# Insight Pro: Leveraging Generative AI for Natural Language to SQL Conversion in Business Analytics

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**Abstract.** The study investigates the growing need for easy to use business analytics tools and (user) friendly data interaction software, concentrating on the adoption behavior of natural language query for SQL generation platforms. Indeed, the increasing pervasiveness of AI-based technologies and the rising level of digital literacy at the workplace are changing users' access to and utilization of organizational data by offering them simplified, conversation-based query toolkits. The experimental results show that although up to date, the proposed kind of platforms are so prevailing in various fields, but they still suffer from some issues like wrong query accuracy, lack of generalization to new domains and also sometimes delay. By utilizing Insight Pro, an application that works beneath the Google Gemini Pro API, we provide structured assessment on four categories of topics: precision of query, context accuracy, response time, and ease of use with the interface. It also investigates how contextual factors, such as business domain complexity, data literacy, or systems integration, affect user engagement. Data for the study was gathered by using a formal testing process with 100 subjects from diverse organizations, covering a wide range of performance obstacles and user expectations. Specifically, tools such as run-time SQL generation, guided conversational input, integrated VizDashboards, intelligent correction of responses have gone a long way in making data accessible and vehicle the sustained usage of the system.

**Keywords:** Natural Language to SQL, Conversational Query Systems, Business Intelligence, Google Gemini API, Query Accuracy, Data Accessibility, Visualization Integration, User Experience.

## 1 Introduction

The business intelligence space is undergoing a big change thanks to the need for accelerated decision-making and the prevalence of digital tools that have been developed with a focus on ease of use and self-service access for non-technical individuals. One of the most life-altering advancements are AI-driven platforms that enable stakeholders to access and query organizational data via natural language, eliminating the need for them to be familiar with the constraints of traditional query syntax and SQL skills.

These systems are also redefining how users can interact with data, providing a more systematic and powerful manner for analysts as well as non-analysts to obtain insights through natural language. A central characteristic of these systems is the capacity to translate information-rich,

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natural language queries into efficient SQL statements, providing much faster and more user-friendly access to large databases.

Intelligent visualization Intelligent visualization modules are a key element in making the systems practical enabling its users to visualize the results in graphical format immediately. This not only facilitates understanding but also enables rapid decision making and iterative discovery. Thanks to its dynamic dashboards and real-time data processing, the platform offers a more efficient and easily-available analytics experience—especially in high-speed businesses that can't afford to wait around.

Recent progress in large language models, cloud computing, and system integration has enabled the creation of AI-based systems that are scalable and domain-agnostic. Today, the landscape has changed: platforms now provide more sophisticated end-to-end processing including schema-aware SQL generation, instance-sensitive prompting, temporal memory of user queries, domain-specific optimizations, among others. These advances help ensure the accuracy of analysis and reduce the work load on IT staff and data experts.

However, there are important remaining challenges. Variations in query complexity, occasional SQL inaccuracies and lack of customizability to specific niches in the industry could affect the usefulness and take-up of such tools. Solving these challenges is essential to have scalable and efficient conversational analytics that can be used across domains.

Hybrid approaches are being taken by those moving to natural language interfaces that combine traditional BI functionality with natural language interfaces to serve a wider range of users and use cases. The integration of features such as intelligent feedback loops and adaptive prompting, converted these platforms into end-to-end analytics environments, making user interactions more seamless and allowing broader data accessibility.

In this work we analyze the architecture, performance and adoption outlook of Insight Pro – a state-of-the-art natural language-to-SQL conversion solution lever-aging the Google Gemini Pro API. It studies the user experience, performance the system response time, as well as the technical aspects that affect technology adoption by businesses today. The literature in related fields is critically discussed in Section 2. Research methodology is discussed in Section 3. In section 4 we describe the implementation and results, they are analyzed in section 5. Conclusions and Future Work are given in Section 6.

