

Bridging Natural Language and Interactive What-If Interfaces via LLM-Generated Declarative Specifications

SNEHA GATHANI, University of Maryland, College Park, USA

SIRUI ZENG, University of Maryland, College Park, USA

DIYA PATEL, University of Maryland, College Park, USA

RYAN ROSSI, Adobe Research, USA

DAN MARSHALL, Microsoft Research, USA

ÇAĞATAY DEMIRALP, AWS AI, USA and MIT CSAIL, USA

STEVEN DRUCKER, Microsoft Research, USA

ZHICHENG LIU, University of Maryland, College Park, USA

What-if analysis (WIA) lets users explore hypothetical scenarios by adjusting parameters, applying constraints, and scoping data through interactive interfaces. Current tools fall short: spreadsheet and BI tools require laborious setup, while LLM-generated interfaces frequently misinterpret analytical intent. It remains unclear whether an explicit intermediate representation is needed, or whether LLMs can generate WIA interfaces directly. We build a benchmark of 405 WIA questions across 11 types and 5 datasets with human-authored ground-truth intent, and find that direct one-shot generation across three LLMs fails to produce a working interface in 17–45% of cases and, when interfaces render, often misrepresents the question’s objective (up to 77.5%) and constraints (up to 58.2%). We therefore present a two-stage workflow that translates NL questions into PRAXA SPECIFICATION LANGUAGE (PSL) specifications, then compiles them into interfaces. Because errors localize to named properties, taxonomy-guided repair raises correctness from 52.42% to 80.42%, unlike errors in directly generated code.

CCS Concepts: • **Human-centered computing** → **Natural language interfaces**; **Graphical user interfaces**; **Interactive systems and tools**; **Visual analytics**; • **Applied computing** → **Enterprise applications**; **Business intelligence**.

Additional Key Words and Phrases: Natural Language Interfaces, What-If Analysis, Large Language Models, Declarative Specifications, Visual Analytics, Business Intelligence

ACM Reference Format:

Sneha Gathani, Sirui Zeng, Diya Patel, Ryan Rossi, Dan Marshall, Çağatay Demiralp, Steven Drucker, and Zhicheng Liu. 2018. Bridging Natural Language and Interactive What-If Interfaces via LLM-Generated Declarative Specifications. *Proc. ACM Meas. Anal. Comput. Syst.* 37, 4, Article 111 (August 2018), 34 pages. <https://doi.org/XXXXXXX.XXXXXXX>

Authors’ Contact Information: Sneha Gathani, sgathani@umd.edu, University of Maryland, College Park, College Park, Maryland, USA; Sirui Zeng, University of Maryland, College Park, College Park, Maryland, USA, szeng124@umd.edu; Diya Patel, University of Maryland, College Park, College Park, Maryland, USA, dpatel90@terpmail.umd.edu; Ryan Rossi, Adobe Research, San Jose, California, USA, ryrossi@adobe.com; Dan Marshall, Microsoft Research, Seattle, Washington, USA, dan.Marshall@microsoft.com; Çağatay Demiralp, AWS AI, New York, New York, USA and MIT CSAIL, Cambridge, Massachusetts, USA, cagatay@csail.mit.edu; Steven Drucker, Microsoft Research, Seattle, Washington, USA, sdrucker@microsoft.com; Zhicheng Liu, University of Maryland, College Park, College Park, Maryland, USA, leozcliu@umd.edu.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

© 2018 Copyright held by the owner/author(s). Publication rights licensed to ACM.

Manuscript submitted to ACM

Manuscript submitted to ACM

1

1 Introduction

What-if analysis (WIA) involves exploring and comparing multiple scenarios by dynamically adjusting parameters, applying explicit constraints, and scoping data subsets to make data-driven decisions. For example, a business analyst interested in how marketing spend affects profit across regions might begin with a what-if question such as: *What happens to Q4 profit if marketing spend increases by 15% in the US but decreases by 10% in Europe?* They may then iteratively vary these parameters across regions, add new effects such as campaign spend, or invert the question to ask what strategy reaches a target profit. Performing such multi-step analyses requires modifying assumptions, examining immediate results, and revisiting previously explored scenarios. This in turn demands interactive interfaces that combine parameter controls (e.g., sliders, selectors, checkboxes) with linked visualizations that update in real time, making it possible to explore scenarios, adjust values fluidly, and compare results.

Current tools, however, do not adequately support this process. Spreadsheet-based tools like Excel and business intelligence (BI) platforms (e.g., Tableau, Power BI, Salesforce Einstein) require users to manually configure parameters, bind formulas, and specify low-level analytic settings. Conversely, LLM-generated interfaces translate natural language (NL) directly into interactive dashboards without manual setup, but are semantically fragile and frequently misinterpret analytical intent.

To understand how often and in what ways this occurs, we conduct a formative experiment on direct one-shot generation under a deliberately strong approach—a prompt iteratively hardened against incidental implementation errors unrelated to analytical understanding, then frozen prior to evaluation—over a stratified set of WIA questions drawn from our benchmark (spanning 11 WIA types and 5 datasets), each with human-authored ground-truth analytical intent (section 3). Across three state-of-the-art LLMs, direct generation frequently fails: it produces no working interface in roughly 17–45% of cases depending on model, and even when interfaces render, they often omit or misrepresent the question’s stated objective (up to 77.5% of applicable cases) and constraints (up to 58.2%) (section 4). Crucially, these are not loud failures: the interfaces render, respond to interaction, and look plausible, so a misrepresented objective or a dropped constraint surfaces only under close, line-by-line inspection of the underlying code. These failures, together with those of spreadsheet and BI tools, share a common root: analytical intent has no existence independent of the artifact that implements it—dispersed across formulas and control bindings in the former, entangled in generated code in the latter—so confirming a question was captured correctly means reading that artifact line by line.

Our results therefore motivate separating analytical intent from its implementation: before generating an interface, the system should first produce an explicit representation of what the analysis is meant to do. Declarative representations offer a promising way to achieve this separation. Across databases [8, 39, 45, 46], data visualization [22, 25, 26, 40, 44], and UI generation [16, 21], grammars and declarative specifications have been used as intermediate representations that capture high-level intent while abstracting away lower-level implementation details. WIA is amenable to a similar formulation because its analytical logic can be expressed compositionally through interconnected primitives.

Recent work by Gathani et al. [11] formalizes this structure through PRAXA, a compositional grammar for WIA, and PRAXA SPECIFICATION LANGUAGE (PSL), a declarative specification language that encodes it. That work establishes the grammar, demonstrates its expressiveness, and illustrates its use as an intermediate representation, but does not establish whether that mediation is *reliable*: whether LLMs can generate valid and semantically faithful specifications from NL questions, what errors arise when they do not, and whether those errors can be systematically repaired. We take up these questions by treating PRAXA SPECIFICATION LANGUAGE as an instance of this explicit representation and building an end-to-end NL-to-interface workflow around it, in two stages (section 5):

(1) NL to Declarative Specification. An LLM translates the NL question into a PRAXA SPECIFICATION LANGUAGE specification that explicitly represents the intended analytical logic. Because intent is represented independently of the interface implementation, errors can be identified, localized, and repaired *before* interface generation—a capability our formative experiment (section 4) shows is largely absent when models produce interface code directly.

(2) Declarative Specification to Interactive Interface. The resulting specification is compiled into an interactive visual interface whose visualizations and parameter controls are bound to the underlying data, enabling users to dynamically explore and compare what-if scenarios.

Although instantiated with PRAXA SPECIFICATION LANGUAGE, this two-stage separation of intent from implementation applies more broadly to structured intermediate representations for analytical interface generation.

Using this workflow as a research probe, we ask:

RQ1. How reliably do LLMs translate NL WIA questions into PRAXA SPECIFICATION LANGUAGE specifications, and where do they fail? (subsection 6.1)

RQ2. Does the explicit structure of PRAXA SPECIFICATION LANGUAGE enable systematic error detection and repair? (subsection 6.2)

RQ3. How do specification errors propagate into compiled interfaces? (subsection 6.3)

We answer these on the same benchmark, generating specifications with three state-of-the-art LLMs and auditing errors against human-authored ground truth (section 6). Across models, half of specifications (52.42%) are correct without intervention, and taxonomy-guided targeted repair raises this to 80.42%. Whereas our formative experiment found that direct generation’s failures are entangled in generated code and surface only under close, line-by-line inspection, PRAXA SPECIFICATION LANGUAGE’s errors are tied to named specification properties—scope, objective, constraints, among others—making them localizable and directly repairable.

In summary, we make the following contributions:

- A *benchmark* of 405 WIA questions across 11 types and 5 datasets, annotated with human-authored ground-truth analytical intent.
- A *formative experiment* on direct LLM generation of WIA interfaces that motivates the need for an explicit intermediate representation, revealing that without one, generation fails both structurally (interfaces that do not render) and silently (interfaces that render but misrepresent intent) across three state-of-the-art models.
- A *two-stage workflow* that operationalizes PRAXA SPECIFICATION LANGUAGE as an intermediate representation, translating NL WIA questions into interactive interfaces while keeping analytical intent explicit, inspectable, and repairable.
- An *error taxonomy* characterizing where and how PRAXA SPECIFICATION LANGUAGE generation fails, and a *targeted repair strategy* that raises specification correctness from 52.42% to 80.42%.
- An analysis of how *undetected specification errors propagate into compiled interfaces*, underscoring why an explicit representation matters for reliable NL-driven WIA.

2 Background

2.1 Overview of What-If Analysis

WIA is a multi-step form of analysis that enables exploring hypothetical scenarios by varying input parameters within an underlying model and observing resulting changes in outcome variables [11]. The underlying model encodes relationships between input parameters (e.g., *Revenue*, *Cost*) and output variables (e.g., *Profit*) which are functions learned via machine

# Major Tasks \ Tools		Spreadsheet-based and BI tools			
		Excel	Tableau	Power BI	Einstein Discovery
Model Specification and Integration					
1	Choose the model	✔ Via "Solver Add-Ins" Supports simple linear or logistic models	✔ Via importing pre-computed model coefficients	✔ Automatic selection by tool Custom models need importing coefficients via "DAX"	✔ Based on user's selection of target variable Custom models not supported
2	Integrate the model	✔ Via formulas in cells	✔ Via formulas in "calculated fields"	✔ Via "DAX" formula	✔
Scenario Construction and Control					
3	Adjust selected parameters	✔ Via overwriting cells or using "Data Tables"	✔ Via changing formulas in "calculated fields"	✔ Via "What-If Parameters" Works for single parameter adjusting, tedious for multiple parameters	✔ Via "What Could Happen" and other features
4	Add constraints on parameters	✔ Within "Solver" formulas	✔ Via hard-code simple constraints	✔ Via hard-coding in "DAX" formula	✔ Explicit bounds or parameter ranges not set for scenarios
5	Create multiple scenarios	✔ Via "Scenario Manager" and "Summary Tables"	✔ Via explicit "calculated fields" for every scenario	✔ Each "What-If Parameter" represents only one scenario	✘ See single what-if adjustment at a time
Design Interactivity and Visuals					
6	Create controls and bind parameters to controls	✔ Sliders, drop-downs Need explicit linking from cell to control	✔ Sliders, dropdowns, radio buttons Via linking which parameters to make adjustable via "Parameters" feature	✔ Sliders for "What-If Parameters" and binding to "DAX" formula Limited to numeric ranges with predefined min/max/step values	✔ Slider, dropdown, radio buttons
7	Create visuals that dynamically update with changing parameters	✔ Need cell and visual to be linked	✔ Feasible only if predictions are expressed as "calculated fields" (i.e., model manually integrated) and linked to visuals	✔ But need expertise for which visuals	✔ Via "Prediction Panels", "Written Summaries", and charts update dynamically on parameter changes
8	Compare and revisit scenarios	✘ Limited via "Summary Tables" from "Scenario Manager" or duplicating entire process	✘	✔ Via bookmarks, saved report views	✘
Ensure Transparency and Trust					
9	Access and modify model internals (model mechanism, parameter change code)	✘ Only coefficients tied to cells when model built manually	✘ Via coefficients added to calculated fields Or limited: indirectly via built-in "Explain Data" feature	✘ Only coefficients added to DAX formulas Limited and opaque in built-in "Key Influencers" feature	✔ Via model performance metrics, parameter importances, etc. but not underlying model or scenario change code
10	Support for prediction interpretability	✘	✘ Only via charts	✔ Via "Key Influencers" feature, but no details (e.g., coefficients, assumptions, code)	✔ Via what-if features, but no details (e.g., assumptions, code)
11	Error handling	✘ Via checking formulas and tracing cell dependencies	✘ Only via checking calculated fields	✘ Only via checking "DAX" formula	✘
12	Guide on follow-up what-if explorations	✘	✘	✘	✔ Suggests improvements and recommendations, but no explicit workflow

Fig. 1. Summary of the authors' formative exploration of spreadsheet and BI tools (columns) across major WIA tasks (rows). Green checkmarks indicate strong support, orange indicate partial or limited support, and red crosses indicate poor or no support for each WIA task.

learning (e.g., $Profit = f(Revenue, Cost, Marketing Spend, Customer Retention Rate)$). Users repeatedly adjust parameters, impose constraints, and focus on different data subsets to examine potential outcomes and compare scenarios.

Types of What-if Analysis. WIA spans several distinct analysis types as characterized in prior work [11]: *sensitivity analysis* examines how changes to input parameters impact outcomes; *goal seeking analysis* works backward from desired outcomes to identify required inputs; and *importance analysis* identifies which inputs most influence outcomes. We discuss variants of these types in section 3.

Major Tasks in Performing WIA. Performing WIA requires several interdependent tasks: (1) selecting and integrating predictive models with data, (2) constructing scenarios by adjusting parameters and imposing constraints, (3) binding various parameters and prediction outcomes to interactive controls and visualizations that update dynamically, and (4) ensuring transparency of the underlying logic to support interpretability, error handling, and trust. Together, these tasks demand an interface that couples parameter controls with linked visualizations that update in real time *and* keeps the underlying analytical logic inspectable, so that a user can verify the analysis matches their intent. We use these requirements—particularly model integration (1), scalable parameter and constraint control (2), and transparency of logic (4)—as the lens through which we examine existing tools.

Existing Tools Available for WIA. Existing tools that support some of these tasks fall into two categories: spreadsheet-based and BI platforms (e.g., Excel [4], Tableau [43], Power BI [5], Salesforce Einstein [33]) and NL-to-dashboard chatbots (e.g., GPT Data Analyst [31], Claude [2]). Despite this breadth, no prior work systematically examines how these tools support WIA or the challenges users encounter. To understand these limitations, we conducted a formative exploration of spreadsheet and BI tools (below); we examine LLM-based generation separately and in greater depth as a formative experiment (section 4), as it is the focus of this work.

2.2 Formative Exploration of Spreadsheet and BI Tools

To ground our understanding of how established tools support WIA, three authors independently attempted six WIA scenarios (e.g., “what happens to churn if estimated salary is doubled?”) across four representative spreadsheet-based and BI platforms: Excel [4], Tableau [43], Power BI [5], and Salesforce Einstein [33]. The scenarios span the three broad WIA categories—point and range sensitivity, goal-seeking and constrained goal-seeking, and importance analysis—and varied parameter configurations, so that each tool was probed across the diversity of WIA questions it might be asked to support (the full scenario set is listed in supplementary material). All explorations used the *Bank Customer Attrition* dataset [27]; authors imported the dataset and consulted documentation and tutorials to explore each tool’s WIA capabilities. Each author invested approximately 4.5 hours across all tools, and sessions were recorded and reviewed.

2.3 Findings

Across all four tools, we observed four recurring challenges, summarized in Figure 1.

C1. Steep learning curve for model integration. Integrating predictive models was cumbersome across all tools. Excel’s *Solver Add-Ins* supported only simple models and required technical expertise. Tableau and Power BI required manually encoding model coefficients as calculated fields or DAX expressions, making model setup error-prone and difficult to iterate (e.g., translating logistic regression coefficients into nested IF statements and binding them to data columns). While Power BI (*Key Influencers*) and Einstein Discovery provided automated modeling, they did not support custom models.

C2. Limited support for parameter control. Although tools support parameter adjustments (e.g., tables, calculated fields, sliders), each scenario required manual setup and explicit formula binding. This was repetitive and difficult to scale across multiple parameters or constraints; for example, enforcing constraints or coordinating multiple variables required complex formulas. Einstein Discovery provided limited support for bounds but not custom constraints.

