AI delegation condition for FS (2) is satisfied, it is prioritized over delegation to the data engineer. However, this preference also depends on the accuracy of AI-generated information being sufficiently high compared to the profit v . Specifically, the "FS feasibility condition" must hold:

$$\alpha_{FS}^* > v. \quad (3)$$

This condition (3) ensures that the expected gain ($\alpha \cdot (+1)$) without validation exceeds the guaranteed profit v . If this condition is not satisfied, it is not justified to use FS, even with a perfect validation effectiveness, as the AI's base accuracy would be insufficient to outperform human delegation. The accuracy threshold (3) for FS is lower than the threshold (1) for

$$\alpha_{FS}^* < \alpha_{PS}^*.$$

This indicates that the inclusion of a validation step in FS broadens the potential applicability of CBA. However, whether FS is advantageous compared to delegation to a data engineer depends on the level of validation effectiveness as defined in the AI delegation condition for FS (2).

The end user, acting as a rational decision-maker, will only increase the AI support level from PS to FS if the probability of successful validation exceeds the probability of successful SQL generation. This requirement is formalized as the "validation dominance condition":

$$E_{FS}(\alpha, \beta) > E_{PS}(\beta) \Leftrightarrow \beta^{**} > \alpha. \quad (4)$$

In condition (4), β^{**} represents the threshold where validation effectiveness exceeds accuracy, making FS more advantageous than PS. It is important to note that all conditions described so far strongly depend on the values of the potential gain (+1) and loss (-1) and the assumption that their magnitudes are equal. If the value of the loss outweighs that of the gain, the threshold for β in the validation dominance condition shifts, allowing a less stringent validation standard for FS to outperform PS.

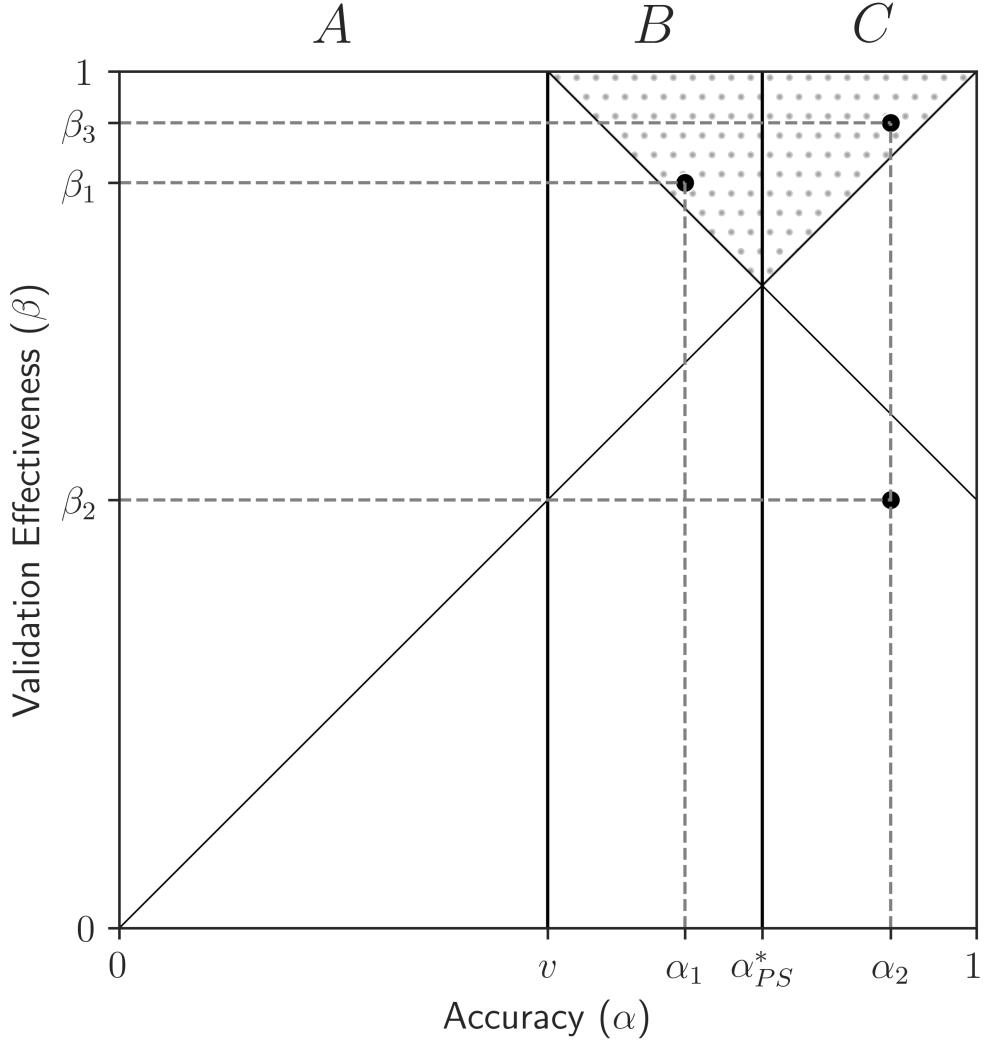


Figure 6: Relationship between accuracy (α) and validation effectiveness (β): conditions for effective AI Delegation.

