# From Data Chaos to Clarity: AI-Driven Data Type Validation for Efficient Database Management

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**Abstract:** To reduce effort for data cleansing, it is proposed in this study that AI to be applied in column creation to verify and correct the data type. Apparently, data scientists spend 50-80% of their time munging data, one survey suggests 60%, potentially leading to analysis -and decision-making- that comes slower. Basic data governance and cleansing come after this data insert which leads to the inefficiency and heavier work loads. By introducing AI into the database table design to be launched, data types can be accurately set and checked in advance before they are entered. In the analysis, visualization and machine learning, this approach minimizes expensive data cleansing and transformation in later stages. Users are ensured greater data quality right from the start at substantially faster and less costly way as data type AI validation simplifies the whole process. Not only can this drive greater productivity, but it also makes it easier to rely on data-driven conclusions.

# Introduction

Data cleansing is a crucial, but time consuming, activity in solve complex data management problems, typically estimated to be 60-80% in data analysis projects [1]. The challenges also involve missing value imputation, consistency checking, and duplicate detection, all of which compromise data quality and application inferences [2]. Conventional data cleansing methods are generally manual and laborious, which result in inefficiency and high cost [3]. In case of large databases, these problems are more escalated and scalable approach is needed to deal with them ``which can ensure accuracy and consistency of the data'' [4]. Reparing these problems is necessary to enhance the integrity of data-driven discovery and decision making.

Recent advancements in data cleansing focus on automation and scalability to reduce manual effort and improve efficiency. Declarative languages and frameworks have been proposed to specify and automate data cleaning tasks, enabling more systematic and repeatable processes [5]. Iterative approaches, such as record linkage, have also been developed to enhance accuracy in cleaning and integrating data from multiple sources [6]. These techniques leverage statistical methods and machine learning to address data quality issues proactively, minimizing the need for post-insertion cleansing [7]. By integrating these solutions into the data pipeline, organizations can achieve higher data quality and streamline workflows, ultimately saving time and resources.

As can be seen from above, cleansing data is a laborious undertaking, and these problems can be addressed even before database table creation. This paper introduces a novel approach to mitigate these challenges by leveraging Artificial Intelligence (AI) during the database creation phase. By validating and correcting data types before data insertion, this method reduces the need for post-insertion cleansing and ensures higher data quality from the start. The proposed solution not only saves time but also enhances the reliability of data-driven insights.

## Current Database Design Process

Data quality issues often arise from mismatched or incorrect data types during database creation. For example, a column intended for numeric values might inadvertently store text, leading to errors during analysis. Traditional data governance frameworks address these issues after data insertion, requiring significant manual effort and computational resources [8].

Common design theory for relational databases will focus on functional dependencies and normalization to eliminate redundancy and anomalies in database schemas. It explains that functional dependencies generalize the concept of keys, where a set of attributes determines another set, ensuring data consistency. In normal circumstances using examples, such as a movie database, it illustrates how functional dependencies help identify poor designs and guide decomposition into smaller, well-structured relations. The standard teaching also introduces super keys and discusses their role in database design. After that the instruction will emphasize the importance of understanding dependencies to create efficient, anomaly-free relational schemas, providing foundational knowledge for database normalization and optimization [9]. Effective database design is critical for ensuring data accuracy, consistency, and integrity in relational database systems. A well-structured logical design serves as the foundation for efficient physical implementation, much like architectural blueprints guide construction. The theoretical underpinnings of relational databases—rooted in set theory and predicate logic—provide a robust framework for predictable and reliable data management. Adopting a systematic design methodology helps avoid common pitfalls such as redundancy, inconsistency, and inefficient query performance. Key design objectives include supporting both predefined and ad hoc queries, enforcing data integrity constraints, and ensuring scalability for future requirements. Simplified approaches to normalization, which avoid overly technical terminology while maintaining rigor, can make these principles more accessible to practitioners without compromising structural soundness [10].