C3. Poor transparency of model internals. Understanding models required tracing formulas across cells or fields, which was labor-intensive and impractical in complex multi-variable analyses. Automated features (e.g., *Key Influencers*, *Top Predictors*) acted as black boxes with limited visibility or control over variables and constraints, making validation of whether the analysis matched user intent essentially infeasible.

C4. Limited error detection and debugging. All tools relied on users to detect and fix errors. Excel required manual debugging of formulas, while Tableau and Power BI produced cryptic errors (e.g., “Cannot mix aggregate and non-aggregate arguments”) with no explanation or repair guidance. No tool provided systematic validation of whether the configured analysis matched the user’s intent.

3 Benchmark

Both our formative experiment on direct generation (section 4) and our evaluation of the intermediate representation-based workflow (section 6) draw on a common benchmark of 405 WIA questions across 11 WIA types and 5 datasets, each annotated with human-authored ground-truth analytical intent. Building it once as shared infrastructure lets both be

#	WIA Type	Definition	Example Question
(1) Sensitivity Analysis: Questions examining how changes in one or more input variables influence the output			
T1	Point Sensitivity	Considers discrete perturbations of input variables	What would customer churn be if complaints were reduced by 50%?
T2	Point Sensitivity with Scope	Restricts analysis to a subset of the data	Given customers predicted to churn in France, what would happen if they had a higher satisfaction score?
T3	Range Sensitivity	Explores trends in outcomes over a range of input values	How does sales revenue vary if marketing spend is gradually increased from \$10K to \$100K?
T4	Range Sensitivity with Scope	Performs the same analysis but within a subset of data	How does churn vary with tenure from 1–10 years for customers in Germany?
(2) Goal Seeking Analysis: Questions identifying input settings that achieve a desired output			
T5	Goal Seek	Identifies parameter changes to reach a target	What salary level reduces churn below 20%?
T6	Goal Seek with Scope	Introduces constraints on adjustable variables	What changes reduce churn below 20% for customers with two products?
T7	Constrained Goal Seek	Adds both constraints and data subset restrictions	What tenure and product changes reduce churn if salary cannot be changed?
T8	Constrained Goal Seek with Scope	Adds both constraints and data subset restrictions	Among periods with Ad Revenue below \$250, what constrained optimization of Sales and Marketing Cost and Premium ARPU would maximize Total Revenue without exceeding \$600 in Sales and Marketing Cost?
T9	Counterfactuals	Identify the closest alternative instance that would change a prediction	Given a customer predicted to churn, who is the most similar customer predicted to stay?
(3) Importance Analysis: Questions focusing on identifying which input variables most influence the outcome			
T10	Importance	Surfaces the most salient drivers of predictions	Which factors contribute most to predicting churn?
T11	Importance with Scope	Computes the same but for a subgroup	Which drivers are most important for predicting churn among customers in Germany?

Fig. 2. Eleven WIA subtypes in our benchmark grouped under three broad categories, with definitions and example questions from the Bank Customer Attrition dataset.

evaluated against the same questions and the same ground truth, on equal footing. We release the full benchmark–questions and ground-truth intent–as supplementary materials [1].

3.1 Datasets

We selected five publicly available datasets (from Kaggle and the UCI ML Repository) representing distinct yet commonly encountered decision-making contexts where WIA is valuable: *Bank Customer Attrition* [27] (D1; customer churn, outcome *Exited*), *Email Campaign Management* [13] (D2; email open/ignore, outcome *Email Status*), *Media Spend and Sales Attribution* [53] (D3; channel spend reallocation, outcome *Sales*), *Marketing Campaign Response* [18] (D4; campaign conversion, outcome *Response*), and *Spotify Revenue, Expenses and Its Premium* [19] (D5; business financials, outcomes such as *Total Revenue*). Together they span customer, campaign, financial, and operational decision-making, yielding varied parameters and outcome variables across WIA types. Full per-dataset feature descriptions are in supplementary material.

3.2 What-If Analysis Types

Building on the three WIA categories (section 2), our benchmark spans 11 subtypes varying by scope, variables, and constraints. We illustrate these in Figure 2 using the *Bank Customer Attrition* dataset. Together, they help the benchmark express the diversity of WIA questions encountered in practice.

3.3 Benchmark Construction

Three coders constructed the benchmark in three steps. First, coders adapted 152 seed questions from prior work [11] to each dataset (e.g., “What would have to change so that person X would get the loan?” became “What would have to change so that customer X would stay with the bank?”) across all 11 WIA types, yielding 181 hand-authored questions (44.69%). Second, GPT-4o scaled beyond manual authoring, generating 224 additional questions (55.31%) with diverse phrasings and variable combinations grounded in dataset context. Third, coders filtered the generated questions for validity, removed redundancies, and ensured balanced coverage across types and datasets, so that every WIA type is represented in every dataset where it is applicable. The final distribution across datasets and types is shown in Figure 3.

To verify construction quality, we confirmed that hand-authored questions preserved the structure of their seed questions (SentenceTransformer similarity 0.63–0.79 across datasets) while LLM-generated questions remained diverse (self-BLEU 0.008–0.051); details are in supplementary material.

3.4 Ground-Truth Analytical Intent

For each question, we establish ground-truth analytical intent decomposed into six components common to any WIA answer regardless of how it is implemented: *scope* (the data subset the analysis applies to, if any); *outcome variable* (the target being analyzed); *perturbation* (which input(s) change, and how—by an amount, to a value, or over a range); *constraints* (bounds the solution must respect); *objective* (whether to minimize, maximize, or reach a target); and *analysis type* (one of the 11 WIA subtypes). Defining ground truth at this level—rather than in terms of any particular representation—is deliberate: it lets us score interfaces produced by different generation approaches against the same criteria, so that no approach is advantaged by how its ground truth is expressed. Two coders independently annotated all 405 questions and reconciled discrepancies through discussion to reach a single ground-truth intent per question. Ambiguous cases (e.g., “How does attrition probability vary for customers with 1 vs. 3 products?”, interpretable as descriptive comparison or as sensitivity analysis) were resolved by aligning on the appropriate WIA type. Of 405 questions, coders initially disagreed on 179 (44.2%); nearly all were resolved through discussion, with only 19 (4.7%) requiring a third coder. This initial disagreement rate reflects the genuine interpretive ambiguity of NL WIA questions rather than annotation error; the reconciled single intent per question serves as ground truth, and we document the reconciliation rationale for the disagreed cases in supplementary material. This representation-neutral intent is scored directly against generated interfaces in our formative experiment (section 4); for the workflow, it is additionally encoded in the structured specification language we introduce in section 5.

4 Motivating Experiment: Limitations of Direct NL-to-Interface Generation

Before introducing an intermediate representation, we first ask whether one is necessary. If an LLM can reliably translate a WIA question directly into a correct interactive interface, an additional representation would add unnecessary complexity. We therefore examine a strong direct-generation setting to understand where this approach fails. Our goal is not to comprehensively benchmark code-generation strategies, but to identify whether direct generation introduces failure modes that motivate separating analytical intent from WIA implementation.

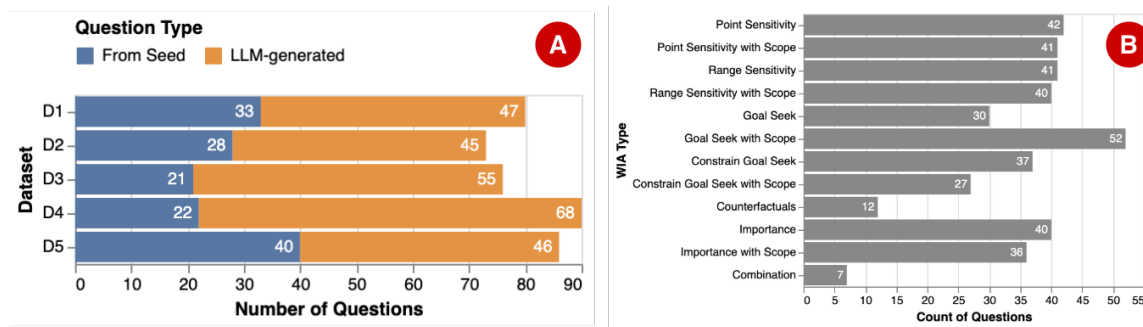


Fig. 3. Distribution of the 405-question benchmark by generation method (manually authored vs. LLM-generated) across datasets (A) and WIA subtypes (B).

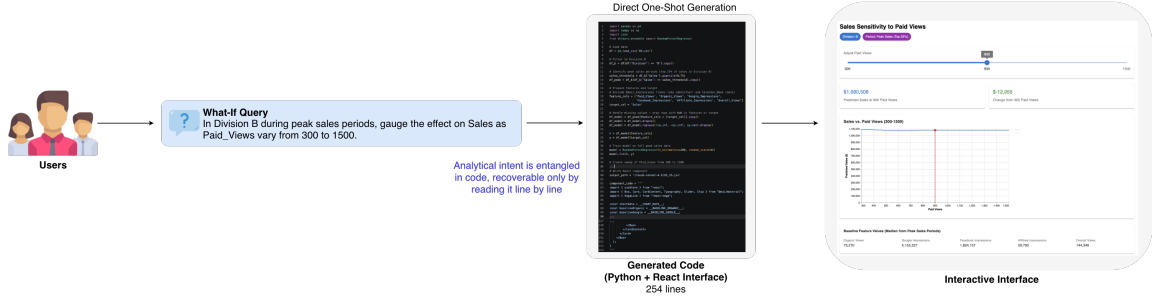


Fig. 4. The direct-generation setup: an LLM receives the NL question and dataset schema and emits, in a single pass, code that both trains the model and renders the interface—with no intermediate representation at which analytical intent can be inspected. Contrast with our two-stage workflow (Figure 7).

4.1 Direct-Generation Setup

For each WIA question, we provide an LLM with the NL question and the corresponding dataset schema and ask it to generate, in a single pass, the Python code that executes the analysis and implements the interactive interface end-to-end (Figure 4). The generated implementation trains the required predictive model (a scikit-learn RandomForest—a classifier for binary outcomes, a regressor for continuous ones) and produces the same three interface elements targeted by our proposed workflow: interactive parameter controls, a linked visualization, and a live prediction readout, rendered with the same stack (React, Material UI controls, and Vega-Lite charts). Using an identical rendering target for both approaches ensures that any difference in outcome is attributable to the presence or absence of an intermediate representation, not to implementation choices—the only difference being that here the interface is authored directly by the LLM rather than compiled from any intermediate representation or specification.

We deliberately give direct generation a strong starting point. Before evaluation, we hardened the prompt on pilot questions (disjoint from the evaluation sample) against incidental implementation pitfalls unrelated to analytical understanding—such as serialization and interface-binding errors—and then froze it, leaving it unchanged for the reported evaluation. The complete prompt and pilot procedure are in supplementary material [1].

Models and sample. We evaluate GPT-5, GPT-4o, and Claude-Sonnet-4.5¹ on a stratified sample of 150 questions per model, drawn proportionally across the 5 datasets and their labeled WIA types so the sample mirrors the full benchmark (section 3).

Correctness and scoring. We examine two forms of correctness. *Execution correctness* asks whether the generated implementation produces a working interactive interface at all. *Semantic correctness* asks whether a rendered interface preserves the six representation-neutral components of analytical intent from subsection 3.4—scope, outcome variable, perturbation, constraints, objective, and analysis type. To assess semantic correctness, an automated judge receives the generated code, its execution output (or, if execution failed, the resulting error), and the ground-truth intent, and labels each of the six components as *matching*, *mismatching*, or *not-applicable* (the last only when the ground truth has no such field for that question, e.g., an unscoped question has no scope component). A generation is semantically correct only if no applicable component mismatches. We validated this automated scoring against independent manual scoring of 40

¹The formative experiment uses Claude-Sonnet-4.5; the workflow evaluation (section 6) uses Claude-Sonnet-4, a snapshot in the same model family that has since been retired by its provider, with Claude-Sonnet-4.5 its closest available successor. Because the two are reported separately and never compared numerically, this difference does not affect any result. All models used are fixed dated snapshots.

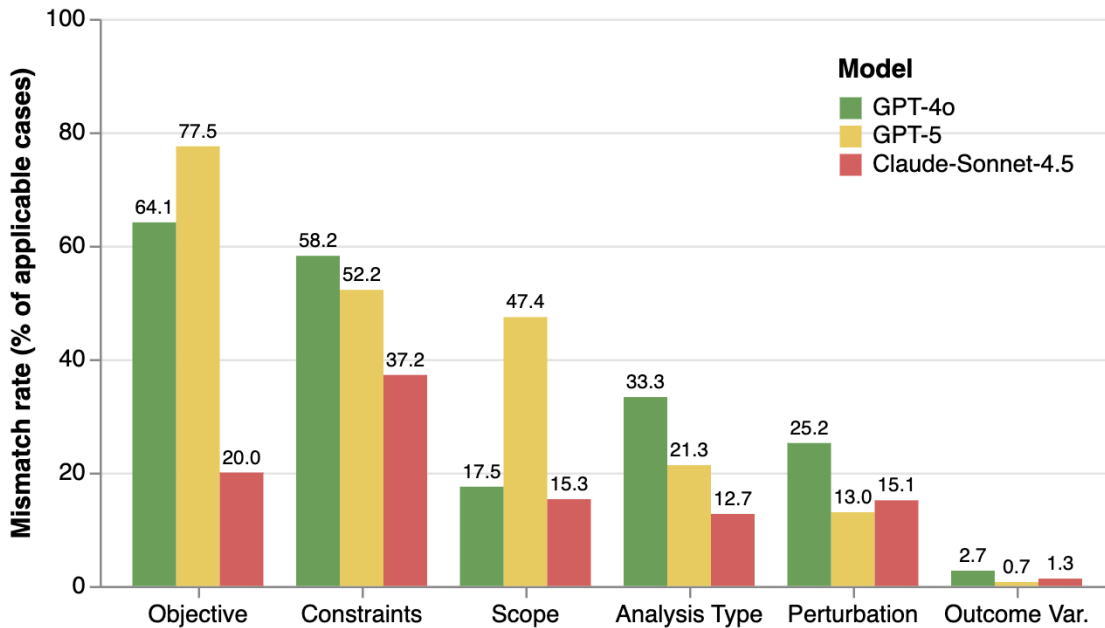


Fig. 5. Per-component mismatch rates for direct generation, by model, over applicable cases. Across all three models, *objective* and *constraints*—the components with no forced representation in generated code—are the most frequently mismatched, while *outcome variable* and *analysis type* are comparatively reliable.

samples, obtaining strong agreement (90.0%, Cohen’s $\kappa = 0.85$); full protocol and validation details are in supplementary material.

4.2 Direct Generation Fails Both Visibly and Silently

Direct generation exhibited two qualitatively different failure modes (Figure 5).

Visible failures. Some generations did not produce a working interface at all: execution failures occurred in 20.7% of GPT-5 generations, 44.7% of GPT-4o generations, and 17.3% of Claude-Sonnet-4.5 generations. These failures are at least self-announcing—the intended interface never becomes usable, so the user knows something went wrong.

Silent failures. More concerning are semantic failures, in which a rendered, interactive interface does not faithfully represent the analysis the question asked for. Among interfaces that rendered successfully, 35.5–81.9% (depending on model) contained at least one component mismatch relative to the ground-truth intent. Crucially, the mismatches concentrated on the components with *no forced representation in code*: for every model, *objective* and *constraints* were among the weakest (Figure 5), with substantial *scope* errors as well. Because these rates are computed only over questions whose ground truth specifies the component, the applicable denominators vary—constraints and objective, in particular, are specified in a subset of questions (43–55 and 80–131 of 150, respectively; full denominators in supplementary material)—so we report them as per-component mismatch rates rather than as a single aggregate.

Why these failures are hard to catch. The defining property of these failures is that the interface looks right: it renders, the controls respond, and the numbers update—yet the analysis underneath is wrong, and nothing on screen reveals it.

Consider a constrained goal-seek: “*Under conditions of less than 15,000 Affiliate_Impressions per week in Division B, specify the increase in Paid_Views and Google_Impressions required to surpass the \$950,000 Sales threshold.*” This asks a concrete question—by how much must two inputs rise to push predicted Sales past a target, within a specified subset of the data—and it has an answer: our workflow, compiling the same intent, finds input increases that reach the target, predicting \$1,253,612 in Sales (Figure 6, right). GPT-5’s directly generated interface (Figure 6, left) instead reports that the target is *unachievable*: its highest reachable prediction is \$933,027, just short of \$950,000, and every summary card shows the goal cannot be met. A user would reasonably conclude the business objective is impossible—when in fact it is not.