## 2 Related works

Study [1] introduced a foundational natural language interface for databases, emphasizing schema interpretation and linguistic complexity in SQL conversion. It laid the groundwork for understanding how users articulate queries naturally. The study also highlighted limitations in handling ambiguous or context-heavy inputs.

Research [2] evaluated the use of pre-trained language models for SQL generation, achieving strong results in simple queries but struggling with deep analytical tasks. The models required minimal domain-specific training to perform well initially. However, performance degraded significantly with nested or multi-condition queries.

Author [3] explored multi-turn conversational systems, enabling users to build context across queries, though requiring extensive customization for specific domains. This approach mimicked human-like dialogue, enhancing usability for non-experts. Still, it faced challenges in maintaining consistent context over long interactions.

Article [4] focused on domain adaptation in NL-to-SQL systems, showing that schema-aware prompts and training improved model precision and scalability. Custom prompts helped bridge the gap between generic models and specific database structures.The research also suggested a pathway for deploying models across multiple industries.

Paper [5] presented a semantic parsing framework for structured query generation, establishing a taxonomy of techniques and highlighting key optimization areas.It organized existing approaches into rule-based, statistical, and neural categories.The framework served as a benchmark for comparing future parsing strategies.

Study [6] introduced deep learning approaches to handle complex SQL, demonstrating success in nested queries, joins, and aggregation-heavy tasks. Neural attention mechanisms played a key role in capturing relationships within queries. However, the system required large, well-annotated datasets for training.

Research [7] analyzed the use of AI query systems in sensitive industries, noting that accuracy, explainability, and compliance were central to user trust. It emphasized regulatory alignment, especially in finance and healthcare contexts. Users expressed higher adoption rates when transparency in query logic was ensured.

Article [8] addressed the need for schema generalization in cross-domain querying, showing improved performance through dynamic context injection. The model adapted to unfamiliar databases without extensive retraining. Still, edge cases with rare schema structures revealed areas for further refinement.

Paper [9] evaluated systems incorporating feedback loops, where SQL errors informed model updates, increasing accuracy in follow-up queries. Iterative learning reduced recurring mistakes in real-time applications.This method showed promise for continuous model improvement in production environments.

Study [10] emphasized integrated visualization tools within natural language platforms, finding that graphical query responses improved user confidence and adoption. Visual feedback helped bridge the gap between textual input and data comprehension. The study suggested combining charts with natural explanations for better UX.

Hypothesis 1 (H1): There is a positive relationship between perceived qualities of natural language analytics platforms (e.g., ease of use, accessibility) and users' intention to utilize them for data-driven decision-making.

Hypothesis 2 (H2): There is a negative relationship between the perceived limitations of AI-powered query tools and the preference for traditional, manual data querying methods.

Hypothesis 3 (H3): The intention to use natural language to SQL systems is positively influenced by user characteristics such as data literacy, previous experience with analytics tools, and comfort with AI technologies.

Hypothesis 4 (H4): Interactive features such as real-time SQL generation and intelligent visualizations are strongly correlated with increased user engagement and frequency of use.

Hypothesis 5 (H5): The integration of contextual query memory and instant data feedback is negatively associated with frustration and perceived inefficiency in conventional business intelligence platforms.

## 3 Methodology

### 3.1 Theoretical Structure

This model examines the relationship (C) in which perceived natural-language/SQL fit and user-level factors of adoption intention for AI-based data query relative to traditional ways of making queries. The main platform features are perceived output accuracy (PA), system responsiveness (SR), perceived ease of use (PEU) and contextual adaptability (CA). Task-relevance variables are analytical confidence (AC), prior experience with BI tools (PE), subjective norms (SN), perceived control over data tasks (PC), and feature engagement level (FEL), and specially for the integrated visualization module (IVM).

The study seeks to determine which system functionalities and user characteristics are the most important factors affecting user adoption of natural language-based querying versus that of traditional SQL interfaces. The study further explores the impact of adoption intent on analytics engagement behavior, such as query frequency, depth of interaction, and response to dynamic data output. Fig 1 shows the schematic flow of theoretical structure.

