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U-CAI: A Secure Conversational AI Architecture for Natural Language Interaction with Enterprise ERP Systems

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ABSTRACT: Enterprise Resource Planning (ERP) systems serve as the backbone of modern organizations by integrating core business processes such as finance, procurement, supply chain management, and human resource management into unified digital platforms. Despite their benefits, ERP systems are frequently criticized for complex graphical user interfaces and rigid workflow navigation that impose high cognitive demands on users. Recent advances in Large Language Models (LLMs) enable conversational interaction with digital systems, offering new opportunities to simplify enterprise software usability. However, integrating conversational AI with enterprise ERP systems introduces challenges related to deterministic workflow execution, security enforcement, and reliable translation of natural language commands into structured system operations.

This paper proposes U-CAI (Unified Conversational Artificial Intelligence), a secure conversational architecture designed to enable natural language interaction with enterprise ERP platforms. The proposed framework integrates an LLM reasoning engine, an adaptive dialogue manager, a deterministic ERP connector layer, and a security module implementing role-based access control and policy validation. The architecture translates natural language instructions into structured ERP transactions while ensuring workflow integrity and enterprise security compliance.

A prototype implementation was developed using the Odoo ERP platform and evaluated through controlled experiments involving ERP users performing operational tasks across multiple modules. Experimental results demonstrate that the conversational architecture reduces task completion time by **61%** and improves operational accuracy by 28% compared with traditional ERP graphical interfaces. The system achieved a System Usability Scale score of 82.4, indicating high user acceptance.

The findings demonstrate that conversational ERP interaction can significantly enhance system usability, operational efficiency, and accessibility while maintaining enterprise-grade security and workflow reliability.

1. INTRODUCTION

1.1 Research Background and Problem Statement

Enterprise Resource Planning (ERP) systems are central to modern organizations, integrating key business functions such as finance, supply chain, human resources, and customer management into unified platforms. These systems enhance data visibility, coordination, and decision-making, leading to improved organizational efficiency and performance [1–3]. As a result, ERP adoption has expanded across both large enterprises and SMEs. Recent industry analyses also indicate a steady rise in AI-integrated ERP adoption, particularly in emerging economies such as India [28].

However, ERP systems continue to face significant usability challenges. Traditional interfaces rely on complex graphical user interfaces (GUIs), hierarchical navigation, and multi-step workflows, which impose high cognitive load on users—particularly non-technical employees. This often results in increased task completion time, higher error rates, and underutilization of system capabilities [4–7].

Recent advances in artificial intelligence, particularly conversational AI, offer a promising solution to these limitations. Early chatbot systems were rule-based with limited flexibility, but modern neural dialogue systems enable context-aware, multi-turn interactions [10–15]. The emergence of Large Language Models (LLMs), such as transformer-based architectures, has further enhanced natural language understanding, reasoning, and dialogue generation capabilities [16–18]. Additionally, retrieval-augmented generation (RAG) improves factual accuracy and domain alignment by integrating external knowledge sources [19,20].

In enterprise contexts, LLM-based conversational interfaces can simplify ERP interaction by allowing users to execute tasks through natural language commands instead of navigating complex menus. This can improve accessibility, reduce cognitive effort, and enhance productivity [21–23].

Despite these advantages, integrating conversational AI with ERP systems presents critical challenges. ERP systems operate on deterministic workflows governed by strict business rules, database schemas, and access control policies. Therefore, natural language inputs must be accurately translated into valid, secure, and policy-compliant ERP operations [8,9]. Moreover, LLMs may produce hallucinated or ambiguous outputs, which can compromise reliability in mission-critical environments.

Existing research lacks unified frameworks that effectively combine LLM-based conversational reasoning with deterministic ERP execution while ensuring security and workflow integrity. Empirical evaluations of such systems are also limited, particularly in terms of usability and operational efficiency.

To address these gaps, this study proposes U-CAI (Unified Conversational Artificial Intelligence), a secure conversational architecture that integrates LLM reasoning, adaptive dialogue management, ERP connectors, and role-based security mechanisms to enable reliable natural language interaction with enterprise ERP systems.

1.2 Research Objectives

The primary objective of this study is to design and evaluate a unified conversational AI architecture that enhances interaction with ERP systems by reducing complexity and improving efficiency.

