## Convera Al



CSET - 301 Artificial Intelligence and Machine Learning

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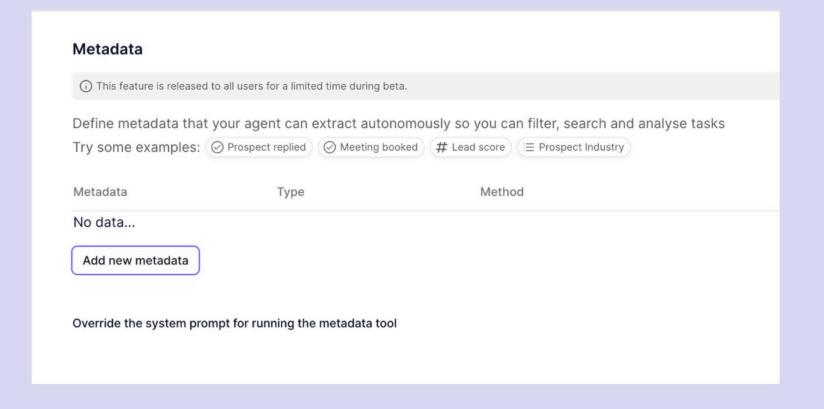
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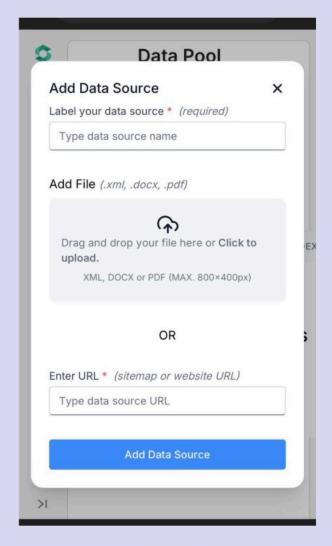
Submitted to -Dr. Yajnaseni Dash

## Problem Statement

Even though low-code AI platforms are becoming more popular, non-technical users still struggle to prepare the structured and personalised data needed for the AI to perform effectively. Most current tools rely on manual input without offering proper guidance, which makes the process confusing and inefficient. As a result, the AI agents often don't align well with the users' actual goals or workflows—especially during the critical early phase of exploring and understanding the data, known as Exploratory Data Analysis (EDA).

# Complex UI OF Existing Platforms



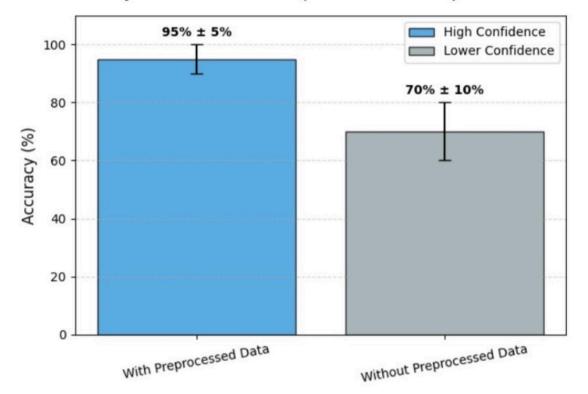


**RELEVANCE AI** 

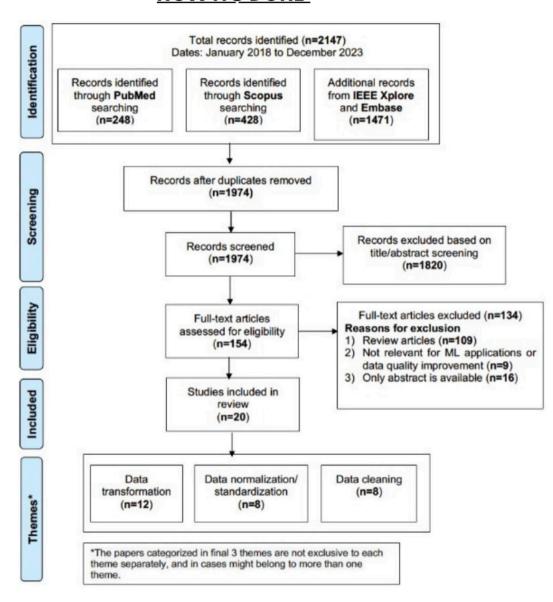
**SMYTHOS** 

### **IMPACT OF DATA PRE-PROCESSING**

Accuracy of Assistant AI: Preprocessed vs. Unprocessed Data



### **HOW ITS DONE**



## Key Challenges

Companies that succeed with modern generative AI tools—such as Microsoft's

MSFT-3.02% ▼ Copilot, Salesforce's CRM-2.82% ▼ Agentforce, or offerings from a raft of new startups—are discovering that in order to get real value from AI, they have to organize their data in ways they might not have before. And this isn't a one-and-done effort. To keep their shiny new AIs up-to-date, the information they feed them must be kept constantly updated—creating more work for humans.