Figure 6 illustrates the relationship between accuracy, validation effectiveness and the profit achievable through delegation to the data engineer (all values are measured in monetary units). The dotted area highlights the range of α and β values where FS outperforms PS and the data engineer, as all three conditions regarding AI delegation (2), the feasibility of FS (3), and the dominance of validation (4) are satisfied. Outside this area, FS does not yield sufficient expected value to justify

its use. The figure also identifies the threshold α_{PS}^* which is determined by the AI delegation condition for PS (1).

The analysis reveals three distinct regions based on the interplay between accuracy, validation effectiveness, and the profit achievable through delegation.

In region *A*, the FS feasibility condition (3) is not met, as the accuracy of information generation is less than or equal to the profit achievable through the data engineer ($\alpha \leq v$). In this situation, neither PS nor FS offers sufficient expected value. PS fails due to low accuracy, and FS is unable to compensate for this limitation, even when validation effectiveness would be perfect. Delegation to the data engineer remains the only viable option for retrieving the KPI. In this scenario, CBA is not utilized because it fails to match the effectiveness of the data engineer, rendering CBA unsuccessful. Furthermore, if the data engineer provides the KPI with significant delay, rendering it irrelevant for the end user due to its diminished value for timely decision-making (v approaching zero), this not only signifies the failure of CBA but also highlights a broader limitation of business analytics in fulfilling its fundamental objective: delivering timely and decision-relevant information.

Moreover, the requirements for accuracy in PS and FS, as well as for validation effectiveness in FS, increase as v rises. A reduction in urgency causes a rightward shift of v , α_{PS}^* , and the delegation threshold condition for FS (2). In other words, the less urgent the KPI (making it less problematic to wait for the data engineer) the greater the performance demands on CBA to generate the correct SQL query and support the reliable assessment of its correctness.

In Region *B*, the FS feasibility condition (3) is met ($\alpha > v$), but the AI delegation condition for PS (1) is not satisfied ($\alpha \leq \alpha_{PS}^*$). In this case, PS is less effective than delegating to the data engineer. However, FS becomes a viable option if validation effectiveness meets the AI delegation condition for FS (2). Under this condition, validation introduces a "boosting effect" by identifying and mitigating errors in SQL queries, ensuring that flawed KPIs do not influence the decision-making process. This boosting effect enables FS to enhance the overall reliability of information, compensating for the limitations of lower accuracy. For example, even if accuracy falls below the threshold required for PS (1) (e.g., α_1), sufficiently high validation effectiveness in FS (e.g., β_1) can still yield an expected value greater than v . While the generation of the SQL query may fail, resulting in incorrect KPI, sufficiently effective validation can still identify these errors, ensuring that incorrect KPIs do not adversely affect the decision process.

In region *C*, where the AI delegation condition for PS (1) is met ($\alpha > \alpha_{PS}^*$), PS becomes a viable alternative to delegation to the data engineer, as it provides sufficient utility on its own. If the AI delegation condition for FS (2) and the validation dominance condition (4) are not fulfilled (e.g., at α_2 and β_2), FS has a "devastating impact" as the validation process undermines the reliability of the SQL queries generated. Not only are erroneous SQL queries less effectively identified, but insufficient validation also leads to the unwarranted rejection of correct SQL queries. Consequently, FS is not only less effective than PS but also inferior to delegation to the data engineer. Therefore, using AI-based assistance for KPI generation with AI-supported validation is not recommended. This underscores the inherent risks of relying on user-based validation without robust mechanisms to support in correctly

evaluating AI-generated SQL queries. In cases where expertise is low or explanations are unclear, FS may inadvertently introduce errors or misjudgments. This highlights the critical need for improved validation tools that reduce user dependency or provide guided assistance during the evaluation process.