The interface gives no hint that anything is amiss. It presents a scope card, a baseline card, sliders for both inputs, and a heatmap of predicted Sales; it is, on its face, a complete and usable goal-seek tool. The error is entirely in the generated code, and takes two forms. First, although the question scopes the analysis to weeks with fewer than 15,000 Affiliate_Impressions, the code applies that condition only to compute baseline values—the model itself is trained on *all* of Division B, so the stated scope never actually shapes the predictions. Second, the code searches for a solution over a fixed grid of input increases that is far too coarse relative to the data: predicted Sales barely move across the entire grid, so the search terminates convinced no combination reaches the target. Neither of these decisions is visible in the rendered interface; both are recoverable only by reading the code line by line.

This pattern—a fully functional interface that silently encodes a wrong analysis—recurs across models and questions. On a question asking to *maximize* response likelihood, two of three models instead optimized total spending, substituting the wrong outcome variable; on another, a model treated a goal-seek phrased around reaching a target rate as a plain sensitivity sweep, never optimizing at all; on a third, two of three models dropped an explicit bound limiting how far a recommended change could deviate from a customer’s profile, leaving those variables unconstrained. In every case the interface rendered and behaved plausibly, and the omitted objective, misapplied scope, or dropped constraint was visible only in the generated code. That the same error often recurs across independently generated models on the same question indicates these are properties of the task as posed, not one model’s slip: nothing in a one-shot generation contract forces a model to name and commit to the scope, objective, or constraint it is actually implementing, so any of them can be quietly mis-encoded while the interface still looks correct. We provide additional worked examples in supplementary material.

4.3 Why an Explicit Representation?

These findings do not imply that direct code generation can never produce correct WIA interfaces; often it does. The problem is that when it does not, nothing reveals it. Across our examples, the failures were not crashes or malformed output but analytically wrong interfaces that rendered and behaved normally—a goal-seek that declared an achievable target impossible, a comparison silently re-scoped to a different set of weeks, an objective quietly dropped in favor of a plain sweep. What these share is a single underlying cause: the meaning of the requested analysis and its implementation are produced simultaneously and embedded in the same artifact. The decisions that determine whether the analysis is correct—which subset to scope to, what to optimize, which bounds to enforce—are never stated anywhere the user can see; they exist only as incidental choices scattered through generated code. As a result, a misinterpreted scope, an omitted constraint, or a substituted objective becomes indistinguishable, from the interface alone, from a faithful analysis. There is no point in the pipeline at which the intended analysis can be checked before it is acted upon.

This motivates a different workflow. Instead of translating a WIA question directly into interface code, we first represent the intended analysis *explicitly*, as a small set of named properties—scope, outcome, perturbation, constraints, objective, analysis type—that stand apart from any implementation. Making intent a separate, inspectable artifact creates exactly the

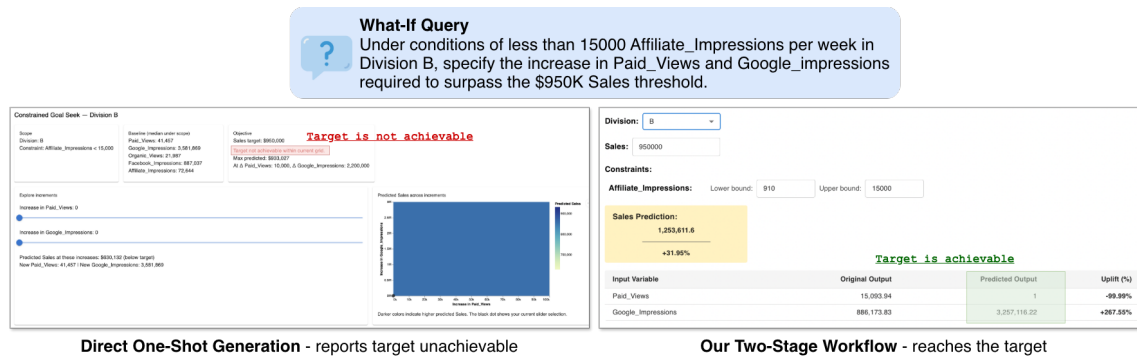


Fig. 6. A directly generated interface that silently encodes a wrong analysis. For the constrained goal-seek “...specify the increase in Paid_Views and Google_Impressions required to surpass the \$950,000 Sales threshold,” GPT-5’s interface (left) renders fully but reports the target as *unachievable* (max \$933,027): the stated scope never shapes the trained model and the search grid is too coarse to move the prediction. Compiling the same intent through our workflow (right) reaches the target, predicting \$1,253,612 with the constraint enforced. The two interfaces are visually comparable; only one is analytically correct.

checkpoint that direct generation lacks: the analysis can be read against the original question, validated, and repaired *before* it is compiled into an interactive interface, so that a scope substitution or dropped constraint is caught as a wrong property rather than discovered as an implausible result, if ever. In the following section, we operationalize this idea using PRAXA SPECIFICATION LANGUAGE (PSL).

5 A Two-Stage Workflow: Separating Analytical Intent from Implementation

Our two-stage workflow (Figure 7) translates NL WIA questions into interactive visual interfaces via a declarative specification as an intermediate representation. This directly addresses the limitations identified earlier: unlike spreadsheet and BI tools (section 2), users specify analytical intent via NL rather than manual formula construction; and unlike direct LLM generation (section 4), where analysis logic is entangled with implementation, the specification separates *what* to analyze from *how* to implement it. This separation links WIA components to interface controls explicitly, makes analysis logic inspectable without reading code, and provides structure for component-level validation and targeted repair rather than debugging arbitrary code.

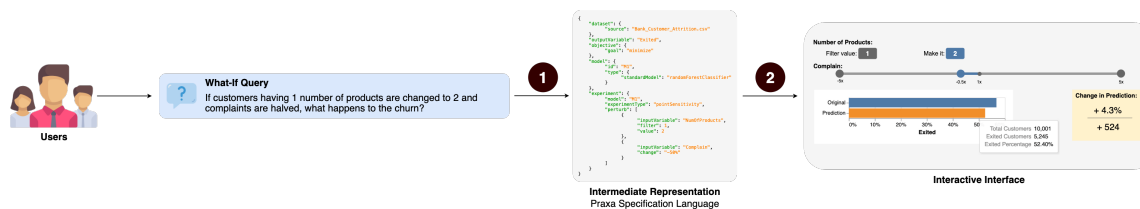


Fig. 7. Our two-stage workflow: (1) translating NL WIA questions into a structured intermediate representation like PRAXA SPECIFICATION LANGUAGE (PSL), and (2) compiling it into an interactive visual WIA interface with linked controls and visualizations.

5.1 Stage 1: NL to Declarative Specification

A user’s NL WIA question is transformed into a structured intermediate representation that captures analytic intent. We instantiate this representation as a JSON-based declarative specification language, PRAXA SPECIFICATION LANGUAGE (PSL), grounded in the compositional grammar of what-if analysis, PRAXA [11]. PRAXA models WIA workflows as compositions of three primitives: *data* (variables under analysis), *model* (predictive mechanisms), and *interaction operations* (paired user actions and system responses, e.g., *perturb* → *rerun*, *constrain* → *optimize*). PSL encodes these primitives as named specification properties—the same six representation-neutral components of analytical intent defined in subsection 3.4—making intent explicit and inspectable against the original question rather than embedded in code. Generation details are provided in section 6.

Intermediate Representation: PSL. We summarize key PSL properties using an example WIA question: “*If customers with one product were changed to two and complaints were halved, what happens to churn?*” (Figure 8).

dataset encodes the data primitive, specifying the dataset over which WIA is performed (e.g., the *Bank Customer Attrition* dataset for D1).

outputVariable encodes the target variable of interest, e.g., mapping ‘churn’ to the *Exited* parameter.

objective encodes the intended goal for the **outputVariable**, e.g., **minimize** churn; other goals include **maximize** or **setTarget**.

model encodes the predictive model connecting input variables to the output variable. Each entry specifies an **id** and **type**, chosen according to the type of the **outputVariable**. In the example, because *Exited* is binary, a **randomForestClassifier** is used, though an alternative such as **logisticRegressor** is also valid.

scope (optional) defines filters restricting analysis to subsets of the **dataset** (e.g., filtering by region), supporting scoped WIA types.

experiment encodes the WIA workflow through interaction operations, specifying an **experimentType** (one of the 11 types in Figure 2) along with an optional **scope** and model. For example, **pointSensitivity** defines perturbations

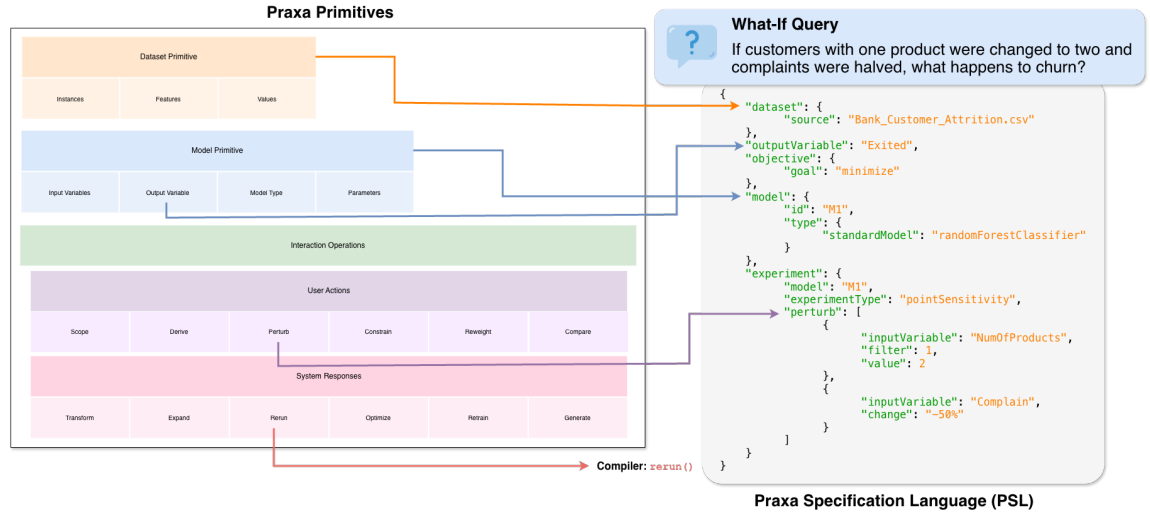


Fig. 8. Example PSL specification for a point sensitivity question, with properties mapping to PRAXA primitives [11].

via `perturb` (e.g., changing variable values or percentages, with optional filters). Other types use properties such as `top` (importance) and `constraints` (goal seek). System responses (e.g., `rerun`, `optimize`) follow the interaction pairing defined in PRAXA [11]. Multiple experiments can be composed within a single specification. Full schema details are in supplementary material.

5.2 Stage 2: Declarative Specification to Interactive Visual Interface

Our compiler translates a PSL specification deterministically into an interactive interface through three stages: parsing, execution, and rendering. First, the specification is *parsed* to extract primitives, validate schema constraints, and populate missing defaults; structural violations are caught here and reported against the specific offending property, before any computation runs. Second, type-specific analysis functions are *executed* against the model and data as the specification dictates. Crucially, the `scope` property filters the data *before* the model is trained and applied, so a scoped analysis is genuinely restricted to the intended subset—not merely used to set a baseline—and the `constraints` and `objective` properties drive the goal-seek search directly, so optimization targets exactly the criterion the specification names. Because these behaviors are fixed in the compiler rather than re-derived by an LLM for each question, they are consistent across questions and runs—the failure modes of [section 4](#), where scope silently failed to shape the model and goal-seek searches were degenerate, cannot arise by construction. Third, results are *rendered* using deterministic visual mappings: each WIA type maps to a fixed visual encoding and set of controls, drawn from a design space of visualizations and controls observed across existing BI tools and research systems [11, 12, 17, 49] ([Figure 9](#)). For each type we use typical visual encodings (e.g., bar charts for point sensitivity, line charts for range sensitivity, prediction cards for goal-seek, ranked bars for importance) with corresponding interaction controls (sliders for continuous variables, dropdowns for categorical variables, filters for scope, and constraint builders for goal-seek); our compiler implements the highlighted subset, while the remaining entries indicate alternatives available in prior systems. User interactions update the underlying specification and trigger re-execution, keeping the interface and the analysis logic in sync. Because this property-to-component mapping is deterministic, the same specification always yields the same interface, every interface element is traceable to the specification property that produced it, and this same mapping defines the surface through which specification errors become visible in the compiled interface—the basis for the error-propagation analysis in [section 6](#).

6 Evaluating PSL: Generation, Repair, and Error Propagation

The motivating experiment ([section 4](#)) showed that direct generation fails precisely because analytical intent has no explicit representation: misread objectives, substituted scopes, and dropped constraints became embedded in code where they could not be seen, checked, or fixed. We now evaluate whether routing generation through PSL—which makes that intent explicit—changes this. We ask three questions: how reliably LLMs translate NL WIA questions into PSL specifications and where they fail (**RQ1**); whether the explicit structure of PSL enables errors to be detected and repaired (**RQ2**); and how residual errors propagate into compiled interfaces (**RQ3**). All three use the benchmark and six-component ground-truth intent from [section 3](#), encoded as PSL for this evaluation ([subsection 3.4](#)).

Two points connect this evaluation to the motivating experiment and frame everything that follows. First, the failures are largely the *same*: the misread objectives, substituted scopes, and dropped constraints that made directly generated interfaces wrong reappear here as errors in PSL generation, confirming that faithfully translating a WIA question is hard regardless of the target. What changes is not whether these errors occur but what can be done about them—in the motivating experiment, diagnosing why an interface was wrong required reading generated React and Python line by line, whereas here the same misinterpretations are visible *in the specification itself*, as wrong values of named properties.

What-if Analysis Type \ Tools	Common Visuals	
	Charts	Controls
T1. Point Sensitivity T2. Point Sensitivity with Scope	Tornado chart, Waterfall chart, Heatmap, Partial dependence plot (PDP), Scenario table, Textual prediction change	Value / percentage slider, Categorical change dropdown, Scope filter/dropdown
T3. Range Sensitivity T4. Range Sensitivity with Scope	Line chart, Small multiples, Two-way heatmap, Scenario table	Min/Max range sliders, Step size slider, Scope filter / dropdown
T5. Goal Seek T6. Goal Seek with Scope	Card (showing predicted output variable), Original vs predicted values (bar charts), Table	Objective dropdown, Scope filter / dropdown
T7. Constrained Goal Seek T8. Constrained Goal Seek with Scope	Card (showing predicted output variable), Original vs predicted values (bar charts), Table	Objective dropdown, Min/Max range sliders / Categorical variable multi-select dropdown, Constrain textboxes, Constraint builder (for functions), Target value input (numeric), Selector to constrain or freeze variables, Scope filter / dropdown
T9. Counterfactuals	Bar chart showing delta for changed features, Card (showing prediction for current data point and counterfactual)	Desired output variable outcome selector, Number of solutions slider, Selector to constrain or freeze variables, Min/Max range sliders / Categorical variable multi-select dropdown, Constrain textboxes, Constraint builder (for functions)
T10. Importance T11. Importance with Scope	Ranked bar chart, SHAP beeswarm / Violin, Heatmap, Pareto chart	Top-K slider, Scope filter / dropdown

Fig. 9. Common visualizations and controls across the 11 WIA types (T1–T11), observed in existing BI tools and research systems. The subset implemented by our compiler is highlighted; remaining entries are alternatives from prior work.

Second, whereas the motivating experiment sampled 150 questions per model to permit interface-level hand-scoring, this evaluation covers the full benchmark (405 questions $\times$ 3 models = 1,215 specifications), auditing each against ground-truth intent at the property level. The two studies are therefore complementary rather than comparable: one measures how often direct generation fails and how those failures hide; the other measures, at scale, whether an explicit representation makes the same class of failures tractable.

6.1 RQ1: Generating PSL Specifications

We evaluate three LLMs (GPT-4o, GPT-5, and Claude-Sonnet-4) via a two-step few-shot prompting strategy (Figure 10).

6.1.1 Specification Generation. Step 1: Classification of WIA Type. Each LLM classified questions into one of 11 WIA types using prompts with dataset context, type definitions, and a few examples. To reduce bias, we randomized type order, collected three predictions per question, and used majority vote. Three coders annotated types as a human baseline.