There is related research on DBDSGN, a physical database design tool for relational databases that optimizes index selection and table configurations to improve query performance. By analyzing workload patterns (e.g., SQL statements and execution frequencies), the tool recommends efficient physical designs while leveraging System R’s optimizer for cost estimation. Key contributions include: (1) a method for evaluating atomic index configurations to minimize computational overhead, (2) heuristic-driven index elimination to discard inefficient options, and (3) tight integration with the database optimizer to ensure alignment with execution plans. Notably, the study focuses exclusively on indexing strategies and table organization, omitting discussions on column design or data type validation—critical aspects of logical design. Experimental results highlight scalability for multi-table joins and maintenance cost efficiency, with the methodology later adopted in IBM’s Relational Design Tool (RDT) [11].

By looking at the books and research the database design flow (see Figure 1).

1. Determine the purpose of your database Clearly defining the database's objectives ensures it meets user needs. This involves identifying stakeholders, use cases, and functional requirements. A well-documented purpose guides all subsequent design decisions [12]. 2. Find and organize the information required Gather all necessary data elements through requirements analysis. Organize them logically, removing redundancies. This inventory becomes the foundation for tables and fields [13]. 3. Divide the information into tables Group related data into separate tables based on subjects (e.g., customers, orders). Each table should represent one entity type to minimize duplication [14]. 4. Turn information items into columns Convert each data attribute into appropriate columns with defined data types (VARCHAR, INT, etc.). Ensure atomic values per column for flexibility [15]. 5. Specify primary keys Choose a column (or combination) that uniquely identifies each row. Surrogate keys (auto-increment IDs) often work best when natural keys are unstable [16]. 6. Set up table relationships Define foreign keys to link tables (1:1, 1:M, M:N). Proper relationships maintain referential integrity through constraints [17]. 7.Refine your design. 8.Apply normalization rules

A black grid with blue lines

AI-generated content may be incorrect.

**FIGURE 1.** Common database design

## The Actual Glitches of Database Design

The real-world database structure and data of an application is presented below. The database is to keep track of the point of origin of the used cooking oil. Due to confidentiality agreements, certain metadata cannot be disclosed, but the anonymized data is available upon request. The data provider requested anonymity; methodological details are provided instead. The database that the organization used was MySQL. Below are the database table structures.

Let us now analyze the orders table and the dataset.

CREATE TABLE `orders` (

`id` int NOT NULL AUTO\_INCREMENT,

`picked\_on` VARCHAR(25) DEFAULT NULL,

`deposited\_on` VARCHAR(25) DEFAULT NULL,

`completed\_on` VARCHAR(25) DEFAULT NULL,

`status` VARCHAR(15) NOT NULL,

`reject\_reason` text,

`points\_earned` FLOAT NOT NULL DEFAULT ‘1’,

PRIMARY KEY (`id`)

)

There are 2000 rows of data acquired as sample. This paper will use 30 to 40 sorted records based on the columns under inspection. Below is the data for the column dropoff\_on.

The following data is extracted using the SQL Select statement below.

SELECT id, dropoff\_on FROM orders ORDER BY dropoff\_on DESC

The SQL query SELECT id, dropoff\_on FROM orders ORDER BY dropoff\_on DESC retrieves specific columns (id and dropoff\_on) from a database table named orders, then sorts the results by the dropoff\_on column in descending (newest-to-oldest) order. This type of query follows standard SQL syntax for data retrieval and sorting, as documented in: SQL queries use the SELECT statement to specify columns, FROM to identify tables, and ORDER BY to sort results, with DESC indicating descending order.

Table 1 shows the results from the SQL statement to ask the database to retrieve from the orders table and sorted by the dropoff\_on column. Unfortunately, the id 495 the dropoff\_on is 31/10/2022, and the id 1369 the dropoff\_on is 31/7/2023. This is incorrect because 31 October 2022 cannot be newer than 31 July 2023. This means the data is not sorted correctly.

**TABLE 1.** Dropoff\_on data from orders table

|  |  |
| --- | --- |
| **Id** | **dropoff\_on** |
| 494 | 31/10/2022 |
| 495 | 31/10/2022 |
| 1362 | 31/7/2023 |
| 1363 | 31/7/2023 |
| 1364 | 31/7/2023 |
| 1365 | 31/7/2023 |
| 599 | 30/11/2022 |

The second column to examine is dropped\_on. The SQL statement is as follows.