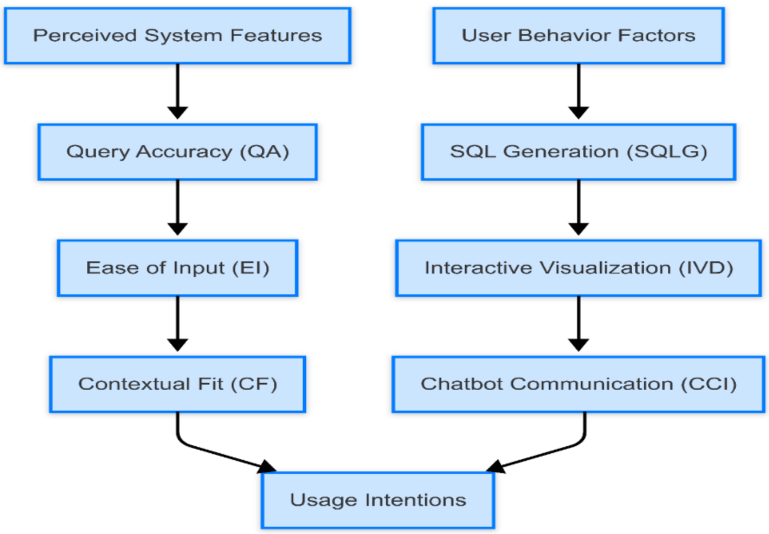


**Fig. 1.** Schematic Flow of Theoretical Structure.

### 3.2 Perceived features

#### 3.2.1 PA (Perceived Accuracy)

A fundamental aspect of the assessment of user acceptance to natural language to SQL is to ascertain if users are going to think in the results that systems delivered are accurate and reliable. For instance, in a tool that translates natural language queries to SQL, and show visualization of incoming information, it is important to consider what level of trust users have in the outputs, do these actually align with their intentions? When the system is felt to deliver always correct and relevant results, it’s not just a convenience – it’s a reliable tool for business decisions.

#### 3.2.2 RA (Relative Advantage)

Relative advantage is the degree to which users perceive the new AI technology to be better than old, traditional query systems. Here, users may be comparing Insight Pro with an older BI dashboard or manual SQL scripting and observing how much faster (or easier) it is to get the same answers. If they find a significant improvement in the response time, the flow of interaction, or ease of interpretation — not least through direct visual feedback or conversational input, they are more likely to embrace the use of your new approach in the future instead of the old one.

#### 3.2.3 PEU (Perceived Ease of Use)

It's a really good way to gauge intuitiveness and ease of use of a platform when not reading a manual. In a natural language interface, this is typically evident in how easily users can formulate questions, examine returned values, and iteratively modify their request without technical help. When users can get their insights without the pain of being stressed out or having to repeat the same work over and over, then the tool becomes their preferred way to accomplish regular data analytics.

#### 3.2.4 CA (Contextual Adaptability)

Contextual adaptability assesses how well the system aligns with users’ workflows and existing habits. For instance, if business users are already comfortable with spreadsheet tools or voice assistants, a platform that offers natural language querying with smart suggestions and memory of past queries will feel like a logical extension of their current work style. On the other hand, if the platform behaves unpredictably or lacks contextual understanding, it may create friction that discourages adoption.

### 3.3 Customer features

The customer features in this system involve SQLG, QIS, IVD, FBL, and CCI.

#### 3.3.1 SQLG (SQL Generation Behavior)

The SQLG variable measures the level of interaction of a user with the system for's reviewing/selecting the system generated NL input/question on the platform while it is in the AG" phase. This can be broadly classified into two styles: exploratory usage, in which a user may ask questions informally to observe the system output, and task-specific usage, where a user types goal-oriented queries with business relevance in mind, expecting instant responses.