Findings. Across 405 questions, we observed 119 LLM–human mismatches (details in supplementary material). Most (102/119) were LLM misclassifications, which typically over-interpreted phrasing or failed to distinguish scoped from unscoped analyses. In the remaining 17 cases, LLMs were more accurate than humans (e.g., correctly classifying a continuous range question as range sensitivity (T3) rather than sensitivity (T1)). We reviewed all 119 cases and adopted the more accurate label before specification generation, so that the generation errors analyzed below are not confounded by upstream type-classification disagreements.

Step 2: PSL Specification Generation. Using the predicted WIA type, each LLM generated a PSL specification via prompts containing dataset context, the assigned type, its definition, the PSL schema, and two to four hand-authored question–specification pairs.² Two coders compared each generated specification against the ground-truth intent at the property level, considering dataset and question context. This process also surfaced schema gaps (e.g., expressive scoping: “For customers with higher estimated salary...” required support for complex functions within the `scope` property, such

²Exemplars were fixed in advance and shared across all models and WIA types; we report generation reliability against this frozen exemplar set and do not tune prompts per model.

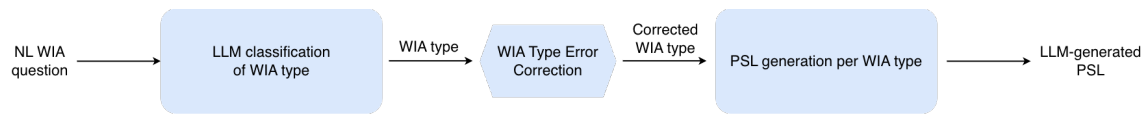


Fig. 10. Strategy adopted for generating PSL for NL WIA questions in benchmark.

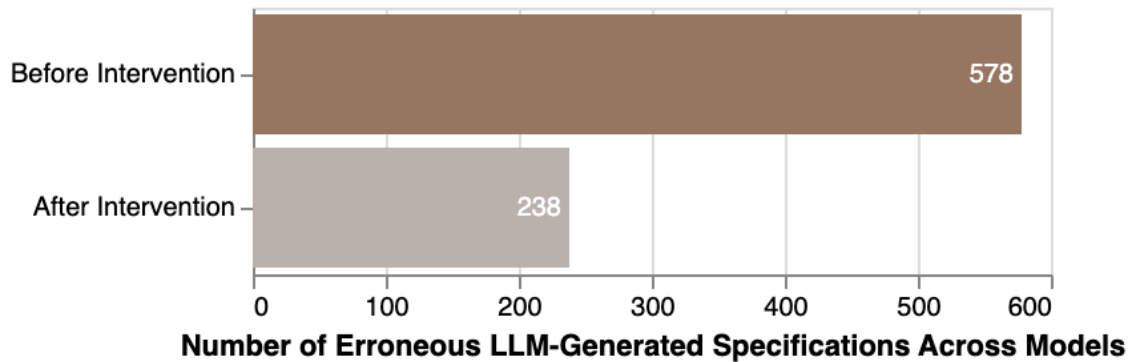


Fig. 11. Number of erroneous LLM-generated specifications across models before and after intervention of targeted repair.

as `"EstimatedSalary": {"operator": ">=", "function": "quartile3"}`), leading to extensions of the `scope` property and re-generation.

Findings. Across all 1,215 model-generated specifications, 637 (52.42%) were generated correctly without intervention, matching the ground truth; 578 were erroneous prior to intervention (Figure 11; per-dataset breakdown in supplementary material). That roughly half of specifications are wrong on the first pass—even with an explicit target schema—reinforces the lesson of the motivating experiment: the hard part of NL-driven WIA is not rendering an interface but faithfully capturing intent, and an explicit representation does not make LLMs better analysts. Its value, as the rest of this section shows, is that it changes what happens to the errors that remain: instead of being entangled in code, they surface as wrong values of specific, named properties.

6.1.2 Error Taxonomy. To analyze failures, we audited the erroneous specifications across all datasets and models in two passes. At the *parsing level*, we checked schema validity and compilability; failures here are *non-functional errors*, since they cannot produce any output. At the *semantic level*, we evaluated whether parsed specifications captured the intended analysis; failures here are *functional errors*, since they compile but produce incorrect outputs. We organize the errors observed *at generation* into nine categories (EC1–EC9) across these two classes; a single specification may exhibit multiple errors (Figure 12). A tenth category, introduced only by repair, is described in subsection 6.2.

Non-Functional Errors (EC1–EC4). Of the 578 incorrect specifications, 58 failed to compile into executable interfaces, falling into four categories.

EC1: Structural / Formatting Errors. These are the classic “won’t run” failures: the LLM not returning any output at all (labeled as complete error in the figure), malformed JSON, dangling commas or quotes, and container-shape mistakes such as emitting a single `perturb` object where an array is required. These appear infrequently and are shallow syntax issues; a smaller fraction are structural mismatches where the structure of a specific WIA schema is incorrect (e.g., a counterfactual missing the feature name to which it wants the closest data point).

#EC	Error Category (EC)	# Errors	Error	GPT-4o	GPT-5	Claude
Non-Functional Errors						
EC1	Structural / Formatting Errors	5	Complete error	6	5	7
			JSON formatting error	1		
			Format of "to" property incorrect	2	1	
			Perturb is object instead of array	11		
			Incorrect counterfactual setup in experiment	1		
EC4	Incorrect Schema Errors	2	Schema for target and value properties not understood	40	10	33
			Scope referenced in the wrong place	2		1
Functional Errors						
EC5	Misunderstanding the Analysis Operation	6	Question type categorization incorrect	18	16	23
			LLM interpretation of question different than ground-truth and incorrect	7	3	
			LLM interpretation of question different than ground-truth but correct	4	6	3
			LLM interpretation of question incorrect			1
			LLM missing percentage, but value correct	1		8
EC6	Misspecifying Variables	7	Whether to change by a certain change value or provide a definite value is not understood	4	13	1
			Incorrect output variable interpreted by the LLM	1	2	
			Missing dependent variables in outputVariable property	1	1	
			Variable within inputVariables property incorrectly understood by LLM		4	2
			Missing inputVariables property within experiment	7		2
			Missing variable within inputVariables property		1	2
			Extra inputVariables property	12	24	8
			Extra validateInputVariables property	2	2	3
EC7	Misspecifying Objectives and Constraints	10	Incorrect goal in objective property	1	28	3
			Objective property includes not-needed target	8		
			Incorrect kind block	12	5	8
			Extra kind block			2
			Function missing in kind block			1
			LLM misunderstands constraints	10	1	
			Constraint property doesn't understand selfFixed key	1	5	
			Unnecessarily complex constraints added by LLM	2		
			Extra constraints in constraint property	1	1	1
			Missing constraints in constraint property			1
Non-Functional Errors						
EC2	Redundancy / Duplication Errors	4	Duplicated experiments		2	
			Duplicated scope			1
			Multiple experiment blocks when multiple scopes are needed			2
			Unnecessary relativeTo key added by LLM	5	5	6
			Missing perturb block	2	1	
EC3	Missing Blocks / Key Errors	3	Missing kind block	4	4	2
			Missing target and value properties	3		7
Functional Errors						
EC8	Misgauging the Scope	8	Incorrect scope property	8	22	3
			Not understanding scope property key-value pairs correctly	6	3	2
			Scope scoping with functions not understood by LLM	4	5	5
			Complex scoping with functions not understood by LLM	13	3	2
			Format of complex scope's incorrect	1	1	
			Unnecessary complex scope added by LLM	6	1	2
EC9	Misusing or Omitting Properties	14	Extras in the scope property	2	9	4
			Reference to the scope missing in experiment property	10	9	10
			Missing filter key	16	5	13
			Incorrect filter property	2	2	2
			Missing across key	5	4	5
			Extra across key	2	2	
			Missing stepSize Key		7	
			Extra upperBound			1
EC9	Misusing or Omitting Properties	14	Missing lowerBound property	7	11	7
			Missing upperBound property	1	7	1
			Incorrect lowerBound property	1	4	2
			Incorrect upperBound property		3	1
			Missing interestOfVariable property	1	1	1
			Missing top property	8	3	6
			Extra top property	3	18	8
			Extra value property			

Fig. 12. We identify 2 classes of errors observed in the LLM-generated specifications: (1) *non-functional errors* where the specifications cannot be parsed and (2) *functional errors* where specifications can be parsed but may not express the correct or entire intent of the what-if questions. For each of these classes, we show a number of error categories (EC), its selected examples of errors within them, and percentage of total specifications showing the error across the three LLMs.

EC2: Redundancy / Duplication Errors. The model sometimes generates redundant content—e.g., duplicated `experiment` blocks, near-identical blocks regenerated, or hallucinated non-schema keys (e.g., `relativeTo`) that the model invents. These errors are infrequent but costly, creating confusion over which block to use, inflating computation, or producing inconsistent results. We also observed cases where redundant blocks masked missing or incorrect parts of the specification, complicating debugging.

EC3: Missing Blocks / Key Errors. Here, although the generated specification is well-formed JSON, it omits a critical block the schema requires—for example, missing `target`, `value`, or `kind` inside a goal-seek experiment, or the entire `perturb` block for a sensitivity experiment. These errors are rare, yet they behave like EC1 at runtime, where the pipeline aborts.

EC4: Incorrect Schema Errors. This is the most prominent non-functional category, referring to violations of the schema during generation. Most notable was swapping the `target` and `value` roles, or referencing `scope` from unsupported positions in the `experiment` block. These mistakes are subtle since on the surface the JSON is clean, but schema validation fails or the engine refuses to run because required invariants (e.g., `kind` needs `target` and `value` performing certain roles) are not satisfied.

Functional Errors (EC5–EC9). Unlike non-functional errors, these specifications compile and produce plausible interfaces but are incorrect because they misinterpret the question (e.g., wrong data subset or constraints). They account for the majority of failures (520 of 578), and they are the direct analogue of the silent failures in section 4—the same

misread objectives, scopes, and constraints, now surfaced as wrong properties rather than buried in code. We group them into five categories (Figure 12).

EC5: Misunderstanding the Analysis Operation. This error captures cases where the specification is structurally valid but semantically mismatches the intended scenario, due to incorrect mapping from NL intent to specification semantics. Common failures include paraphrasing the question, especially in compound cases with implicit constraints (e.g., “within budget”), multiple perturbations (e.g., “increase A and decrease B but hold C fixed”), or ambiguous quantifiers (e.g., “small increase”). LLMs may misinterpret these, leading to deviations from ground truth. Additional errors include misreading perturbations (e.g., relative vs. absolute changes, percentage vs. value) and omitting required experiments. Even when the analysis type is pre-specified correctly, LLMs occasionally generate incorrect PSL (e.g., treating a constrained goal-seek as a sensitivity analysis).

EC6: Misspecifying Variables. The generated PSL runs but uses the wrong features in the dataset or omits the right ones. These include an incorrect `outputVariable` chosen for the experiment, missing `outputVariables` when the question inquires about more than one feature, a model choice inappropriate for the specified `outputVariable`, forgetting to include the `inputVariables` the question inquires about, restricting focus to only some `inputVariables`, missing or misinterpreting variable names within `inputVariables`, confusing “change by” vs. “set to” semantics within `perturb`, or spurious properties unknown to the schema (e.g., `validateInputVariables`).

EC7: Misspecifying Objectives and Constraints. These errors arise in goal-seeking and constrained experiments, where the specification must encode both a desired outcome and the bounds within which the system should search. Most involve misspecified objectives—minimizing when the question asks to maximize, adding optimization targets where none are needed, or failing to express complex target functions (e.g., “solutions where Revenue increases by 10%”). Incorrect or duplicate `kind` blocks cause the optimization to converge to the wrong criterion, producing an interface that displays an “optimal” solution optimizing the wrong thing. Other errors involve constraints: reversed inequality bounds (e.g., $\geq$ instead of $\leq$), constraints applied to the wrong variable (e.g., bounding *Revenue* when the question constrains *Spend*), misuse of the `setFixed` property, and gratuitous complexity where the LLM introduces redundant nested constraints not present in the question. The resulting interface enforces incorrect feasibility bounds, producing recommendations that violate the analyst’s intended restrictions or exclude valid solutions.

EC8: Misgauging the Scope. These errors arise when analyses are restricted to data subsets but the `scope` is malformed, incomplete, or extraneous, altering which rows are evaluated. Common issues include incorrect key–value mappings, especially for categorical features encoded numerically (e.g., *Email_Type* as 1 or 2 vs. “Transactional” or “Promotional”). LLMs also generate unsupported or over-engineered expressions (e.g., SQL-like clauses, regex, or unnecessary nested logic). Another recurring issue is that the `experiment` block fails to reference the defined scope, causing filters to be ignored. As a result, analyses run on incorrect subsets, yielding misleading conclusions.

EC9: Misusing or Omitting Properties. This is one of the most pervasive errors. The generated specification often has missing properties (e.g., `stepSize`, `lowerBound` and `upperBound` in sensitivity experiments, or `top` for importance experiments) or incorrect property values (e.g., not within the dataset bounds), which distort the search space of experiments. Conversely, additional unwarranted properties can yield plausible but misleading results.

The taxonomy is itself the evidence for inspectability. Every one of these categories is tied to a *named property* of the specification, and this is not incidental—it is the central advantage of an explicit representation made concrete. The entire audit above, assigning each of 578 failures to specific components, was possible only because intent is readable in the specification: the same audit on the directly generated interfaces of section 4 would have required reading hundreds of bespoke programs line by line, with no guarantee of finding where—or whether—intent was misencoded. Here it reduces

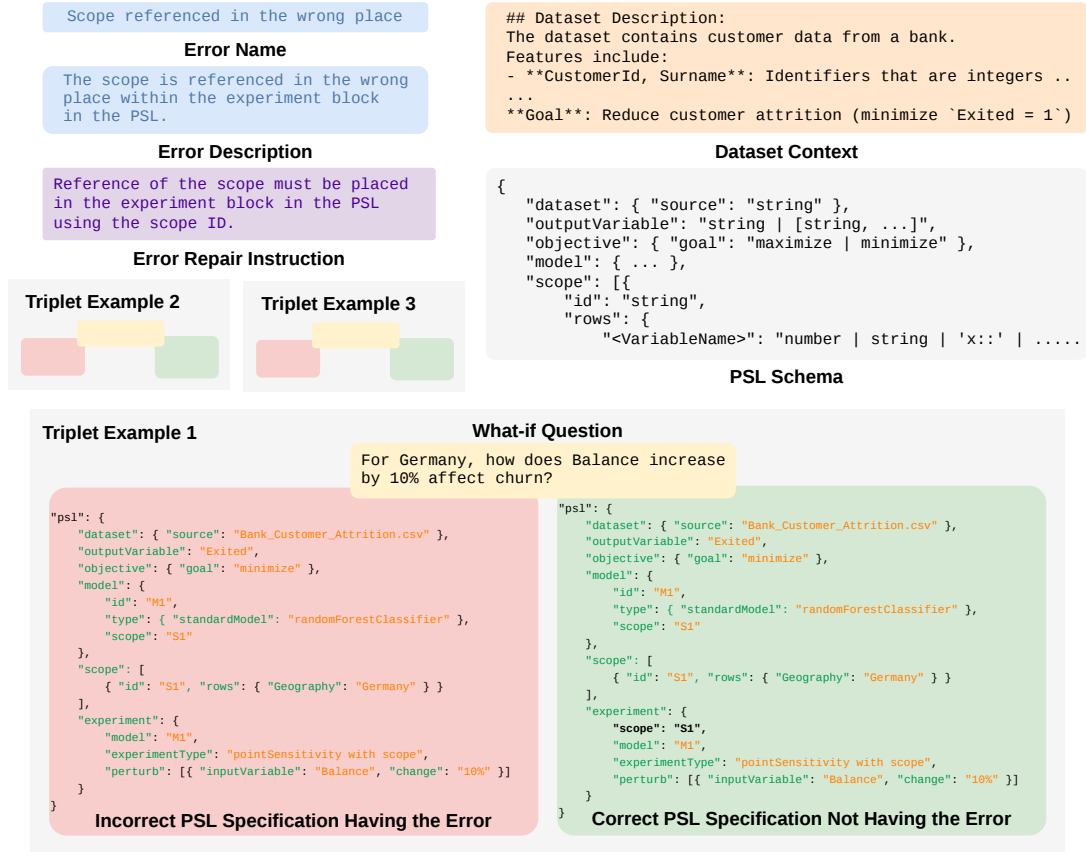


Fig. 13. Example of a targeting prompt contents for correcting the “Scope referenced in the wrong place” error.

to inspecting a handful of named fields against the question. That same localizability is what makes the errors not only detectable but repairable, which we turn to next.