SELECT id, dropped\_on FROM orders ORDER BY dropped\_on DESC

This time the statement issues the command to sorted by the column, dropped\_on. Table 2 shows the results from the SQL statement to ask the database to retrieve from the orders table and sorted by the dropped\_on column. Unfortunately, the id 263 the dropped\_on is 31/8/2022 17:52, and the id 1364 the dropped\_on is 31/7/2023 15:49. The result shows 31 August 2002 at 5:52 pm is the latest than 31 July 2023 3:49 pm, this cannot be true as well.

**TABLE 2.** Dropped\_on data from orders table

|  |  |
| --- | --- |
| Id | dropped\_on |
| 491 | 31/10/2022 16:01 |
| 490 | 31/10/2022 16:00 |
| 263 | 31/8/2022 17:52 |
| 1364 | 31/7/2023 15:49 |
| 1363 | 31/7/2023 15:46 |

When INT values (e.g., “2023-01-05”, “12:30:45”) are stored in TEXT/VARCHAR columns, they cannot be sorted or compared chronologically because:

1. Lexicographical (Alphabetical) Sorting

Databases compare TEXT values character-by-character, not as temporal values. For example:

* 1. “2023-01-10” sorts before “2023-01-2” because ‘1’ < ‘2’ in string comparison.
  2. “1 PM” sorts after “11 AM” because ‘1’ > ‘1’ (first character match), then ‘ ‘ > ‘1’.

1. Inconsistent Formats
   1. Without validation, TEXT allows mixed formats (e.g., “Jan 5, 2023”, “05/01/23”), making comparisons meaningless.
2. No Native Date Operations
   1. Functions like DATE\_ADD() or DATEDIFF() fail on TEXT columns unless explicit casting is used, degrading performance.

Storing INTs as strings bypasses database optimizations for temporal logic, leading to sorting errors and inefficient queries. When INTs are stored as strings, the database cannot apply built-in date arithmetic or indexing optimizations designed for temporal data, forcing expensive string parsing during queries. This results in incorrect chronological ordering (e.g., ‘2023-01-10’ appearing before ‘2023-01-2’) and slower performance, as simple operations like date ranges require full-text scans instead of leveraging time-optimized algorithms.

Let us inspect another real database table, agent.

CREATE TABLE `agents` (

`account\_title` TEXT NULL DEFAULT NULL COLLATE ‘latin1\_swedish\_ci’,

`bank\_name` TEXT NULL DEFAULT NULL COLLATE ‘latin1\_swedish\_ci’,

`account\_number` TEXT NULL DEFAULT NULL COLLATE ‘latin1\_swedish\_ci’,

`pending\_location` TEXT NULL DEFAULT NULL COLLATE ‘latin1\_swedish\_ci’,

`pending\_latlong` TEXT NULL DEFAULT NULL COLLATE ‘latin1\_swedish\_ci’,

PRIMARY KEY (`agent\_id`) USING BTREE

)

The SQL statement below extracts the agent\_id and latlong columns from the agents database table.

SELECT agent\_id, latlong FROM agents ORDER BY agents.latlong DESC

Table 3 shows the results from the SQL statement to ask the database to retrieve from the agents table and sorted by the latlong column.

**TABLE 3.** Latlong data from agents table

|  |  |
| --- | --- |
| Agent\_id | latlong |
| 2313 | undefined |
| 94 | undefined |
| 1858 | 6.9123606,116.8465908 |
| 789 | 6.883057099999999,116.8466165 |
| 999 | 6.4958249,116.7609682 |
| 1003 | 6.4958249,116.7609682 |

The data appears to be corrected. Somehow it will sooner run into the problem when storing numeric data into a TEXT data type explained below.

When store numbers in a TEXT column (or any string-type column like VARCHAR), they are treated as character strings rather than numeric values. This leads to incorrect sorting because:

1. Lexicographical (Alphabetical) Ordering

* Databases sort TEXT values character-by-character (like dictionary order), not by numeric value.
* Example: “10” sorts before “2” because ‘1’ < ‘2’ in ASCII/Unicode.

1. No Numeric Interpretation

* TEXT cannot infer that “100” > “99” because it compares them as strings (‘1’ vs ‘9’).