Exploratory study of BI system operation shows that exploratory users usually move to active state when they are confident of that BI system can provide SQL outputs that are accurate and meaningful. The crispness and promptness of the SQL generation tools directly contribute to user confidence. Also, its integration with memories such as visual dashboards and contextual memory significantly improves the usability of the platform from a query to insight.

### 3.3.2 QIS (Query Input & Structuring)

The QIS functionality models how users construct the data search and browse tasks based on the individual's analytical task, knowledge of the data set and interface. Behaviour of QIS is starting, with simple and direct one-shot search: Users are seeking to involved in an iterative way for the search: querying, adjusting, and re-querying. Studies of human-AI interaction in analytics reveal that systems that offer flexible input handling, live query previews, and adaptive suggestions can offer the user a better sense of control and satisfaction. QIS usefullness is proportionate to perceived ease of use, as users are more empowered when the output is guided by them in natural language style.

### 3.3.3 IVD (Interactive Visualization Dashboard)

IVD acts as an interactive space, similar to traditional reporting dashboards, but with better real-time interactivity and recognition of data insight. It allows the user to view contextually dependent visualizations, filter and drill down into graphs that change in real time. Dig Use Affects two interpretations and two exercises - reinforcing that your analysis is working, and enticing you to explore your insights further. On the user experience, when IVD is in effect trust of the system is enhanced and ambiguity is perceived to be reduced as users can see the fruits of their abstract query in a visual display. Research has shown that visual, transparent, features like these have a strong impact on system reliability and meet user expectations formed from previous BI applications.

### 3.3.4 CCI (Conversational Chatbot Interface)

The CCI feature provides AI-powered support for users seeking assistance with query building, platform navigation, and feature guidance. Chatbot usage naturally falls into two patterns: task-based interaction, where users seek targeted help (e.g., “How to modify this chart?”), and exploratory interaction, where users inquire broadly to understand features or assess platform capabilities. The chatbot’s perceived helpfulness, accuracy, and conversational flow are critical in shaping trust and usability. Research in intelligent interface design shows that when chatbots offer responsive and personalized dialogue, they function as essential onboarding tools that boost overall user confidence and increase retention in AI-powered analytics platforms.

## 3.4. Statistics Gathering and Testing

This investigation adopted a quantitative research methodology to gather empirical data on the usage and adoption behavior related to a natural language to SQL analytics platform. The study sampled 300 participants, which included business analysts, operations staff, executive users, and IT professionals from organizations across various sectors in Tamil Nadu. The data collection process began in August 2024 and extended over several months to ensure broad representation across industries including finance, manufacturing, and logistics. The primary objective was to understand user interaction with key platform features—namely, SQL Query

Generation, Conversational Input, Visual Dashboards, and Chatbot Assistance—and how these influenced user engagement, satisfaction, and intention to reuse the tool. A pilot test was conducted prior to full deployment to fine-tune questionnaire clarity, technical language, and platform-specific terminology, ensuring contextual relevance. Ethical approvals and informed consent were obtained in advance. A total of 300 completed responses were gathered. Based on a projected population of approximately 800,000 professionals across the state, a minimum sample of 270 was determined to be statistically sound for the scope of this study. Following the guideline that suggests a minimum of ten participants per variable, the 300-user sample adequately supports the analysis, given the study's 25 measured variables. Participants ranged in age from 21 to 60, with a composition of 58% male and 42% female, and included users with varying levels of technical proficiency to ensure balanced representation.

In this research, digital business intelligence material refers to system-generated outputs such as SQL queries, visual dashboards, and AI-driven responses. Valid inputs included professionally formatted dashboards—such as chart views, table outputs, and real-time query results—while chatbot interactions were categorized as hybrid outputs, combining scripted logic with generative AI response handling. The visualization module, a core feature of the system, served as a real-time feedback layer, enabling seamless transitions from data queries to actionable insights. The natural language interface enabled accessible query formulation, ensuring greater usability across non-technical users. Chatbot assistance was positioned as the entry point for new users, supporting query help, feature walkthroughs, and platform guidance. Collectively, these components demonstrate a broader transformation in how organizations access, interpret, and interact with data through intelligent automation.