6.2 RQ2: Detecting and Repairing Errors

Having shown that errors localize to named properties, we now ask whether they can be found automatically and fixed. We find that identification is best left to humans and repair to the model—a division of labor the explicit representation uniquely enables.

6.2.1 Automated Error Detection. We evaluate whether LLMs can detect errors in generated specifications through two experiments. In the first (*binary detection*), we asked LLMs to predict whether a specification contained any error (yes/no), compared against majority-vote labels from three human annotators. Across all 405 questions, LLMs achieved 64.06% accuracy with modest agreement ($\kappa = 0.218$), but over-flagged errors (64.06% vs. 44.43% by humans). This suggests LLMs can act as high-recall screeners that surface likely-problematic specifications for human review, but are not reliable as final decision-makers.

#EC	Class of Error	# Errors	Change in Errors after Repair Strategy	Error	GPT-4o			GPT-5			Claude		
					After Repair	Change from Initial Errors	After Repair	Change from Initial Errors	After Repair	Change from Initial Errors			
Non-Functional Errors													
EC1	Structural / Formatting Errors	4	-2 and +1	Complete error	6	S	14	I	0	D			
				JSON formatting error	1	S							
				Format of 'top' property incorrect	1	D	2	I	2	I			
				Incorrect perturb block			1		1				
EC2	Redundancy / Duplication Errors	3	-3 and +2	Unnecessary relative key added by LLM	0	D	0	D	1	D			
				When experiments are to be performed for multiple scopes, multiple experiment blocks are added			3						
EC3	Missing Blocks / Key Errors	3	-1 and +1	Multiple experiments not specified properly									
				Missing kind block	0	D	3	D	1	D			
Functional Errors													
EC5	Misunderstanding the Analysis Operation	5	-3 and +1	LLM interpretation of question incorrect				1	S				
				LLM interpretation of question different than ground-truth but correct	0	D	1	D	3	I			
				Question type categorization incorrect	16	D	10	D	17	D			
				Whether to change by a certain change value or provide a definite value is not understood	0	D	15	I	0	D			
EC6	Mis-specifying Variables	8	-1 and +1	One of the experiment's is incorrectly specified	1								
				Missing dependent variables in output/variable property	0	D	0	D	1	I			
				Variable within input/variables property incorrectly understood by LLM	1	I	4	S	1	D			
				Missing input/variables property within experiment	5	D			1	D			
EC7	Mis-specifying Objectives and Constraints	6	-5 and +6	Missing variable within input/variables property			0	D	1	D			
				Extra input/variables property	0	D	7	D	0	D			
				Extra validate input/variables property	1	D	0	D	0	D			
				Extra variables within input/variables property	4		2		4				
EC8	Scope Specification Errors	15	+7	Incorrect goal in objective property	9	D	11	D	4	I			
				Objective property includes not-needed target	12	I							
				Incorrect kind block	12	S	7	I	7	D			
				Extra kind block	10	I			0	D			
EC9	Mis-specifying Properties	15	-3 and +4	LLM misunderstands constraints	1	D	0	D					
				Constraint property doesn't understand self-fixed key	0	D	3	D	5	I			
				Extra constraints in constraint property	5	I	0	D	0	D			
				Missing constraints in constraint property	1	I			0	D			
EC10	Cross-Property Substitution Errors	7	+7	Missing value property inside kind property	2				1				
				Incorrect value of target inside kind block	5								
				self-fixed key incorrect	4								
				Constraints have comparison instead of lowerbound and upperbound	2								
EC10	Cross-Property Substitution Errors	7	+7	Constraint property format is incorrect	1		1		2				
				Unnecessary constraint property	1								
				Incorrect scope property	1	D	11	D	3	S			
				Scope property partially specified	3	D	3	S	0	D			
EC10	Cross-Property Substitution Errors	7	+7	Not understanding scope property key-value pairs correctly	0	D	1	D	0	D			
				Complex scoping with functions not understood by LLM	3	D	2	D	6	I			
				Format of complex scope's incorrect	0	D	2	I					
Non-Functional Errors													
EC4	Incorrect Schema Errors	6	+4	Missing target and value properties	0	D			1	D			
				Missing to block									
				Schemas for target and value properties not understood	11	D	1	D	19	D			
				Scope referenced in the wrong place	0	D			1	S			
EC4	Incorrect Schema Errors	6	+4	Not understanding scope values right									
				Scope values not according to the dataset values	3								
				Name of source the incorrect	6								
				Reference to scope incorrect			2						
Functional Errors													
EC9	Mis-specifying Properties	15	-3 and +4	Unnecessary complex scope added by LLM	1	D	6	I	0	D			
				Extras in the scope property	0	D	0	S	1	D			
				Reference to the scope missing in experiment property	3	D	1	D	0	D			
				Incorrect scope property value	3								
EC9	Mis-specifying Properties	15	-3 and +4	Format of scope property incorrect	6								
				LLM interpretation of scope property different but correct	10								
				Extra scope property but experimentType is correct	1		3		0				
				Missing scope property but experimentType is correct	3								
EC9	Mis-specifying Properties	15	-3 and +4	Extras in scope which must be in constraint	1								
				Unnecessary comparisonWith property in scope	1								
				Missing filter key	0	D	0	D	2	D			
				Incorrect filter property	3	I	2	S	0	D			
EC9	Mis-specifying Properties	15	-3 and +4	Extra scores key	3	I	0	D	0	D			
				Missing stepSize key			1	D					
				Missing lowerbound property	6	D	0	D	3	D			
				Missing upperbound property	5	I	0	D	1	S			
EC9	Mis-specifying Properties	15	-3 and +4	Incorrect lowerbound property	6	I	2	D	3	I			
				Incorrect upperbound property	2	I	2	D	1	S			
				Missing top property	0	D	1	D	6	S			
				Extra top property	1	D	0	D	5	D			
EC9	Mis-specifying Properties	15	-3 and +4	Incorrect value property value	1	S							
				Incorrect stepSize key			1						
				Missing intervalRange property			1		3				
				Incorrect top property value			1		3				
EC10	Cross-Property Substitution Errors	7	+7	Extra change property									
				Filter key replaced with scope property			2						
				Incorrect intervalRange and stepSize and instead having change property	1								
				lowerbound and upperbound keys instead of self-fixed key			2						
EC10	Cross-Property Substitution Errors	7	+7	Perturb blocks replaced by scope property					1				
				Scope property instead of top key									
				Input/variables property missing and instead added to constraint			1						
				Filter property replaced by value property and duplicate perturb blocks					4				

Fig. 14. Error distribution after targeted repair across error categories (EC1–EC10) and models. For each error, we report the count after intervention and the direction of change from before intervention (D = decrease, I = increase, S = same). New errors introduced during repair are marked in blue. Most categories decrease, but new error types emerge like cross-property substitutions (EC10).

In the second experiment (*per-category diagnosis*), we tested whether LLMs could identify the specific error category (EC1–EC9) when provided with error definitions and contrastive positive and negative examples alongside each specification. On a sample of 420 specifications (140 questions $\times$ 3 models), overall agreement was only fair ($\kappa \approx 0.23$ – 0.25), with LLMs over-flagging at 3 – $23\times$ the human rate. LLMs were better calibrated on functional errors (EC5–EC9) than non-functional ones (EC1–EC4). Full details are in supplementary material.

These findings show that LLMs can detect *that* a specification is likely incorrect but struggle to diagnose *what* is wrong, necessitating human input for precise error categorization. This motivates a human-in-the-loop division of labor—a human identifies the error category, and the LLM applies a category-specific fix. Crucially, that division of labor is only meaningful because the representation is inspectable: a human can identify *which* named property is wrong by reading the specification against the question—an act that has no counterpart when intent is dispersed through generated code.

6.2.2 Targeted Repair. For each erroneous specification (N = 578 across 3 models), we prompted the generating LLM with a tailored repair prompt including: (1) the error name and a one-sentence description, (2) a short error-specific repair instruction, (3) 2–3 triplets of question, incorrect specification, and corrected specification demonstrating the fix, (4) dataset context, and (5) the PSL schema (Figure 13). Two coders then re-evaluated the repaired specifications against ground truth.

Findings. Repair reduced erroneous specifications from 578 to 238, raising overall correctness from 52.42% (before intervention) to 80.42% (after intervention) (Figure 11). The significance is less the specific gain than what makes

it achievable: each repair targets a *named* property identified as wrong—a missing `scope`, an inverted `objective`, an out-of-range `top`—rather than an unlocalized defect somewhere in generated code. The same errors, when embedded in the directly generated interfaces of [section 4](#), offered no comparable point of intervention: there is no property to correct, only code to rewrite, and no way to confirm the rewrite preserved everything else.

At the category level, we observed two opposing effects ([Figure 14](#)). First, several previously observed errors decreased or were eliminated. Among non-functional errors, structural formatting issues such as complete failures and malformed JSON decreased across all models (EC1, -2 net), and missing blocks were resolved (EC3, -1 net). Among functional errors, question-type miscategorization and value-vs-change confusion decreased (EC5, -3 net), several variable-specification errors were resolved including missing `inputVariables` and incorrect `outputVariable` interpretations (EC6, -1 net), and property omissions such as missing `lowerBound` and `top` were partially addressed (EC9, -3 net).

Second, new errors emerged. Incorrect schema errors increased (EC4), driven by new failures in understanding scope values and dataset-specific encodings. Scope specification errors grew substantially (EC8), with new patterns including incorrect scope property values, misunderstood scope formats, and LLM-interpreted scope properties differing from ground truth. Objective and constraint errors also increased (EC7, -5 resolved but 6 new), with new errors including incorrect `kind` block values, `setFixed` misuse, and constraint format issues. Most notably, a new category emerged that was absent at generation and introduced only by repair—*cross-property substitutions* (EC10, 7 entirely new)—where LLMs replaced one structural construct with another (e.g., `perturb` blocks replaced by `scope`, `filter` replaced by `value` while duplicating `perturb`, or `inputVariables` removed and replaced with constraints). These patterns suggest that when LLMs repair a targeted property, they inadvertently edit adjacent properties, introducing higher-order faults.

These results highlight both the strength and the current limits of the intermediate representation for repair. The explicit structure of PSL makes first-order errors localizable and fixable through targeted prompts. Preventing higher-order cross-property drift, however, likely requires stronger guardrails—block-level schema validation after each repair, slot-filling approaches that modify only the targeted property rather than regenerating the full specification, or richer contrastive exemplars with explicit instructions. Notably, even these mitigations are only expressible *because* the representation is explicit: each names a property or block to constrain—a guardrail that could not be stated, let alone enforced, over free-form generated code.

6.3 RQ3: How Errors Propagate into Interfaces

The repair analysis shows that most errors can be caught and fixed; RQ3 examines what happens to the ones that are not. These residual functional errors—specifications that compile and render but misrepresent intent—are the direct counterpart of the silent failures in [section 4](#): interfaces that look right but are wrong. The difference is that here each has a traceable cause. As described in [section 5](#), compilation is deterministic, so any error in a specification propagates directly into the interface and every interface defect is traceable back to the property that produced it. [Figure 15](#) shows, for each functional error category, the WIA question, the specific specification error, the incorrect interface produced, and the correct interface from a repaired specification.

Change-by vs. set-to (EC5). The question asks to increase `Subject_Hotness_Score` *by* 0.5, but the specification sets the value *to* 0.5. The incorrect interface shows a slider set to 0.5 (absolute), while the correct interface increases the baseline by 0.5—yielding different predictions that mislead the analysis.

Missing a dependent variable (EC6). Asked about the effect of changing `Paid_Views` (by 200) and `Organic_Views` (by -100) on *both* `Overall_Views` and `Sales`, the specification omits `Overall_Views` from `outputVariables`. The interface shows the effect on `Sales` only—a partial answer, with nothing signalling the omission.

Missing constraints in constrained goal-seek (EC7). For a constrained goal-seek requiring “less than 15,000 Affiliate Impressions per week,” the specification omits the constraint entirely, while the correct interface respects it and highlights it visually for transparency.

Missing scope (EC8). The question targets “transactional emails,” but the specification omits the `scope` property. The incorrect interface computes email opening rates over the full dataset, whereas the correct interface filters to transactional emails only.

Inverted property value (EC9). Asked for the *most* predictive variables, the specification sets `top` to `-5` instead of `5`, so the interface surfaces the *least* significant variables—rendered identically to a correct ranking.

Cross-property substitution (EC10). The question asks to increase number of products *from* 1 to 30 while keeping all other rows, requiring a `filter` followed by `perturb`. During repair, the LLM replaced the `filter` with the `scope` property, so the incorrect interface applies the perturbation only to rows with number of products equal to 1, rather than perturbing those rows and comparing across geography as intended.

These are exactly the failures of [section 4](#)—interfaces that render, respond, and look plausible while encoding a wrong analysis. The decisive difference is that here the wrongness is not lost in code. Because PSL makes analytical intent explicit as named properties, each of these defects traces to a specific component—a missing `scope`, an inverted `objective`, a substituted `filter`—and can be caught by inspecting the specification before the interface is ever rendered. Across the three analyses, one thread holds: an explicit representation does not stop LLMs from misinterpreting WIA questions—the same misinterpretations recur throughout—but it converts those misinterpretations from silent, code-buried failures into named, inspectable, and repairable ones.

7 Discussion

An explicit representation targets exactly where direct generation fails. The central finding connecting our two studies is that the failures of direct generation and the strengths of an explicit representation concern the *same* properties. Direct generation most often mishandled objective and constraints ([section 4](#))—precisely the aspects of a question with no forced representation in generated code, so a model can omit them while the interface still renders plausibly. PSL makes these same aspects named, first-class properties, and it is exactly these that targeted repair is able to localize and fix, raising correctness from 52.42% to 80.42% ([subsection 6.2](#)). Where a conflated scope condition in direct generation produced an unrecoverable crash, PSL’s `scope` primitive is enforced structurally through compilation, removing that failure class by construction rather than by chance. The properties hardest to get right without an explicit representation are thus the ones an explicit representation is best positioned to name, check, and repair.

Declarative specifications as intermediate representations for WIA. More broadly, declarative specifications offer an effective middle ground between the manual effort of spreadsheet and BI tools and the opacity of direct code generation. By encoding analytical intent as named properties (e.g., `experimentType`, `objective`, `scope`, `perturb`, `constraints`), PSL represents intent in a form that is both executable and inspectable, extending to WIA the role SQL plays for queries and Vega-Lite for visualizations [[20](#), [35](#)]. Two properties make this valuable. First, intent is preserved as a persistent, named artifact rather than being entangled in implementation code, so it can be examined against the original question before any interface is produced. Second, because compilation is deterministic, each property maps to a specific interface element, so intended behavior can be inspected prior to execution—a transparency absent from both manual formula construction and opaque code generation.