1. Padding Issues

Uneven string lengths (e.g., “5” vs “005”) worsen sorting problems.

Storing numbers in string columns invites sorting and calculation errors. Always match data types to the domain (e.g., INT for integers) (Endow, 2023). Storing numbers as strings (e.g., in TEXT or VARCHAR columns) leads to incorrect sorting and calculation errors because databases treat them as character sequences rather than numeric values. For example, the string ‘10’ sorts before ‘2’ lexicographically, and arithmetic operations like summing balances may fail or produce invalid results. Additionally, string-based comparisons force the database to parse text into numbers during queries, adding unnecessary computational overhead, whereas native numeric types (e.g., INT, DECIMAL) enable efficient binary operations and accurate mathematical processing.

There are more errors in the data than the three of them that were shown. The result of the data was causing the organization to revamp the entire application.

Recent advancements in AI, particularly in natural language processing (NLP) and machine learning (ML), offer new opportunities to automate and improve data type validation processes because the database table structure is created. By integrating AI into the database creation phase, organizations can proactively address data quality issues, reducing the burden on data scientists to understand the data, cleansing the data, and improving operational efficiency.

## Experiment of Generative AI with Database Design

The proposed solution involves using generative AI to verify the data type before the columns creation or to get the next step, integrating AI into the database creation process to validate and correct data types before data insertion table creation. Let us feed the proven problematic SQL statement for creation database table from the Generative AI to validate the data type then we will propose at which database design flow to insert the AI capabilities.

There are few renown Generative Ais such as ChatGPT (by OpenAI), a conversational AI that generates human-like text responses across topics like coding, writing, and analysis. GitHub Copilot, an AI pair programmer that suggests code completions and entire functions in real-time within development environments. Gemini (by Google), a multimodal AI assistant (formerly Bard) that combines text, image, and code generation with real-time web search integration. DeepSeek, a specialized AI for complex reasoning and coding tasks, offering long-context understanding (up to 128K tokens) and file analysis support.

The SQL statement to create the “orders” and “agents” database tables is sent to Generative AI to be refined. We then compare the consistency between the original SQL statement and the resulting refinement by Generative AI. For our study, we used Microsoft 365 Copilot and DeepSeek.

The first statement to send to Generate AI will be the SQL statement to create the “orders” table. The following is the prompt and the SQL statement that sent in to the Generative AI.

What should be the correct data type of the following create SQL statement for creating “orders”.

CREATE TABLE `orders` (

`id` int NOT NULL AUTO\_INCREMENT,

`user\_id` int NOT NULL,

`picked\_on` VARCHAR(25) DEFAULT NULL,

`deposited\_on` VARCHAR(25) DEFAULT NULL,

`completed\_on` VARCHAR(25) DEFAULT NULL,

`status` VARCHAR(15) NOT NULL,

`reject\_reason` text,

`points\_earned` FLOAT NOT NULL DEFAULT ‘1’,

PRIMARY KEY (`id`)

)

Table 4compares the columns and the data types between the application developer (original) and the Generative AI for the orders table.

**TABLE 4.** Data type from original (application developer), DeepSeek, and Microsoft 265 Copilot for orders

|  |  |  |  |
| --- | --- | --- | --- |
| Column Name | Original | DeepSeek | Microsoft 365 Copilot |
| weight | FLOAT | DECIMAL(10,2) | - |
| uco\_price | FLOAT | DECIMAL(10,2) | DECIMAL(10,2) |
| total | FLOAT | DECIMAL(10,2) | DECIMAL(10,2) |
| agent\_total | FLOAT | DECIMAL(10,2) | DECIMAL(10,2) |
| dropoff\_on | TEXT | DATETIME | DATETIME |
| dropped\_on | TEXT | DATETIME | DATETIME |
| picked\_on | VARCHAR(25) | DATETIME | DATETIME |
| deposited\_on | VARCHAR(25) | DATETIME | DATETIME |
| completed\_on | VARCHAR(25) | DATETIME | DATETIME |
| Status | VARCHAR(15) | VARCHAR (20) | - |

The following are the suggestions from DeepSeek for the orders table.