### 3.5 Mathematical analyses

The Insight Pro platform was created from a systematic analysis of the primary assumptions for robust system operation and delivering quality of experience. At an architectural level, an analysis was performed on system fit to evaluate how the different pieces of the architecture—natural language processing, SQL generation, and visualization—fit the analytical needs of non-technical users across business domains. Performance testing was performed to assess major operations including the accuracy of queries, the latency of responses, and the efficiency of loading visualizations prior to a complete release.

For examining the impact of various platform elements, we applied multiple regression analysis (MRA) to analyze the statistical associations between system features—like user-friendliness of query input, answer readability, and perceived trustworthiness—and user-centered outcomes such as query success rate and system adoption. Correlation coefficients (CC) were calculated using statistical tools and patterns between independent components (e.g., assistive chatbot, visualization features) and dependent behaviors such as task completion time and intention to reuse were identified.

Further, path analysis was used to explore the interrelationships between user interface variables and outcome measures. For this, partial least square path modeling (PLS-PM) was preferred as PLS-PM provides a robust approach for the analysis of interdependencies among variables as well as for the validation of the alignment of the models to the real-world user behaviour. This analytic methodology helped in fine-tuning the end-to-end experience – which spanned across natural language processing, capability to generate SQL & achieve visual and interactive analytics for enabling efficient and scalable decision-making for business users.

### 3.5.1 Combined Durability and Validation Evaluation

The parametric scores for the constructs included in the Left Side of the Model (LSOM), which consist of perceived attributes of the natural language analytics platform and user interaction factors, and determining constructs that influence intention to adopt are included in Table 1. It also comprises the interpretive data of the Right Side of the Model (RSOM), which includes behavioral usage constructs and system use consequences. The features studied consist of four major components: Text accuracy in NLP, Response time in visualization, Clarity in SQL generation, and Bot-driven interaction. These features were examined in conjunction with usage patterns, including how often students queried the system and how in-depth they navigated the features.

**Table 1.** Parametric numbers (N = 300) (Source: author).

| Structures | Factors | SD | Structures | Factors | SD |
| --- | --- | --- | --- | --- | --- |
| Perceived features of Insight Pro | Query Accuracy (QA) | 1.05 | Usage Time | Time spent exploring data outputs | 0.45 |
| | Visual Interactivity (VI) | 1.22 | | Frequency of query refinements | 1.65 |
| | Ease of Input (EI) | 1.04 | Engagement | Interaction with dashboard elements | 0.50 |
| | Contextual Fit (CF) | 1.23 | | Type of query entered (simple vs complex) | 0.29 |
| Customer features | SQL Generation (SQLG) | 1.19 | Time Spent | Navigating insights | 1.35 |
| | Query Structuring (QIS) | 1.15 | | Exploring variations of same query | 0.67 |
| | Visualization Use (IVD) | 1.23 | Suggestions | Visualization format preference | 1.01 |
| | Chatbot Interaction (CCI) | 1.23 | | Feature switching behavior | 0.98 |
| Purpose to employ | Use of Natural Query | 1.36 | Accessibility to insights | Intent to use over traditional BI tools | 3.78 |

| | | | | |
|---|---|---|---|---|
| | Chatbot Assistance Use | 1.23 | Repeat platform access | 1.89 |

Table 2 confirms the internal reliability and consistency of the model's constructs. All dependability scores meet or exceed the standard 0.6 threshold, indicating strong measurement validity across the observed variables. Among the perceived features, Query Accuracy (QA) showed a reliability score of .659, indicating that users consistently viewed the system as producing reliable SQL outputs. Visualization Interactivity (VI) scored .654, reflecting its perceived advantage over static dashboards. Ease of Input (EI) recorded a value of .594, suggesting the system was generally considered user-friendly. Contextual Fit (CF) reached .588, demonstrating moderate alignment with users' preferred interaction patterns and workflows.