Human–AI collaboration, not full automation. Our results point to a division of labor rather than end-to-end automation. LLMs generate correct specifications only about half the time (52.42%) and, while they can flag *that* a specification is

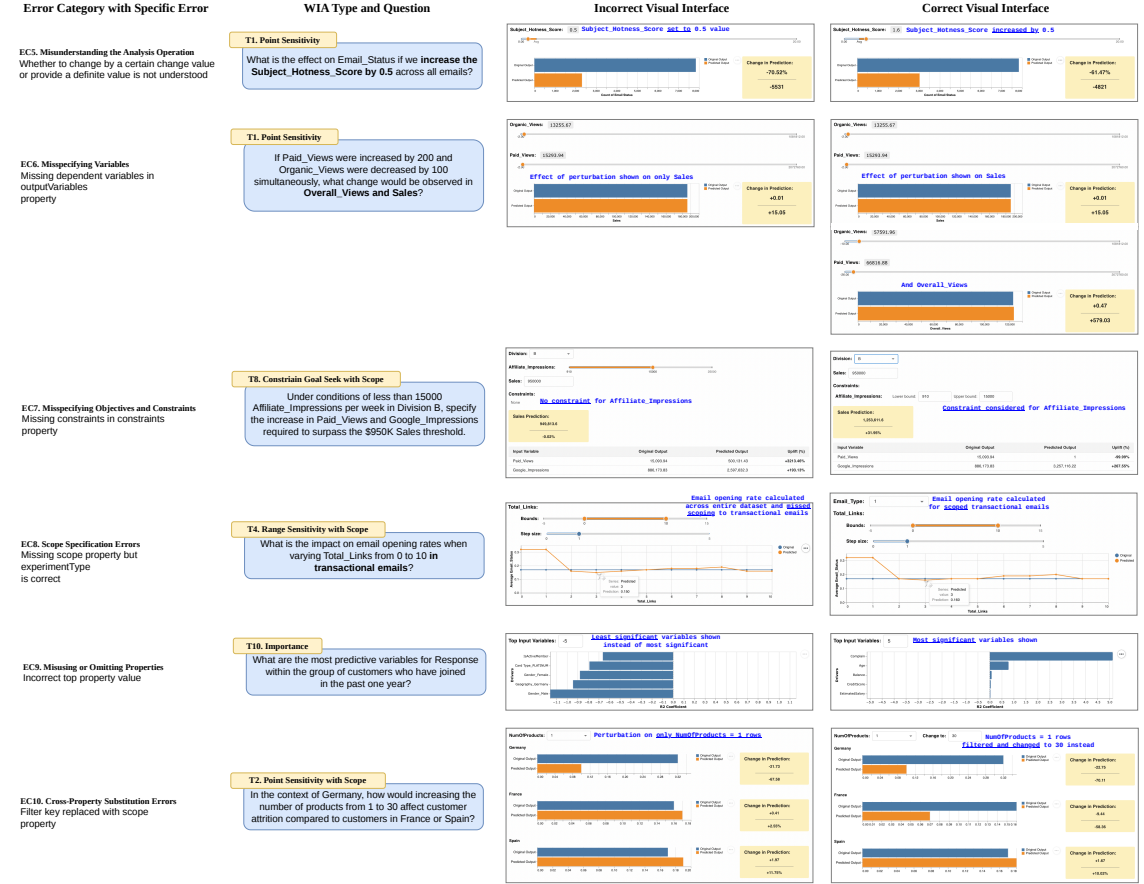


Fig. 15. Example of an error across all functional errors (EC5–EC10) and their impact on the visual interface. We show interfaces produced by erroneous specifications (incorrect behavior) and instead the intended corrected interfaces if specifications are repaired.

likely wrong (64.06% binary-detection accuracy), they cannot reliably diagnose *which* property is at fault ($\kappa \approx 0.23$; subsection 6.2). Yet once a human identifies the error category, LLM-applied targeted repair raises correctness to 80.42%. This suggests LLMs are best used as high-recall generators and screeners, with humans providing high-precision categorization and verification. Concretely, NL-driven WIA systems should expose the PSL specification alongside generated outputs, surface component-level signals that highlight likely errors, and support inline editing with immediate re-compilation—focusing human effort on high-impact judgments such as resolving ambiguity, validating constraints, and refining scope.

Why an explicit representation rather than an agentic loop. An alternative to an explicit representation is an agentic generation loop that iteratively executes and self-corrects generated code. Such loops can remove incidental implementation faults, but they do not address the failures we observe: a dropped constraint or substituted objective produces code that runs and renders correctly, so there is no execution signal for the loop to correct against. Our contribution is orthogonal to the generation method—the value of PSL is that it gives analytical intent an existence

Manuscript submitted to ACM

independent of the implementation, making these silent errors inspectable and repairable however the specification was produced. An agentic loop and an explicit representation are therefore complementary rather than competing.

Limitations and future directions. Several limitations bound our claims. First, our motivating experiment (section 4) scores semantic correctness with an automated comparison validated against human judgment on 40 interfaces ($\kappa = 0.85$); while agreement is strong, a larger human-scored evaluation would tighten the estimate, and we read the objective rates—where agreement was lowest—with corresponding caution. It also evaluates a stratified 150-question subsample per model rather than the full benchmark, a deliberate trade-off to permit manual verification. Second, and most importantly, our evaluation establishes that PSL makes intent inspectable and repairable at the *system* level—errors are localizable to named properties and fixable through targeted repair—but does not establish whether *end users* can read, validate, and repair PSL specifications in practice. Whether PSL-grounded interfaces improve user understanding, task performance, and error recovery relative to direct generation is an open question we regard as the essential next step. Third, cross-property substitution errors (EC10) show that targeted repair can introduce higher-order faults; lightweight inter-block dependency rules (e.g., “*scope* must not wrap *filter*”) and slot-filling generation that edits only the targeted property [29] are promising mitigations. Fourth, our benchmark covers 11 WIA types across 5 tabular datasets but excludes temporal, causal, and multi-step chained analyses [51]; extending PSL with temporal operators, causal structures, and nested experiments would broaden coverage while preserving the separation of what is analyzed from how it is implemented. Although PSL is our instantiation, the two-stage workflow (NL→structured representation→interface) should generalize to other analytical tasks with well-defined structure [34, 37]. Finally, our two evaluations use different Claude snapshots within the same model family—`claude-sonnet-4` for the workflow evaluation and `claude-sonnet-4.5` for the formative experiment—as provider snapshots are periodically retired and superseded. As with all LLM evaluations tied to dated snapshots, exact reproduction depends on provider availability; because our two evaluations are reported separately rather than compared, this difference does not affect our conclusions.

8 Related Work

Our work relates to WIA systems, NL data analysis interfaces, and declarative intermediate representations.

What-if Analysis Systems. WIA has been studied as a tool for exploring hypothetical scenarios and supporting data-driven decision-making. Prior systems support WIA across domains, including business analytics [10, 12], healthcare [3, 23], social media [52], environmental modeling [15, 24], and many others. These systems enable users to vary parameters, explore outcomes, and compare scenarios, but typically require substantial manual effort in implementation. Recent work synthesizes prior WIA systems into a unified grammar of workflows through compositional primitives [11], and introduces PSL as a declarative encoding of this grammar. That work establishes the grammar and illustrates its use as an intermediate representation, but does not evaluate whether it can reliably mediate between NL questions and interactive interfaces—whether LLMs can generate faithful specifications, what errors arise, or whether those errors can be repaired. Our work operationalizes PSL in an end-to-end workflow—including LLM-based generation from NL, a taxonomy-driven error analysis, and targeted repair—and, prior to that, examines through a formative experiment whether an explicit intermediate representation is needed at all, rather than assuming it.

NL Interfaces for Data Analysis. NL interfaces aim to lower the barrier to data analysis by allowing users to express intent in natural language [42]. Systems such as Eviza [38], NL4DV [30], and Leva [55] support interactive visualization and multi-step analysis through conversational interaction. Other systems focus on statistical analysis and data transformations, including Iris [7], Analyza [6], DataTone [9], and FlowSense [54]. More recent LLM-based tools generate charts and transformations from NL, including ChartGPT [44] and Data Formulator 2 [48], the latter observing that single-turn,

fully-specified NL prompts are ill-suited to iterative authoring—a limitation an explicit, editable intermediate representation directly addresses. Other applications include interface customizations [47] and collaborative sensemaking [41].

However, these approaches primarily support querying, visualization generation, or statistical operations, and do not capture the multi-step, model-driven nature of WIA. They lack support for parameter manipulation, constraints, model-based reasoning, and iterative scenario exploration. Our work addresses this gap by translating NL WIA questions into structured specifications that compile into interactive interfaces supporting these capabilities.

Declarative Specifications as Intermediate Representations. Declarative representations separate what to compute from how to implement it, enabling transparency, validation, and systematic error handling across domains. In databases, SQL serves as an interpretable intermediate representation for NL-to-SQL systems, supporting inspection and correction [8, 45, 46]. In visualization, declarative grammars such as Vega-Lite [35], VizQL [14], and ggplot2 [50] enable systems to generate and manipulate visualizations through structured specifications [25, 40, 44]. Declarative approaches have also been applied to interface generation and interactive documents [16, 21, 28]. Building on prior work in declarative representations, we introduce PSL, a declarative intermediate representation grounded in the PRAXA framework [11]. As shown in this paper, PSL captures model-driven, iterative WIA workflows and serves as a structured bridge between NL questions and interactive interfaces, preserving analytic intent, consistent with how analysts engage with declarative grammars in practice [32]. This explicit structure further enables targeted repair of LLM-generated specifications, extending declarative interaction design to NL-driven analytical workflows [36].

9 Conclusion

We asked whether generating interactive WIA interfaces requires an explicit representation of analytical intent, or whether a capable LLM can produce them directly. A motivating experiment across three state-of-the-art LLMs showed that direct one-shot generation fails both visibly—producing no working interface in 17–45% of cases—and silently, rendering plausible interfaces that misrepresent the question’s objective and constraints, with errors detectable only by reading the underlying code. Motivated by these findings, we presented a two-stage workflow that first translates a WIA question into a PSL specification—making analytical intent explicit, inspectable, and independent of implementation—and then compiles it into an interactive interface. On a benchmark of 405 questions across 11 WIA types and 5 datasets, LLMs generate correct specifications in 52.42% of cases; because errors are localized to named specification properties, taxonomy-guided targeted repair raises this to 80.42%, and we show how undetected errors would otherwise propagate into plausible but misleading interfaces. Together, these results show that the difficulty of reliable NL-driven WIA lies not in rendering interfaces but in faithfully capturing intent—and that an explicit intermediate representation is what makes that intent auditable and repairable.

References

- [1] Anonymous. 2025. Supplementary Materials: OSF. https://osf.io/hsu6t/overview?view_only=ec9b0bd336c845e1a45408ae25349d4d.
- [2] Anthropic. 2025. Claude (Opus 4.1) [Large language model]. <https://claude.ai/>.
- [3] Aditya Bhattacharya, Jeroen Ooge, Gregor Stiglic, and Katrien Verbert. 2023. Directive explanations for monitoring the risk of diabetes onset: introducing directive data-centric explanations and combinations to support what-if explorations. In *Proceedings of the 28th international conference on intelligent user interfaces*. 204–219.
- [4] Microsoft Corporation. 2025. Microsoft Excel. <https://office.microsoft.com/excel>.
- [5] Microsoft Corporation. 2025. Microsoft Power BI. <https://powerbi.microsoft.com>.
- [6] Kedar Dhamdhere, Kevin S McCurley, Ralfi Nahmias, Mukund Sundararajan, and Qiqi Yan. 2017. Analyza: Exploring data with conversation. In *Proceedings of the 22nd International Conference on Intelligent User Interfaces*. 493–504.
- [7] Ethan Fast, Binbin Chen, Julia Mendelsohn, Jonathan Bassen, and Michael S Bernstein. 2018. Iris: A conversational agent for complex tasks. In *Proceedings of the 2018 CHI conference on human factors in computing systems*. 1–12.

- [8] Han Fu, Chang Liu, Bin Wu, Feifei Li, Jian Tan, and Jianling Sun. 2023. Catsql: Towards real world natural language to sql applications. *Proceedings of the VLDB Endowment* 16, 6 (2023), 1534–1547.
- [9] Tong Gao, Mira Dontcheva, Eytan Adar, Zhicheng Liu, and Karrie G Karahalios. 2015. Datatone: Managing ambiguity in natural language interfaces for data visualization. In *Proceedings of the 28th annual acm symposium on user interface software & technology*. 489–500.
- [10] Sneha Gathani, Madelon Hulsebos, James Gale, Peter J Haas, and Çağatay Demiralp. 2021. Augmenting decision making via interactive what-if analysis. *CIDR* (2021).
- [11] Sneha Gathani, Kevin Li, Raghav Thind, Sirui Zeng, Matthew Xu, Peter J. Haas, Cagatay Demiralp, and Zhicheng Liu. 2025. PRAXA: A Grammar for What-If Analysis. arXiv:2510.09791 [cs.HC] <https://arxiv.org/abs/2510.09791>
- [12] Sneha Gathani, Zhicheng Liu, Peter J Haas, and Çağatay Demiralp. 2025. What-if Analysis for Business Professionals: Current Practices and Future Opportunities. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. 1–17.
- [13] Gokagglers. 2024. Email Campaign Management Dataset for Predicting Whether Email is Opened or Not. https://www.kaggle.com/datasets/loveall/email-campaign-management-for-sme?select=Train_psoll3n.csv
- [14] Pat Hanrahan. 2006. Vizql: a language for query, analysis and visualization. In *Proceedings of the 2006 ACM SIGMOD international conference on Management of data*. 721–721.
- [15] Subhashis Hazarika, Haruki Hirasawa, Sookyoung Kim, Kalai Ramea, Salva R Cachay, Peetak Mitra, Dipti Hingmire, Hansi Singh, and Phil J Rasch. 2023. HAIVA: Hybrid AI-assisted Visual Analysis Framework to Study the Effects of Cloud Properties on Climate Patterns. In *2023 IEEE Visualization and Visual Analytics (VIS)*. IEEE, 226–230.
- [16] Jeffrey Heer, Matthew Conlen, Vishal Devireddy, Tu Nguyen, and Joshua Horowitz. 2023. Living papers: A language toolkit for augmented scholarly communication. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. 1–13.
- [17] Fred Hohman, Andrew Head, Rich Caruana, Robert DeLine, and Steven M Drucker. 2019. Gamut: A design probe to understand how data scientists understand machine learning models. In *Proceedings of the 2019 CHI conference on human factors in computing systems*. 1–13.
- [18] Kaggle. 2024. Marketing Analytics Dataset for Predicting Accepted Campaigns. <https://www.kaggle.com/code/karltontkxb/marketing-analysis-classification-and-clustering/input>
- [19] Kaggle. 2024. Spotify Revenue, Expenses and Its Premium. <https://www.kaggle.com/code/rohithreddy0920/spotify-revenue-expenses-and-its-premium/input>
- [20] Hyeok Kim, Ryan Rossi, Fan Du, Eunyee Koh, Shunan Guo, Jessica Hullman, and Jane Hoffswell. 2022. Cicero: A declarative grammar for responsive visualization. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–15.
- [21] Kenrick Kin, Björn Hartmann, Tony DeRose, and Maneesh Agrawala. 2012. Proton: multitouch gestures as regular expressions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2885–2894.
- [22] Hyung-Kwon Ko, Hyeon Jeon, Gwanmo Park, Dae Hyun Kim, Nam Wook Kim, Juho Kim, and Jinwook Seo. 2024. Natural language dataset generation framework for visualizations powered by large language models. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. 1–22.
- [23] Sonia Laguna, Julian N Heidenreich, Jiugeng Sun, Nilüfer Cetin, Ibrahim Al-Hazwani, Udo Schlegel, Furui Cheng, and Mennatallah El-Assady. 2023. ExpLIMEable: A Visual Analytics Approach for Exploring LIME. In *2023 Workshop on Visual Analytics in Healthcare (VAHC)*. IEEE, 27–33.
- [24] Wei Luo, Michael Steptoe, Zheng Chang, Robert Link, Leon Clarke, and Ross Maciejewski. 2017. Impact of spatial scales on the intercomparison of climate scenarios. *IEEE Computer Graphics and Applications* 37, 5 (2017), 40–49.
- [25] Yuyu Luo, Nan Tang, Guoliang Li, Chengliang Chai, Wenbo Li, and Xuedi Qin. 2021. Synthesizing natural language to visualization (NL2VIS) benchmarks from NL2SQL benchmarks. In *Proceedings of the 2021 International Conference on Management of Data*. 1235–1247.
- [26] Yuyu Luo, Nan Tang, Guoliang Li, Jiawei Tang, Chengliang Chai, and Xuedi Qin. 2021. Natural language to visualization by neural machine translation. *IEEE Transactions on Visualization and Computer Graphics* 28, 1 (2021), 217–226.
- [27] Sagar Maru. 2024. Bank Customer Dataset for Predicting Customer Churn. <https://www.kaggle.com/datasets/marusagar/bank-customer-attribution-insights>.
- [28] Microsoft. 2025. Chartifact. (2025). <https://microsoft.github.io/chartifact/>
- [29] Dominik Moritz, Chenglong Wang, Greg L Nelson, Halden Lin, Adam M Smith, Bill Howe, and Jeffrey Heer. 2018. Formalizing visualization design knowledge as constraints: Actionable and extensible models in draco. *IEEE transactions on visualization and computer graphics* 25, 1 (2018), 438–448.
- [30] Arpit Narechania, Arjun Srinivasan, and John Stasko. 2020. NL4DV: A toolkit for generating analytic specifications for data visualization from natural language queries. *IEEE Transactions on Visualization and Computer Graphics* 27, 2 (2020), 369–379.
- [31] OpenAI. 2024. Data Analyst GPT. <https://chatgpt.com/g/g-HMNCp6w7d-data-analyst?model=gpt-4o>. Custom GPT available via ChatGPT.
- [32] Xiaoying Pu and Matthew Kay. 2023. How Data Analysts Use a Visualization Grammar in Practice. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) (CHI '23). Association for Computing Machinery, New York, NY, USA, Article 840, 22 pages. doi:10.1145/3544548.3580837
- [33] Inc. Salesforce. [n.d.]. Salesforce Einstein Analytics. <https://www.salesforce.com/products/einstein/overview>.
- [34] Arvind Satyanarayan and Jeffrey Heer. 2014. Lyra: An interactive visualization design environment. In *Computer graphics forum*, Vol. 33. Wiley Online Library, 351–360.