1. Changed FLOAT to DECIMAL(10,2) for weight, uco\_price, total, and agent\_total to avoid FLOATing-point precision issues.

There is a FLOATing-Point Precision Issues with FLOAT data type. FLOAT (and DOUBLE) in MySQL uses binary FLOATing-point arithmetic, which can lead to rounding errors when storing DECIMAL numbers. This is because some DECIMAL fractions (e.g., 0.1) cannot be represented exactly in binary, leading to small inaccuracies [19].

1. Changed text/VARCHAR to DATETIME for all timestamp fields (dropoff\_on, dropped\_on, picked\_on, deposited\_on, completed\_on).

There are problems with storing dates as Strings (TEXT/VARCHAR) because MySQL will not prevent invalid dates like "2023-02-30" or "Not a date". Strings take more space than binary DATETIME (8 bytes vs. variable-length strings) [20]. String also cannot do natively calculate between the date and time intervals (e.g., completed\_on - dropoff\_on). The most serious issue is databases sort TEXT values character-by-character (like dictionary order), not by numeric value, example, "10" sorts before "5" because '1' < '5' in ASCII/Unicode.

1. Increasing the status field from VARCHAR(15) to VARCHAR(20) accommodates potential future status values without requiring schema changes, ensuring flexibility as business rules evolve while maintaining minimal storage impact.
2. Changing reject\_reason from TEXT to VARCHAR(255) optimizes storage efficiency while accommodating typical rejection messages, as TEXT fields incur overhead and are unnecessary for shorter, structured responses
3. Changing points\_earned from FLOAT to INT ensures precise storage of whole-number point values, avoiding FLOATing-point rounding errors for loyalty or scoring systems [21].

The following are the suggestions from Microsoft 365 Copilot.

1. Changed uco\_price, total, and agent\_total to DECIMAL(10, 2) for better precision.

The suggestion from Microsoft 365 Copilot is in sync with DeepSeek Generative AI even though it omitted the suggestion to the weight column as compared to DeepSeek,

1. Changed dropoff\_on, dropped\_on, picked\_on, deposited\_on, and completed\_on to DATETIME.

Change the columns dropoff\_on, dropped\_on, picked\_on, deposited\_on, and completed\_on is suggested by Microsoft 365 Copilot. This is similarly to what DeepSeek recommended.

The second statement to send to Generate AI will be the SQL statement to create the “agents” table. The following is the prompt and the SQL statement that sent into the Generative AI.

What should be the correct data type of the following create SQL statement for creating "agents".

CREATE TABLE `agents` (

`agent\_id` INT(10) NOT NULL AUTO\_INCREMENT,

`contact\_person` TEXT NULL DEFAULT NULL COLLATE 'latin1\_swedish\_ci',

`account\_number` TEXT NULL DEFAULT NULL COLLATE 'latin1\_swedish\_ci',

`status` VARCHAR(11) NOT NULL DEFAULT 'pending' COLLATE 'latin1\_swedish\_ci',

`joined` VARCHAR(25) NOT NULL COLLATE 'latin1\_swedish\_ci',

`pending\_location` TEXT NULL DEFAULT NULL COLLATE 'latin1\_swedish\_ci',

`pending\_latlong` TEXT NULL DEFAULT NULL COLLATE 'latin1\_swedish\_ci',

PRIMARY KEY (`agent\_id`) USING BTREE

)

Table 5 compares the columns and the data types between the application developer (original) and the Generative AI for the agents table.

**TABLE 5.** Data type from original (application developer), DeepSeek, and Microsoft 265 Copsilot for agents database table

|  |  |  |  |
| --- | --- | --- | --- |
| **Column Name** | **Original** | **DeepSeek** | **Microsoft 365 Copilot** |
| balance | FLOAT | DECIMAL(10,2) | DECIMAL(10,2) |
| hub\_capacity | FLOAT | DECIMAL(10,2) | DECIMAL(10,2) |
| joined | VARCHAR(25) | DATETIME | DATETIME |
| bank\_name | TEXT | VARCHAR | VARCHAR |

Table 5 compares the original data types of the "agents" table with the recommendations from DeepSeek and Microsoft 365 Copilot. Both AI tools suggest replacing TEXT fields with VARCHAR for columns like full\_name, email, and location, optimizing storage and query performance. DeepSeek uniquely recommends using the POINT data type for latlong to leverage spatial indexing, while Copilot sticks to VARCHAR for simplicity. Both tools advise changing balance and hub\_capacity from FLOAT to DECIMAL(10,2) to avoid precision issues, and converting joined from VARCHAR(25) to DATETIME for proper date handling. These changes highlight the AI's focus on precision, efficiency, and adherence to best practices in database design.