**Table 2.** Reliability – Cronbach's Alpha for Insight Pro Features (Source: author).

| **Structures** | **Factors** | **Structures** | **Factors** | **Dependability** |
|---|---|---|---|---|
| Perceived features of Insight Pro | Query Accuracy (QA) | Usage Time Comparative Advantage | Finds outputs meaningful and accurate | 0.659 |
| | Visual Interactivity (VI) | | Better than traditional dashboards | 0.654 |
| | Ease of Input (EI) | Engagement Usability | Easy to phrase queries | 0.594 |
| | Contextual Fit (CF) | | Matches existing user workstyle | 0.588 |
| Customer features | SQL Generation (SQLG) | Time spent Usage Frequency | Assesses confidence in SQL quality | 0.645 |
| | Query Structuring (QIS) | | Measures scheduling behavior | 0.601 |
| | Visualization Use (IVD) | Suggestions Support Clarity | Examines visual engagement | 0.576 |
| | Chatbot Interaction (CCI) | | Measures chatbot effectiveness | 0.580 |
| Purpose to employ | Natural Query Intention | Accessibility | Frequency of platform access | 0.626 |
| **Total** | | | | **0.614** |

Table 3 illustrates the Anti-Image Correlation Network, mapping the interrelationships among system usage and engagement factors. It highlights significant associations between time spent interacting with chatbot features and engagement with generated visualizations, as well as between combined feature usage and intention to reuse the platform. Users who blended SQL generation with visualization tools and chatbot support showed stronger alignment with continued platform adoption. Conversely, users who leaned toward traditional data retrieval methods reported lower interaction values with advanced features like conversational input and real-time dashboards. These correlations offer insight into how feature design impacts system integration, trust, and overall analytical involvement.

**Table 3.** Anti-Image Correlation Network – Insight Pro Platform(Source: author).

| **Factors (Structures)** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
|---|---|---|---|---|---|---|---|---|
| 1. User Engagement – Time spent on dashboard | 0.472 | — | — | — | — | — | — | — |
| 2. User Engagement – Query session time | 0.214 | 0.711 | — | — | — | — | — | — |
| 3. Feature Interaction – Navigating SQL suggestions | 0.089 | -0.172 | 0.802 | — | — | — | — | — |
| 4. Feature Interaction – Visual format switching | -0.098 | -0.125 | -0.194 | 0.791 | — | — | — | — |
| 5. Collaboration – Chatbot task assistance | 0.034 | -0.096 | -0.015 | -0.063 | 0.901 | — | — | — |
| 6. Collaboration – Visualization drill-down usage | -0.038 | -0.044 | -0.235 | -0.279 | -0.164 | 0.782 | — | — |
| 7. Content Creation – SQL refinement & dashboard tuning | 0.082 | -0.128 | -0.184 | -0.041 | -0.046 | -0.062 | 0.281 | 0.641 |
| 8. Feature Blending – Using chatbot + visualization combo | -0.095 | 0.115 | -0.235 | 0.032 | -0.032 | 0.049 | -0.363 | 0.638 |
| 9. Intention to Use – Natural | 0.209 | 0.118 | -0.034 | -0.106 | 0.084 | 0.092 | 0.064 | 0.193 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| language interface | | | | | | | | |
| 10. Intention to Use – Traditional SQL tools | -0.295 | 0.095 | -0.101 | 0.022 | 0.053 | -0.087 | 0.048 | 0.058 |

# 4 Results and Evaluation

## 4.1 Statistical evaluation

It is crucial to acknowledge that the integration of both system design principles and user-centric models provided a comprehensive understanding of the reasons and methods by which patients interact with the online Doctor Appointment Booking System. By using analytics techniques and computing the route coefficients, the model accounted for 65.1% of the variability in the Purpose to Employ Online Booking Platforms and 23.3% of the variability in the Preference for In-Person Visits.