- [35] Arvind Satyanarayan, Dominik Moritz, Kanit Wongsuphasawat, and Jeffrey Heer. 2016. Vega-lite: A grammar of interactive graphics. *IEEE transactions on visualization and computer graphics* 23, 1 (2016), 341–350.
- [36] Arvind Satyanarayan, Kanit Wongsuphasawat, and Jeffrey Heer. 2014. Declarative interaction design for data visualization. In *Proceedings of the 27th annual ACM symposium on User interface software and technology*. 669–678.
- [37] Hans-Jörg Schulz, Thomas Nocke, Magnus Heitzler, and Heidrun Schumann. 2013. A design space of visualization tasks. *IEEE Transactions on Visualization and Computer Graphics* 19, 12 (2013), 2366–2375.
- [38] Vidya Setlur, Sarah E Battersby, Melanie Tory, Rich Gossweiler, and Angel X Chang. 2016. Eviza: A natural language interface for visual analysis. In *Proceedings of the 29th annual symposium on user interface software and technology*. 365–377.
- [39] Yuanfeng Song, Raymond Chi-Wing Wong, Xuefang Zhao, and Di Jiang. 2022. VoiceQuerySystem: A voice-driven database querying system using natural language questions. In *Proceedings of the 2022 International Conference on Management of Data*. 2385–2388.
- [40] Yuanfeng Song, Xuefang Zhao, Raymond Chi-Wing Wong, and Di Jiang. 2022. Rgvisnet: A hybrid retrieval-generation neural framework towards automatic data visualization generation. In *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 1646–1655.
- [41] Arjun Srinivasan, Bongshin Lee, Nathalie Henry Riche, Steven M Drucker, and Ken Hinckley. 2020. InChorus: Designing consistent multimodal interactions for data visualization on tablet devices. In *Proceedings of the 2020 CHI conference on human factors in computing systems*. 1–13.
- [42] Arjun Srinivasan and John T. Stasko. 2017. Natural Language Interfaces for Data Analysis with Visualization: Considering What Has and Could Be Asked. In *EuroVis 2017 - Short Papers*, Barbora Kozlikova, Tobias Schreck, and Thomas Wischgoll (Eds.). The Eurographics Association. doi:10.2312/eurovisshort.20171133
- [43] a Salesforce Company Tableau Software. 2025. Tableau. <https://www.tableau.com>.
- [44] Yuan Tian, Weiwei Cui, Dazhen Deng, Xinjing Yi, Yurun Yang, Haidong Zhang, and Yingcai Wu. 2024. Chartgpt: Leveraging llms to generate charts from abstract natural language. *IEEE Transactions on Visualization and Computer Graphics* 31, 3 (2024), 1731–1745.
- [45] Yuan Tian, Jonathan K Kummerfeld, Toby Jia-Jun Li, and Tianyi Zhang. 2024. Sqlucid: Grounding natural language database queries with interactive explanations. In *Proceedings of the 37th Annual ACM Symposium on User Interface Software and Technology*. 1–20.
- [46] Yuan Tian, Daniel Lee, Fei Wu, Tung Mai, Kun Qian, Siddhartha Sahai, Tianyi Zhang, and Yunyao Li. 2025. Text-to-SQL Domain Adaptation via Human-LLM Collaborative Data Annotation. In *Proceedings of the 30th International Conference on Intelligent User Interfaces*. 1398–1425.
- [47] Priyan Vaithilingam, Elena L Glassman, Jeevana Priya Inala, and Chenglong Wang. 2024. Dynavis: Dynamically synthesized ui widgets for visualization editing. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. 1–17.
- [48] Chenglong Wang, Bongshin Lee, Steven M Drucker, Dan Marshall, and Jianfeng Gao. 2025. Data formulator 2: Iterative creation of data visualizations, with ai transforming data along the way. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. 1–17.
- [49] James Wexler, Mahima Pushkarna, Tolga Bolukbasi, Martin Wattenberg, Fernanda Viégas, and Jimbo Wilson. 2019. The what-if tool: Interactive probing of machine learning models. *IEEE transactions on visualization and computer graphics* 26, 1 (2019), 56–65.
- [50] Hadley Wickham. 2011. ggplot2. *Wiley interdisciplinary reviews: computational statistics* 3, 2 (2011), 180–185.
- [51] Kanit Wongsuphasawat, Zening Qu, Dominik Moritz, Riley Chang, Felix Ouk, Anushka Anand, Jock Mackinlay, Bill Howe, and Jeffrey Heer. 2017. Voyager 2: Augmenting visual analysis with partial view specifications. In *Proceedings of the 2017 chi conference on human factors in computing systems*. 2648–2659.
- [52] Yingcai Wu, Shixia Liu, Kai Yan, Mengchen Liu, and Fangzhao Wu. 2014. Opinionflow: Visual analysis of opinion diffusion on social media. *IEEE transactions on visualization and computer graphics* 20, 12 (2014), 1763–1772.
- [53] Yogesh Agrawal. 2024. Media Spends Dataset for Predicting Sales. <https://www.kaggle.com/datasets/yugagrawal95/sample-media-spends-data>
- [54] Bowen Yu and Cláudio T Silva. 2019. FlowSense: A natural language interface for visual data exploration within a dataflow system. *IEEE transactions on visualization and computer graphics* 26, 1 (2019), 1–11.
- [55] Yuheng Zhao, Yixing Zhang, Yu Zhang, Xinyi Zhao, Junjie Wang, Zekai Shao, Catatay Turkay, and Siming Chen. 2024. Leva: Using large language models to enhance visual analytics. *IEEE transactions on visualization and computer graphics* 31, 3 (2024), 1830–1847.

#	Scenario	WIA Type	Description
1	What happens to churn if estimated salary is doubled?	Point Sensitivity	One input perturbed
2	If products changed to 2 and complaints halved, what happens to churn?	Point Sensitivity	Multiple inputs perturbed
3	For German customers, how does balance (\$0–\$200K) affect exit?	Range Sensitivity with Scope	Inputs varied over range on subset
4	Most and least influential features for exit outcome?	Importance	Rank inputs by impact
5	Changes needed for 15% decrease in attrition?	Goal Seek	Find inputs for target outcome
6	Actionable recommendations without infeasible changes?	Constrained Goal Seek	Goal seek with input constraints

Fig. 16. Six WIA scenarios spanning different analysis types used in our formative exploration of spreadsheet and BI tools.

10 Supplementary

10.1 Formative Exploration Details

This section provides additional detail on the formative exploration of spreadsheet and BI tools reported in the main paper (Section 2): the dataset used, the full set of scenarios, and the procedure followed. The four resulting challenges (C1–C4) are reported in full in Section 2. (LLM-based generation is examined separately as a formative experiment in Section 4 and is not part of this exploration.)

10.1.1 Dataset. The *Bank Customer Attrition* dataset [27] was used for exploration. Features in the dataset involve customer demographics (e.g., *Age*, *Gender*, *Geography*), account-related features (e.g., *CreditScore*, *Tenure*, *Balance*, *NumOfProducts*, *HasCrCard*, *IsActiveMember*, *EstimatedSalary*), service feedback metrics (e.g., *Complain*, *SatisfactionScore*, *CardType*, *Points Earned*), and a binary churn outcome (*Exited*).

10.1.2 WIA Scenarios Used in the Formative Exploration. To explore the WIA capabilities of the tools, six WIA scenarios were performed in each. These scenarios are listed in Figure 16.

10.1.3 Procedure. Three authors independently attempted all six WIA scenarios in each of the four tools. We imported the dataset and explored each tool’s WIA capabilities to answer the scenarios, consulting documentation, blogs, and tutorials to overcome tool-specific learning barriers. Each author spent approximately 4.5 hours, with sessions recorded and jointly reviewed.

10.2 Benchmark Details

This section provides additional detail on the datasets, construction quality metrics, ground-truth reconciliation, and PSL encoding of the benchmark introduced in Section 3.

10.2.1 Datasets. We selected five publicly available datasets from Kaggle and the UCI Machine Learning Repository, representing distinct decision-making contexts where WIA is valuable.

D1. Bank Customer Attrition [27]. The same dataset used in our formative exploration of existing tools. It supports what-if questions around customer churn at a bank, with demographic attributes (e.g., *Geography*), account-related features (e.g., *CreditScore*, *Tenure*), service feedback (e.g., *Satisfaction Score*, *Points Earned*), and a binary churn outcome (*Exited*).

D2. Email Campaign Management [13]. Supports what-if questions around what influences whether customers open or ignore campaign emails, with campaign attributes (e.g., *Email Campaign Type*, *Email Source Type*), content features (e.g., *Word Count*, *Total Links*, *Total Images*), contextual information (e.g., *Customer Location*, *Time Email Sent Category*), and a binary open/ignore outcome (*Email Status*).

D3. Media Spend and Sales Attribution [53]. Supports what-if questions around how reallocating spend or impressions across channels impacts sales, with temporal attributes (e.g., *Calendar Week*), channel-level exposure features (e.g., *Google Impressions*, *Email Impressions*), aggregate engagement (*Overall Views*), and the business outcome (*Sales*).

D4. Marketing Campaign Response [18]. Supports analysis of customer responses to direct marketing campaigns, with socio-demographic attributes (e.g., *Income*, *Age*), purchasing behavior (e.g., *MntWines*, *MntFruits*), campaign interaction features (e.g., *NumDealsPurchases*, *NumWebPurchases*, *NumCatalogPurchases*), campaign acceptance indicators (*AcceptedCmp1*–*AcceptedCmp5*), service feedback (*Complain*), and a binary success outcome (*Response*).

D5. Spotify Revenue, Expenses and Its Premium [19]. Captures business-level financial and subscription performance over time, supporting what-if questions around profitability, pricing, user adoption, and marketing/R&D investment. It includes temporal attributes (*Date*), financial indicators (e.g., *Total Revenue*, *Gross Profit*), premium-specific metrics (e.g., *Premium Revenue*, *Premium Gross Profit*), advertising-related metrics (e.g., *Ad Revenue*, *Ad Gross Profit*), user engagement (e.g., *MAUs*), and operational expenses (e.g., *Sales and Marketing Cost*).

10.2.2 Construction Quality Metrics. We report the construction-quality checks summarized in Section 3. To confirm that hand-authored questions preserved the structure of the seed questions they were adapted from, we measured SentenceTransformer similarity between each adapted question and its seed; similarity ranged from 0.63 to 0.79 across datasets (Figure 17A), indicating consistent structure. To confirm that LLM-generated questions were not repetitive, we measured self-BLEU; low scores (0.008–0.051; Figure 17B) indicate high diversity in phrasing.

10.2.3 Ground-Truth Reconciliation. Two coders independently annotated all 405 questions on the six intent components (Section 3.4) and reconciled discrepancies through discussion. Of the 179 questions with initial disagreement, the majority stemmed from interpretive ambiguity in the NL question rather than annotation error—most commonly, whether a question implied a scoped or full-dataset analysis, and whether a continuous change implied point or range sensitivity. For each

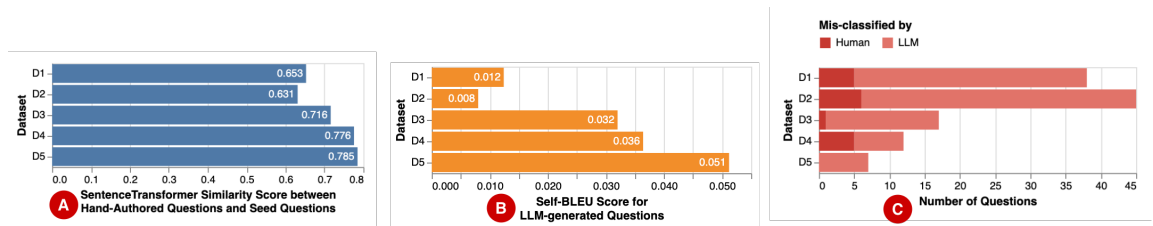


Fig. 17. Benchmark construction analysis. (A) SentenceTransformer similarity between seed and hand-authored questions across datasets, indicating preservation of linguistic structure. (B) Self-BLEU scores for LLM-generated questions, indicating high diversity in phrasing. (C) Distribution of WIA-type interpretations by humans and LLMs across datasets.

such case we record the source of disagreement and the rationale for the reconciled intent; 19 cases that could not be resolved by the two coders were adjudicated by a third.

10.2.4 Encoding Ground-Truth Intent as Intermediate Representation via PSL. For the workflow, each question’s six-component ground-truth intent is additionally encoded as a PSL specification using the schema. Encoding surfaced schema refinements—for example, adding a `top` property for importance questions (e.g., `"top": 1` for “What is the most salient feature?”). The reconciled intent for each question determined its canonical specification.

10.3 Direct-Generation Experiment: Details

This section provides the full setup, scoring protocol, validation, and additional qualitative examples for the motivating experiment in Section 4.

10.3.1 Generation Setup and Prompt Hardening. For each question, the model is given the NL question and a schema summary of the dataset (column names and types), and asked to emit a single self-contained Python script that (i) trains a scikit-learn RandomForest—a classifier for binary outcomes, a regressor for continuous ones—and (ii) emits an interactive React component with Material UI controls (sliders for continuous variables, selectors for categorical ones, labeled badges for scope) bound to a linked Vega-Lite visualization and a live prediction readout. This matches the rendering stack and three-part output contract our workflow compiles to (Section 5); the sole difference is that here the interface is authored directly by the LLM rather than compiled from a specification.

To ensure the experiment tests analytical understanding rather than incidental coding robustness, we hardened the generation prompt on pilot questions (disjoint from the evaluation sample) against implementation pitfalls unrelated to analytical intent: string-escaping collisions between generated JSX and Python, Vega-Lite data-binding conventions, and numeric-type serialization between the model and the front end. Guardrails addressing these were added until pilot generations were free of such errors, at which point the prompt was frozen and left unchanged for the reported evaluation. The full prompt is included on our OSF supplementary materials [1].

10.3.2 Sample. From the 405-question benchmark (Section 3) we drew, per model, a stratified random sample of 150 questions using a fixed seed, allocating proportionally across the 5 datasets and, within each dataset, across its labeled WIA types, so the sample mirrors the composition of the full benchmark. All three models were evaluated on the same sampled questions. The formative experiment uses Claude-Sonnet-4.5, whereas the workflow evaluation (Section 4) uses Claude-Sonnet-4, a snapshot in the same model family; provider snapshots are periodically retired and superseded. The two evaluations are reported independently and never compared to one another, so this difference does not affect any result.

10.3.3 Scoring Protocol. Each generated interface is scored on the six representation-neutral components of analytical intent defined in Section 3.4: scope, outcome variable, perturbation, constraints, objective, and analysis type. An LLM judge receives the generated code, its execution output (or, if execution failed, the resulting error), and the ground-truth intent, and returns for each component a judgment of match, mismatch, or not-applicable together with a one-line justification. A component is marked not-applicable only when the ground truth has no such field for that question (e.g., an unscoped question has no scope component); such cases are excluded from that component’s denominator. Because a crashed generation’s code still reveals the analysis the model attempted, non-rendering interfaces are scored on the same basis and are included in the component rates.

Table 1. Applicable N (match + mismatch) per component per model, i.e., the number of sampled questions (out of 150) whose ground truth specifies that component. Rates in the main text are computed over these denominators.