The recommendations reveal a strong consensus on critical improvements, such as avoiding TEXT for structured data and using appropriate numeric types. However, differences emerge in handling specialized data like latlong, where DeepSeek's spatial data type suggestion offers advanced functionality. The AI tools also prioritize consistency, such as standardizing string lengths (e.g., phone as VARCHAR(20)). These refinements aim to prevent common pitfalls like sorting errors and inefficient storage, demonstrating how AI can enhance database robustness while reducing manual oversight. The results underscore the potential of AI to streamline schema design and improve data integrity from the outset.

The original data types chosen by the application developer, such as storing dates as TEXT and numeric values as FLOAT, had significant negative impacts on business operations and machine learning workflows. Storing DATETIME values (e.g., `dropoff\_on`, `joined`) as strings led to incorrect sorting and comparison issues, as seen in Table 1 and Table 2, where chronological order was violated due to lexicographical sorting. This undermined time-based analytics, reporting accuracy, and decision-making. Additionally, using FLOAT for financial columns like `balance` and `total` introduced FLOATing-point precision errors, risking incorrect calculations in billing, payroll, and forecasting (MySQL(1), n.d.).

For machine learning, these data quality issues compounded during preprocessing. Inconsistent date formats and numeric rounding errors required extensive cleansing, consuming up to 60% of data scientists' time. Text-stored numbers (e.g., `latlong`) disrupted geospatial analysis, while unvalidated strings (e.g., `status`) introduced noise in categorical modeling. Such inefficiencies delayed model deployment and reduced reliability. By contrast, AI-recommended types (e.g., DATETIME, DECIMAL) would ensure cleaner data upfront, minimizing preprocessing overhead and improving model accuracy. The original design thus imposed hidden costs on both operational and analytical workflows.

## Proposed Database Design Solution

To reduce the amount of data transforming and data cleansing for business and machine learning applications, additional can be added to the existing database design stack. AI-Driven Database Column Data Type Optimization is an AI-driven data type verification for databases step that should add in between the step “turn information items into columns” and “specify primary keys” step. So, the modernized database design will haves 9 steps instead of 8. The 9 steps as follows.

1. Determine the purpose of your database
2. Find and organize the information required
3. Divide the information into tables
4. Turn information items into columns
5. AI-Driven Database Column Data Type Optimization
6. Specify primary keys
7. Set up table relationships
8. Refine your design
9. Apply normalization rules

Technically, AI-Driven Database Column Data Type Optimization can be executed manually semi-automated or automatically. Manually, the software architect can validate the create table SQL statement to get feedback from the Generative AI before the application developer runs the SQL statement against the production database [22]. The SQL statement that uses to create the database table can be sent to Generative AI using API, this will be the semi-automated way. In order to achieve this automatically, the capability must build into the database engine such as Microsoft SQL Server, Oracle or MySQL.

# Conclusion

Integrating AI into database design offers a proactive solution to data quality issues, significantly reducing the need for post-insertion cleansing, which consumes up to 60% of data scientists' time. By validating data types during column creation, AI enhances data accuracy and streamlines workflows. Positioned between column creation and primary key specification, this AI-driven step reduces sorting errors and improves machine learning preprocessing. Experiments using tools like DeepSeek and Microsoft 365 Copilot showed AI’s effectiveness in suggesting optimal data types, e.g., DATETIME for timestamps and DECIMAL for financial values—thereby addressing issues like lexicographical sorting and FLOAT precision errors. This alignment with best practices demonstrates AI’s value in schema design. Future work may focus on broader adoption and integration across systems, enhancing data integrity and efficiency across industries

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