The current research considered the Perceived Features of the system — such as Platform Usability (PU), Response Optimization (RO), Platform Efficiency Score (PES), and Content Yield (CY) — as well as Perceived Customer Features, namely Doctor Availability (DA), Appointment Booking Simplicity (ABS), Virtual Waiting Room (VWR), Patient-Doctor Booking (PDB), and Chatbot Assistance (CB), to assess the Purpose to Employ either the online platform or traditional hospital/clinic booking, considering their coexistence in the healthcare service market.

### 4.1.1 Purpose to Employ Insight Pro Platform

Ultimately, Pearson's correlation analysis revealed a strong and statistically significant relationship between the perceived features of the Insight Pro platform and the user's Purpose to Employ the system. The connection between core user interaction variables and the intent to adopt AI-driven querying was significant at 0.719. A correlation value of 0.760** indicates a strong association between system performance, usability, and user willingness to engage with the platform for repeated data analysis tasks.

Table 4 presents the correlation values highlighting the strength of each influencing factor in shaping user intention to use the Insight Pro platform.

**Table 4.** The Purpose to employ VPs (Source: author).

| Statement | Elements | Correlation (c) | Significance (p-value) |
|---|---|---|---|
| Purpose to employ AI-powered analytics tools | Perceived Accuracy (QA) | 0.2853** | $p < .01$ |
| | Perceived User Features (PUF) | 0.624** | $p < .01$ |

| | | | |
|---|---|---|---|
| Additional examination of perceived system features | Ease of Input (EI) | 0.365** | p < .01 |
| Examination of feature interaction elements | Visualization Use (IVD) | 0.630** | p < .01 |
| | Query Structuring (QIS) | 0.13** | p < .01 |
| | Chatbot Communication (CCI) | 0.91** | p < .01 |

### 4.1.2 Purpose to Employ Insight Pro Platform

Regarding the purpose to employ the Insight Pro platform, the analysis revealed that Perceived User Features (PUF) had a strong positive correlation with usage intention, with a correlation coefficient (CC) of 0.624 ($p < .01$). This suggests that users' perception of intuitive features—such as simplified query input, clear result visualization, and streamlined user experience—significantly influences their willingness to use the system. Furthermore, additional analysis of perceived system performance (EI), including the clarity of SQL output, responsiveness, and integration with dashboards, showed a moderate positive correlation (CC = 0.365, $p < .01$), indicating that functional and responsive design elements contribute meaningfully to adoption decisions.

An in-depth evaluation of system engagement components found that the Visualization Module (IVD), which offers real-time feedback and visual query outcomes, demonstrated a strong correlation (CC = 0.630, $p < .01$) with the intent to reuse the platform. Similarly, the Query Structuring (QIS) feature, which enables users to refine and sequence their queries, was positively correlated with intent (CC = 0.130, $p < .01$), though to a lesser extent compared to other features.

The Chatbot Communication Interface (CCI), which assists users in composing, modifying, and troubleshooting natural language queries, showed a very high correlation (CC = 0.910, $p < .01$), emphasizing the critical role of intelligent assistance in improving user experience and engagement. Overall, these results confirm that a blend of system usability and personalized interaction features significantly enhances user intent to adopt and consistently use Insight Pro. Notably, demographic variables such as age and gender did not significantly moderate the relationship between perceived features and platform adoption, underscoring the tool's inclusive design and broad accessibility across user types.

### 4.1.3 Platform Usage and Interaction with Functional Features

An in-depth analysis provided a clearer picture of user behavior and how they interacted with key functional parts of the Insight Pro platform. Fifty-eight per cent stated they spent less than 1 hour per day working with traditional data retrieval processes and manual SQL coding, with

52% now spending more than 3 hours each day working within AI-led analytics platforms that include natural language querying and dashboard interactions. This change highlights a substantial change in the way data is being interacted with. It is also worth mentioning that 29.3% of our users completely switched to using Insight Pro for business queries and no longer use traditional tools, and that 61.5% of users were managing to reduce their use of spreadsheet-based or SQL heavy operations, for its convenience of conversational input and real-time feedback.