#### Every company needs a 'knowledge base'

link

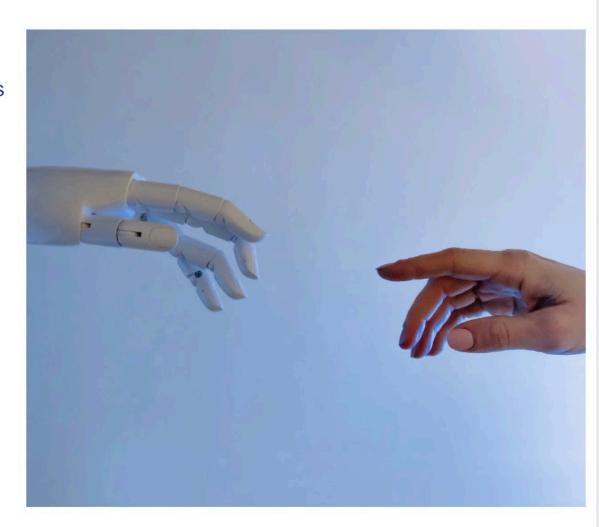
Every company I talked with mentioned that to get real value out of their shiny new generative AI systems—no matter the application—they needed to overhaul or double down on their strategy for feeding it the kind of data that today's AI excels at processing—"unstructured" data.

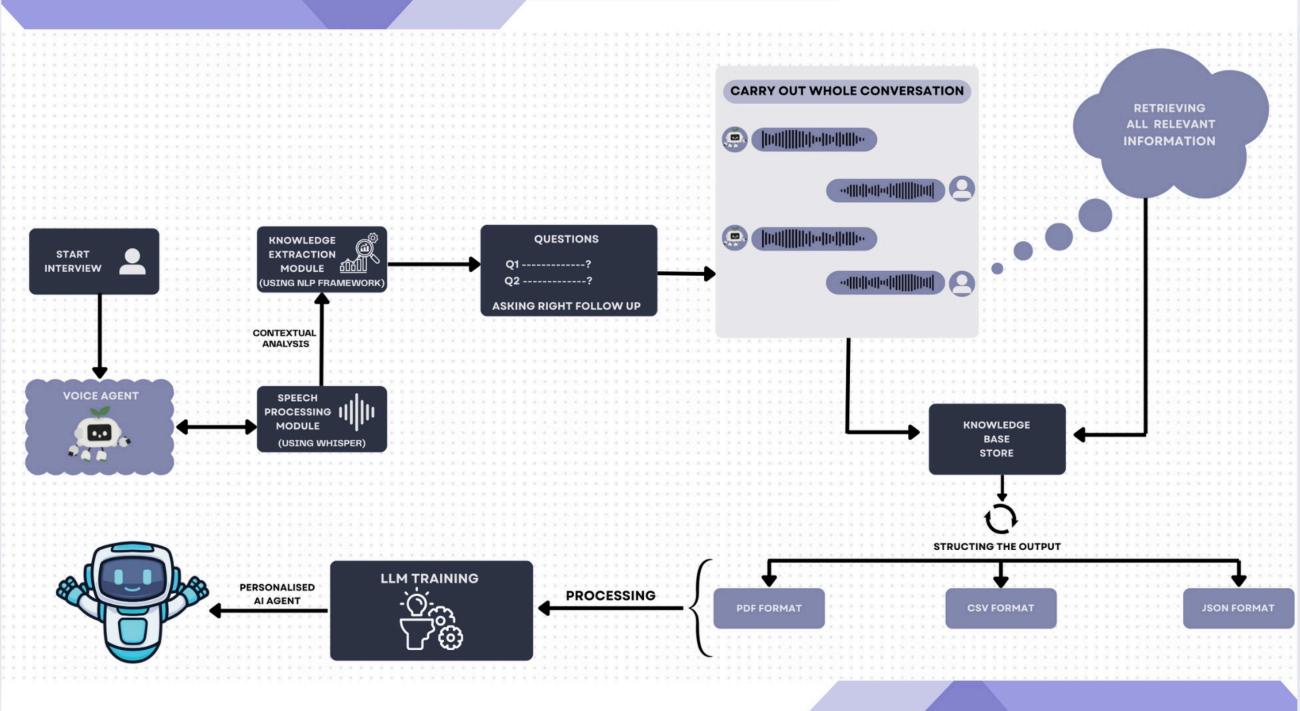
After prompting your LLM and receiving a response back in plain text. Quite straightforward for simple exchanges. It is not very practical for more complex applications and tasks What we will need is some form of structured output. A common practice within the community and among various tools is to instruct the LLM to output in a JSON format, with specified keys where values can be parsed. These instructions are specified in your prompt. Here is an example from LangChain [5]. It doesn't have to be in JSON format, it can be even a simpler structure that you may want to engineer that can be parsed with Regex.