FS becomes favorable when, in region C , both conditions, (2) and (4), are fulfilled (e.g., at β_2 and α_3). In such cases, the validation process enhances the reliability of the generated KPI and maximizes the benefits of FS. As accuracy increases, the requirements for validation effectiveness must also rise to ensure that FS remains beneficial. A particular challenge arises when accuracy is very high; in such scenarios, user-based validation must become even more effective to provide added value over PS. This places significant demands on validation mechanisms, especially in terms of users' ability to evaluate and assess complex SQL queries based on the given explanations.

These findings highlight the critical interplay between accuracy and validation effectiveness in determining the optimal use of PS or FS in CBA. High accuracy favors PS, while lower accuracy requires robust validation effectiveness for FS to deliver reliable results. Insufficient validation, however, compromises performance, making delegation to a data engineer the preferable alternative. This analysis emphasizes the importance of aligning validation performance with accuracy to enhance the effectiveness of CBA. Although FS can improve decision-making, its success depends on validation mechanisms that appropriately scale with accuracy. When this balance cannot be achieved, PS or data engineer may offer more dependable outcomes.

5 Conclusion

This study analyzes CBA, an emerging approach with considerable potential to address the competency gaps inherent in traditional self-service analytics. Through the use of LLMs, CBA facilitates natural language interactions, enabling end users to independently perform tasks such as data retrieval, preparation, and insight generation. In this context, CBA represents a new form of task delegation, shifting the responsibility for generating and interpreting information from human experts to AI, thus making advanced analytics more accessible to users without technical expertise. A focus of this study is Text-to-SQL, a well-established semantic parsing technology that has seen transformative advancements through the application of LLMs, enhancing its ability to translate natural language requests into structured SQL statements.

The models developed in this study examine the conditions under delegation to AI, through PS and FS, outperforms the delegation of tasks to human experts. PS is effective when the accuracy (α) exceeds a specified threshold, as outlined in condition (1). FS, however, is only beneficial when three conditions are met: the AI delegation condition ((2)), FS feasibility condition ((3)), and validation dominance condition ((4)).

The study highlights the critical role of validation effectiveness (β) in FS. While FS can significantly improve decision-making when validation is robust, the use of user-based validation introduces risks, particularly when users lack the necessary expertise or when explanations are unclear. These risks can undermine decision

quality, making FS less effective than PS and, in worst case, even less effective than delegation to a data engineer. This underscores the necessity of robust validation mechanisms to assist users in accurately evaluating AI-generated information. Without such mechanisms, the advantages of CBA may be significantly compromised.

This study also opens several avenues for future research. The uncertainties associated with user-based validation warrant further investigation. Future research could explore techniques to support end users in the validation process, including training programs to build technical expertise and AI-driven tools that provide guidance during validation. Moreover, there is an urgent need for empirical studies that more clearly define the boundaries of user-based validation based on explanations, particularly in real-world scenarios involving complex SQL queries and data models.

While the primary goal of CBA is to overcome the technical barriers that hinder the use of traditional self-service analytics, user-based validation poses a paradox. The process relies on the same competencies that were insufficient for conducting independent analyses in the first place. This raises a critical question: is it advisable to involve end users with limited technical expertise in the validation of results, given that they may face similar challenges in assessing the quality of the analysis as they did in performing it?

This question highlights the importance of more clearly delineating the boundaries of user-based validation. While CBA relies on end-user interaction, additional support mechanisms may be necessary to help users validate the accuracy of results without risking misinterpretation or circular reasoning. One promising avenue for future research is the development of hybrid approaches that combine expertise with automated validation mechanisms.

Future studies could explore the implementation of automated techniques to independently assess the reliability of generated KPIs. Potential approaches might include statistical methods such as confidence intervals to evaluate KPI correctness, automated tools for schema alignment and comparison, and cross-validation with pre-validated KPIs. Integrating such methods could reduce reliance on user expertise, thereby enhancing the robustness and scalability of CBA systems.

The models presented in this study rely on several simplifying assumptions. First, the gain from correct decisions is fixed at +1 and the loss from incorrect decisions at -1, which may not fully capture the variability observed in real-world scenarios. Additionally, the analysis adopts a static perspective, assuming a single execution cycle for KPI generation and validation, thus overlooking the iterative nature of real-world analytics. The models also omit costs associated with LLM usage, data storage, and processing, which may lead to an overestimation of the economic feasibility of CBA. Expanding these models to incorporate dynamic, cost-sensitive, and multi-stage decision processes could provide deeper insights.

In conclusion, this study illustrates the transformative potential of CBA in addressing the limitations of traditional self-service analytics. However, realizing its full potential depends on addressing the inherent challenges of validation, advancing user support mechanisms, and exploring automated alternatives. Through continued innovation, CBA has the potential to evolve into a reliable and indispensable tool for data-driven decision-making across a wide range of business contexts.

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