Model	Scope	Outcome Var.	Perturbation	Constraints	Objective	Analysis Type
GPT-5	78	150	123	46	102	150
GPT-4o	80	150	131	55	131	150
Claude-Sonnet-4.5	85	150	126	43	80	150

10.3.4 Validation Against Human Judgment. To assess the reliability of the automated scoring, one author independently hand-scored a stratified random sample of 40 questions from the 150 questions used in this experiment. For each question, the generated code and interface were evaluated against the same ground truth and scoring rubric, without access to the automated judgments. Across the resulting 240 component judgments ($40 \text{ interfaces} \times 6 \text{ components}$), the human and automated scores agreed on 216 cases (90.0%, Cohen’s $\kappa = 0.847$). Agreement was 90.0% on the random subsample alone, the curated subset alone, and the two combined, indicating the curated cases did not inflate the estimate. Per-component agreement was highest for outcome variable (100%) and scope (97.5%) and lowest for objective (80.0%, $\kappa = 0.678$); we accordingly read the objective rates in the main text with somewhat greater caution than the other five components.

10.3.5 Additional Qualitative Examples. The main paper (Section 4) presents one worked example—a constrained goal-seek that renders fully yet reports an achievable target as impossible. Here we detail four further examples spanning the other functional error types, including a case where the same scope confusion produces an outright crash rather than a silent error.

Scope silently re-defined (importance with scope). For “*During calendar weeks with high promotional activity, assess the comparative significance of Affiliate vs. Paid Views in propelling Sales,*” the intended scope is high-sales weeks (Sales above the third quartile). Claude-Sonnet-4.5 instead interpreted “high promotional activity” as high promotional impressions, scoping to weeks where combined Google, Facebook, and Affiliate impressions exceed their third quartile—a different, though plausible, set of weeks. The generated interface is otherwise correct—it identifies the right outcome, performs the requested comparison, and even labels its scope prominently (“High Promotional Activity Weeks: Total Promo Impressions $\geq 1,340,852$ ”). But that label reflects the model’s own interpretation, silently substituted for the intended one; a user cannot tell that the entire comparison rests on a different subset of weeks than they asked about. The scope choice exists only in the generated code, so the substitution is undetectable from the interface.

Objective neglect (goal-seek answered as a sweep). For “*Determine the level of MntSweetProducts and NumDeal-sPurchases needed for customers with PhDs to reach a Response rate of 85%,*” the ground-truth objective is to maximize response. GPT-5’s generated code instead sweeps the two inputs and reports where predicted response crosses the fixed 85% figure, with no optimization step anywhere in the generated implementation. The rendered interface exposes sliders and a prediction readout and appears to answer the question; the absence of any objective is visible only by reading the computation itself.

Outcome-variable substitution (same error, two models). For “*Considering constraints that Income should not surpass \$75,000 and NumCatalogPurchases must remain under 8, what are optimal settings for other spending categories?,*” the ground truth specifies Response as the outcome to maximize. Both GPT-4o and Claude-Sonnet-4.5 independently optimized MntTotal (total spending) instead; GPT-5, given the identical question, optimized Response correctly. Two of three models substituting the same wrong target on the same question indicates the error is a property of the task as

posed rather than one model’s slip: nothing in a one-shot generation contract forces the model to name and commit to the variable it is actually optimizing.

Constraints silently dropped (same error, two models). For “*To reduce the risk of customer attrition, what actionable recommendations can be made without suggesting infeasible changes, such as drastically increasing the customer’s age or reducing their tenure?*,” the ground truth bounds any recommended change to Age within ± 5 years and Tenure within ± 3 years. Both GPT-5 and GPT-4o generated code applying no such bounds, leaving Age and Tenure unconstrained. The bound was stated only in NL and had no forced representation in the generated code, so it was dropped entirely while the resulting recommendations still appeared reasonable.

10.4 Workflow Evaluation: Details

This section provides additional detail for the workflow evaluation in Section 6: the WIA-type classification step and its agreement with a human baseline, the per-dataset distribution of generation errors, and the two automated error-detection experiments.

10.4.1 WIA-Type Classification. Before generating a PSL specification, each LLM classifies a question into one of the 11 WIA types (Section 6.1). Each model was prompted with dataset context, type definitions, and a few examples; to reduce ordering effects we randomized the presentation order of the types, collected three predictions per question, and took the majority vote. Three coders independently annotated the WIA type of every question to serve as a human baseline.

Across the 405 questions, we observed 119 questions on which the majority LLM label disagreed with the human label. On inspection, these fell into two groups. The large majority (102 of 119) were genuine LLM misclassifications: the model over-interpreted phrasing (e.g., reading an incidental mention of a subgroup as a scoping requirement) or failed to distinguish scoped from unscoped variants of the same analysis type. The remaining 17 were cases where the LLM label was in fact more appropriate than the human label—most often continuous-range questions that a coder had labeled as point sensitivity (T1) but that are more precisely range sensitivity (T3). We reviewed all 119 cases and adopted the more accurate label before specification generation, so that generation errors downstream are not confounded by upstream type-classification disagreements.

10.4.2 Per-Dataset Distribution of Generation Errors. Figure 18 reports the number of erroneous specifications per dataset per model, before and after targeted repair. Error counts before intervention range from 26 to 62 per model–dataset cell, with higher counts for GPT-4o (e.g., 62 on D4) and GPT-5 (e.g., 51 on D2) and comparatively higher counts for Claude-Sonnet-4 on D1 (47) and D5 (46). After intervention, counts decrease across all datasets and models, typically to the 13–45 range (e.g., D4 falls from 62 to 45 for GPT-4o, and from 28 to 17 for Claude-Sonnet-4). Aggregated across models, total errors per dataset fall from 99–127 before intervention (e.g., 127 on D4, 122 on D2) to 57–82 after (e.g., 79 on D4, 82 on D2), a consistent reduction across datasets.

10.4.3 Automated Error-Detection Experiments. We report the two error-detection experiments summarized in Section 6.3. Both ask whether an LLM can identify errors in a generated specification; both compare LLM judgments against human annotators.

Experiment A: Binary detection. *Task.* Given a WIA question and its LLM-generated PSL specification, the model predicts whether *any* error is present (yes/no), without identifying a category.

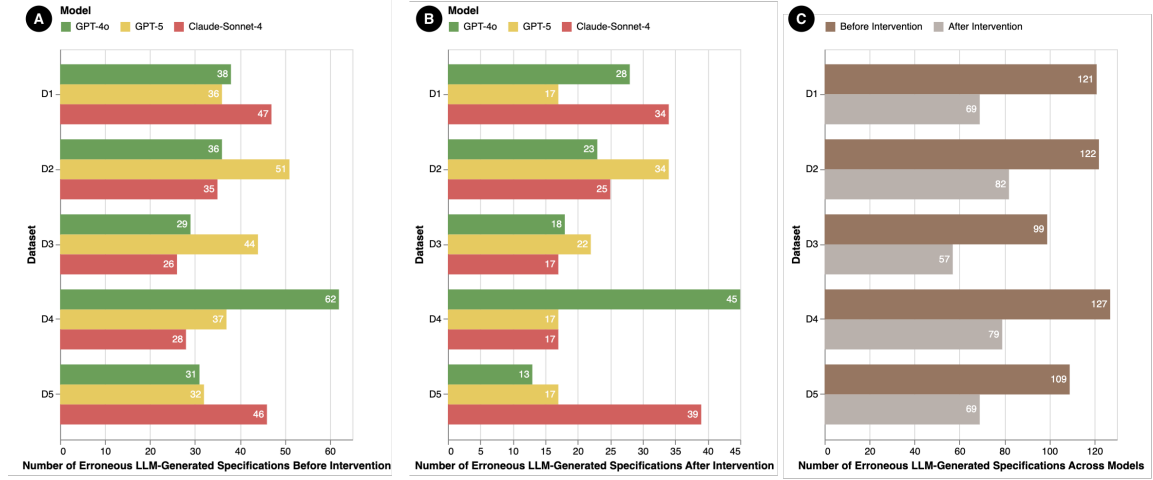


Fig. 18. Number of erroneous LLM-generated specifications per dataset and model, before and after targeted repair.

Setup. Each LLM receives the question, dataset context, the PSL schema, and the generated specification, and outputs a binary label (1 = error, 0 = no error). Three human annotators independently label the same specifications, with majority vote as reference. Evaluation covers all 405 questions per model.

Results. Across models, accuracy is 64.06% (TP = 145, TN = 103, FP = 87, FN = 70; precision = 0.625, recall = 0.674, F1 = 0.649), with modest agreement ($\kappa = 0.218$). LLMs flag 64.06% of specifications as erroneous versus 44.43% flagged by humans, indicating systematic over-detection. Model-wise, GPT-4o and Claude-Sonnet-4 over-estimate errors while GPT-5 slightly under-estimates them (Figure 19).

Experiment B: Per-category diagnosis. *Task.* For each specification, the model predicts which error categories (EC1–EC9) are present.

Setup. Inputs include the question, dataset context, the PSL schema, the generated specification, and, for each category, a definition bundle with 2–3 positive and negative examples. For each category the model outputs a binary present/absent decision; human annotators provide reference labels under the same protocol. To balance coverage and cost we sampled 140 questions and evaluated all three models, yielding 420 specifications, each model evaluating its own outputs.

Results. Agreement is low ($\kappa \approx 0.23$ – 0.26), with LLMs over-flagging errors at 3–23 $\times$ the human rate. Non-functional errors (EC1–EC4) show none-to-slight agreement, reflecting over-sensitivity to structural issues; functional errors (EC5–EC9) show fair-to-moderate agreement, indicating better calibration on semantic interpretation. Per-category human and LLM positive rates, rate gaps and ratios, and Cohen’s κ are reported in Figure 20. Overall, LLMs surface potential errors but cannot reliably categorize them—the basis for the human-in-the-loop repair strategy in Section 6.3.

Received 10 September 2026

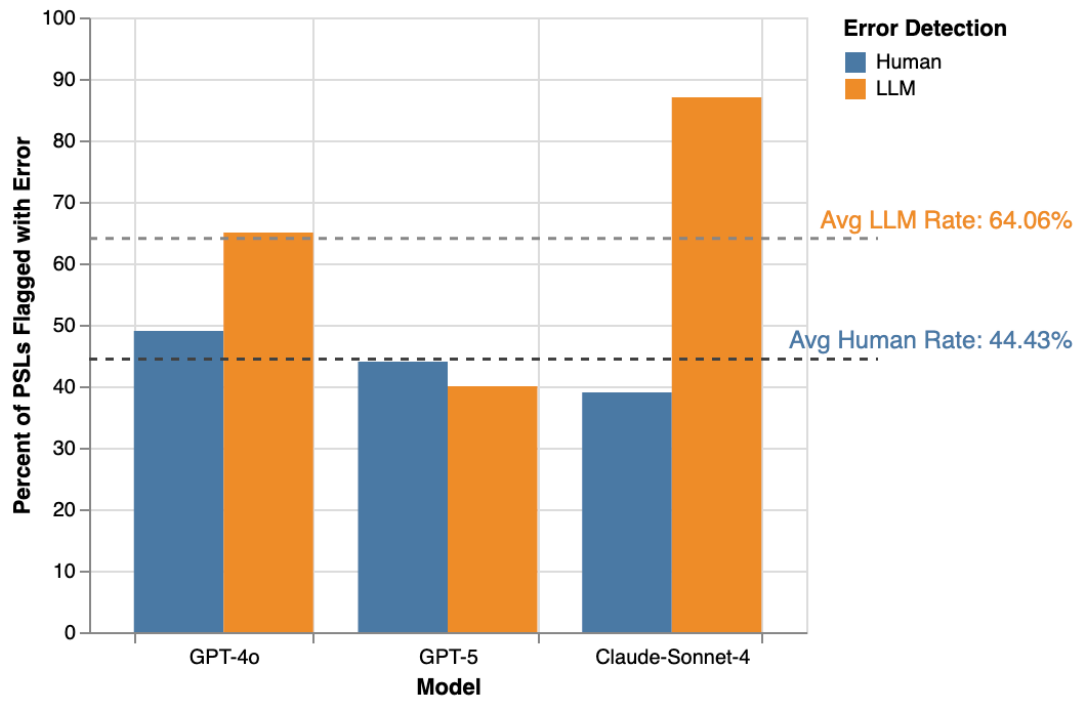


Fig. 19. Experiment A: binary detection of any error in LLM-generated specifications, by model, against the human flagging rate.

EC #	Error Category Name	Human Rate	LLM Rate	Rate Gap	Rate Ratio	Cohen's Range	k_mid	Interpretation of Agreement
Claude								
EC1	Structural / Formatting Errors	0.0057	0.0257	0.0200	4.5088	[-0.0094, 0.3576]	0.1741	Slight
EC2	Redundancy / Duplication Errors	0	0.0036	0.0036	inf	[0.0000, 0.0000]	0	None
EC3	Missing Blocks / Key Errors	0.0024	0.0238	0.0214	9.9167	[-0.0043, 0.1783]	0.087	Slight
EC4	Incorrect Schema Errors	0	0.0393	0.0393	inf	[0.0000, 0.0000]	0	None
EC5	Misunderstanding the Analysis Operations	0.0091	0.0096	0.0005	1.0549	[0.0000, 0.8323]	0.4132	Moderate
EC6	Mis-specifying Variables	0.0018	0.0063	0.0045	3.5000	[-0.0028, 0.4429]	0.2201	Fair
EC7	Mis-specifying Objectives and Constraints	0.0153	0.015	-0.0003	0.9804	[-0.0076, 0.8700]	0.4321	Moderate
EC8	Misgauging the Scope	0.0027	0.0018	-0.0009	0.6667	[-0.0021, 0.7996]	0.3987	Fair
EC9	Misusing or Omitting Properties	0.0071	0.0105	0.0034	1.4789	[-0.0086, 0.8092]	0.4003	Moderate
Overall Summary		0.0049	0.0151	0.0102	3.1580		.23616666	Fair
GPT-4								
EC1	Structural / Formatting Errors	0	0.0233	0.0233	inf	[0.0000, 0.0000]	0	None
EC2	Redundancy / Duplication Errors	0	0.0042	0.0042	inf	[0.0000, 0.0000]	0	None
EC3	Missing Blocks / Key Errors	0.0028	0.0167	0.0139	5.9643	[-0.0048, 0.2823]	0.1388	Slight
EC4	Incorrect Schema Errors	0.0042	0.0625	0.0583	14.8810	[-0.0079, 0.1181]	0.0551	Slight
EC5	Misunderstanding the Analysis Operations	0.0071	0.0048	-0.0023	0.6761	[0.0057, 0.7989]	0.3966	Fair
EC6	Mis-specifying Variables	0.0021	0.0042	0.0021	2.0000	[-0.0028, 0.6657]	0.3315	Fair
EC7	Mis-specifying Objectives and Constraints	0.0273	0.0195	-0.0078	0.7143	[-0.0115, 0.7663]	0.3774	Moderate
EC8	Misgauging the Scope	0.0021	0.0021	0.0000	1.0000	[-0.0033, 0.4426]	0.2197	Fair
EC9	Misusing or Omitting Properties	0.0072	0.0094	0.0022	1.3056	[-0.0083, 0.8656]	0.4287	Moderate
Overall Summary		0.0059	0.0163	0.0104	3.7916		.21642222	Fair
GPT-5								
EC1	Structural / Formatting Errors	0.0059	0.003	-0.0029	0.5085	[-0.0040, 0.6653]	0.3307	Fair
EC2	Redundancy / Duplication Errors	0	0	0.0000	1.0000	[0.0000, 0.0000]	0	None
EC3	Missing Blocks / Key Errors	0	0.0074	0.0074	inf	[0.0000, 0.0000]	0	None
EC4	Incorrect Schema Errors	0	0.0444	0.0444	inf	[0.0000, 0.0000]	0	None
EC5	Misunderstanding the Analysis Operations	0.0014	0.0062	0.0048	4.4286	[0.0000, 0.6662]	0.3324	Fair
EC6	Mis-specifying Variables	0.0056	0.0056	0.0000	1.0000	[-0.0056, 1.0000]	0.4972	Moderate
EC7	Mis-specifying Objectives and Constraints	0.0148	0.0204	0.0056	1.3784	[-0.0082, 0.4538]	0.2228	Fair
EC8	Misgauging the Scope	0.0018	0.0044	0.0026	2.4444	[-0.0057, 0.7679]	0.3811	Fair
EC9	Misusing or Omitting Properties	0.0074	0.0059	-0.0015	0.7973	[-0.0066, 0.8882]	0.4408	Moderate
Overall Summary		0.0041	0.0108	0.0067	1.6510		0.245	Fair

Fig. 20. Experiment B: per-category agreement between human annotators and LLMs (EC1–EC9). For each category we report the human positive rate, the LLM positive rate, the rate gap (LLM–human, percentage points), the rate ratio (LLM/human), and Cohen’s κ . Higher gap and ratio values indicate greater LLM over-estimation of errors.