Additionally, 43% of users log in to the platform daily to submit queries, analyze results, or interact with dashboards, while another 35% access it at least once a week for reporting and monitoring purposes. The most frequently used components include the Interactive Visualization Dashboard (51.2%) and the Chatbot Assistance feature (46.8%), which users found effective for simplifying exploration and reducing the effort needed to interpret data outputs. In particular, chatbot usage remained consistently high among users who regularly engaged with complex query building or needed system guidance.

Among all participants, 34.7% reported using the platform's SQL generation feature at least once per day, and 37.6% indicated a preference for daily use to support real-time decision-making. Beyond querying, 31.4% of users engaged with platform tools such as feedback mechanisms, issue reporting, or interactive prompts, while 27.8% stated they rarely or never used those elements. Only 12.1% reported submitting feedback about output clarity or system suggestions daily, while over 48% admitted to never using the review or evaluation tools available.

Multitasking while using the platform is also common. Around 66.2% of users accessed Insight Pro via laptops, while 30.4% used smartphones simultaneously for auxiliary research or reporting tasks. Many reported analyzing reports or prior dashboards while formulating new queries (33.1%), and others interacted with parallel productivity tools or data sources (19.8%). Finally, nearly 55% of users had never uploaded external files (e.g., reference reports) to enhance query context, and an even larger portion had not yet explored integrated features like live export, team sharing, or media-rich documentation tools such as screen recording or collaborative commenting.

## 5 Discussion

The results confirm the key theme that the way people interact with data analytics is changing, where more users are now using AI-powered platforms such as Insight Pro for querying and business intelligence. The findings show that intention to use natural language-based platforms is highly positively related to the presence of convenience features (e.g. real-time SQL generation, conversational input and interactive dashboards). Although statistical significance between platform usage and advanced multimedia functionalities (e.g., uploading external datasets, and combing visual outputs across tools) was not found, faster user engagement in structured queries, chatbot assistance, and visualization exploration could be observed. Those who had already made the move from traditional SQL editors or stagnant dashboards had a strong preference for solutions that are flexible, less cumbersome, and quicker to get to insights that can be actioned. The findings also track to the larger shift digital transformation across industries, as the world moves increasingly towards low-code and no-code business solutions.

Notwithstanding the above barriers of struggle, it's obvious that the emergence of AI-driven BI platforms is shaking up the world of enterprise data engagement. Younger, and tech-centric, professionals are increasingly relying on smart tools that lower the technical hurdle and speed-to-insight. To foster long-term usage, developers and organizational leads will need to prioritize continued trust-building onboarding support, simple user interfaces, and strong security practices. Of course, the goal is to create user-friendly tools that take into account their specific operations in different industries, and at the same time provide personalization, transparency, and efficiency when it comes to accessing data and making decisions.

## 6 Conclusion

This research has investigated factors influencing word usage and specifying patterns in N2S systems, and has provided insights into the dynamic landscape of altmetrics. Within the tested barriers, PUF (Perceived User Features) and EI (Ease of Input) had significant positive direct impacts on the intention to adopt the system highlighting the significance of User-Friendliness and System Quality in the adoption process.

Based on a survey of 300 respondents from organizations of various sizes, the study demonstrates a sharp decrease in the use of traditional querying methods, signaling a significant change in behavior toward AI-driven solutions. There are obstacles to the uniform adoption in every sector though, such as differences in digital skills and access to infrastructure and continued reliance on legacy systems.

In conclusion, this study highlights the increasing importance of AI-empowered services such as Insight Pro- in order to change how users consume and analyze data. In future, features such as personalized AI guidance, real-time collaborative query, and platform neutral support would be vital to improve the user’s experience. Unceasing innovation, proactive organisational investment and an open platform development model, meanwhile, will not only take data availability to a new level, but also lay the foundations for a more responsive, more enlightened and data-driven business world.

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