- Data Collection Complexity
- Lack of Guided Interaction
- Data Structuring & Contextualisation
- Misalignment Between User Intent and Al Interpretation
- Limited Accessibility of Existing Tools

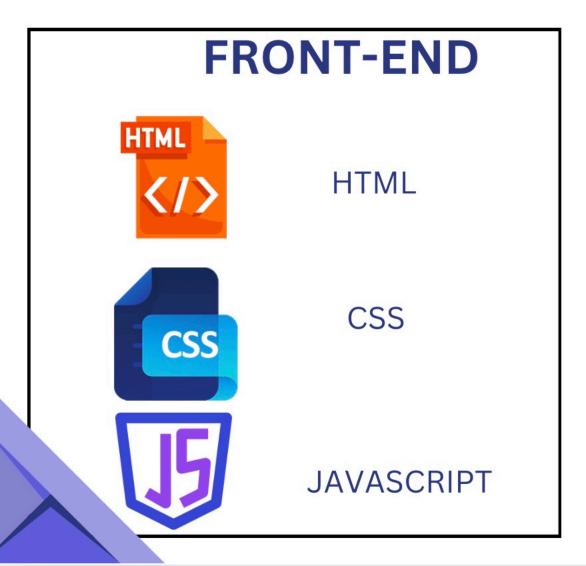
## Solution

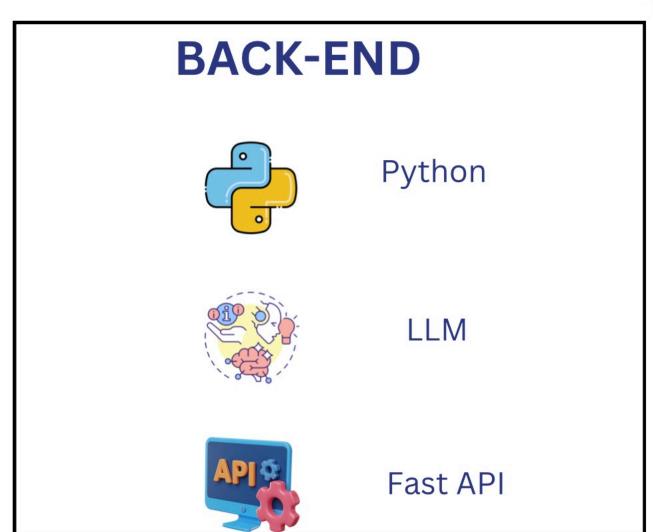
- We propose a voice-first conversational engine that guides users through intelligent, adaptive interviews.
- The system asks context-aware questions to extract relevant goals, workflows, and domain knowledge.
- It dynamically adjusts its dialogue based on real-time responses for a personalized experience.
- Collected information is automatically structured into clean, usable knowledge bases.
- These outputs are optimized for direct use in low-code Al platforms, simplifying agent creation.





## TECH STACK





## Impact and benefits

### Empowers Non-Technical Users

Makes AI agent creation accessible to domain experts without requiring coding or data science skills. Enables intuitive voice-based interaction to gather and organise knowledge effortlessly.

### Bridges the Data-to-Agent Gap

Automates the Exploratory Data Analysis (EDA) phase through guided conversational input. Reduces friction in preparing domain-specific data for AI agent deployment.

### Personalised, High-Quality Agents

Ensures agents are context-aware, aligned with real-world workflows, goals, and constraints. Minimises misalignment between agent behaviour and user expectations.

### Accelerates Al Adoption

Drastically reduces time from ideation to deployment of intelligent agents. Facilitates smoother onboarding and faster prototyping for AI solutions.

#### Scalable Across Domains

Applicable to a wide range of industries including healthcare, education, customer support, and more. Adapts to diverse terminologies and workflows through intelligent, domain-sensitive dialogue.

## <u>Feasibility</u>

- Proven Tech: Uses reliable voice, NLP, and low-code integration tools.
- Scalable Design: Easily deployable with structured outputs and adaptive dialogue.

### <u>Viability</u>

- Strong Demand: Solves key pain points for non-technical users.
- Efficient & Unique: Saves time, reduces cost, and offers a voice-first edge.

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