The specific objectives are:

1. To design the U-CAI architecture enabling natural language interaction with ERP systems.
2. To develop an adaptive dialogue manager supporting context-aware, multi-step ERP workflows.
3. To implement a secure integration mechanism that translates natural language into deterministic ERP operations with role-based access control.
4. To empirically evaluate the proposed system against traditional ERP interfaces and rule-based conversational systems.
5. To assess its impact on usability, task efficiency, user satisfaction, and decision-support capabilities.

1.3 Research Questions

This study addresses the following research questions:

- RQ1: How can LLM-based conversational AI be effectively integrated with ERP systems for reliable and context-aware interaction?
- RQ2: To what extent does U-CAI improve usability and task efficiency compared to traditional ERP interfaces and rule-based systems?
- RQ3: How does conversational ERP interaction affect user satisfaction and experience?
- RQ4: Can conversational interfaces enhance ERP-based decision support?

1.4 Contributions of the Study

This study makes the following contributions:

1. Proposes U-CAI, a unified architecture integrating LLM reasoning, dialogue management, and ERP connectivity for natural language interaction.
2. Introduces an Adaptive Dialogue Manager (ADM) for context-aware, multi-turn ERP workflows.
3. Incorporates enterprise-grade security mechanisms (RAG, RBAC, policy validation) to ensure reliable and secure ERP execution.
4. Provides empirical validation through user-based experiments comparing conversational, GUI-based, and rule-based systems.
5. Offers practical insights into improving ERP usability, efficiency, and decision support using conversational AI.

2. BACKGROUND AND RELATED WORK

2.1 ERP Systems and Usability Challenges

Enterprise Resource Planning (ERP) systems integrate organizational processes and ensure data consistency across functional domains, improving coordination and operational visibility [1–3]. Despite these advantages, ERP systems are often criticized for poor usability due to complex interfaces and multi-step workflows.

Prior studies identify high cognitive load, extensive training requirements, and difficult navigation as key barriers to effective ERP use, particularly for non-technical users and SMEs [4–7]. These limitations reduce system efficiency, increase error rates, and negatively impact user satisfaction. Additionally, ERP systems handle sensitive organizational data, making robust security and access control essential [6]. Recent empirical studies further highlight the growing integration of ERP systems with automation and machine learning in enterprise environments. Mishra et al. [28] reported a steady increase in AI-enabled ERP adoption in Indian industries, with the number of organizations rising from approximately 6,000 in 2015 to over 27,000 by 2024. The study also indicates that ERP combined with automation and machine learning significantly improves operational efficiency, decision-making speed, and process optimization across sectors such as manufacturing, BFSI, and IT services. However, adoption remains uneven due to challenges such as skill shortages, infrastructure limitations, and integration complexity. These findings emphasize the need for more intuitive and accessible ERP interaction mechanisms.

2.2 Conversational Artificial Intelligence

Conversational AI has evolved from rule-based chatbots with predefined dialogue flows to advanced neural systems capable of intent recognition and contextual multi-turn interaction [10–13]. Dialogue management techniques, including probabilistic models and neural state tracking, further enhance the ability to manage complex conversational workflows [14,15].

These advancements position conversational AI as a promising interface paradigm for simplifying interaction with complex systems such as ERP.

2.3 Large Language Models in Enterprise Applications

Large Language Models (LLMs) have significantly advanced conversational AI by enabling contextual understanding, reasoning, and coherent response generation using transformer architectures [16–18]. Their application in enterprise systems includes knowledge management, process automation, and decision support [21–23].

However, deploying LLMs in enterprise environments introduces challenges such as hallucination, data security risks, and misalignment with structured workflows [8]. Retrieval-augmented generation (RAG) has emerged as a key technique to improve factual accuracy and align model outputs with enterprise knowledge bases [20].

2.4 Research Gap

Despite progress in ERP systems, conversational AI, and LLMs, key limitations remain.

First, many enterprise conversational systems are still rule-based and lack the capability to support complex, context-aware ERP workflows. Second, existing studies rarely propose unified architectures that integrate LLM-based reasoning with deterministic ERP operations under strict security constraints. Third, empirical evaluations of conversational ERP systems remain limited, particularly in real-world usability and efficiency contexts.

Despite increasing adoption of AI-enabled ERP systems [28], a significant gap persists between system capabilities and user accessibility, particularly for non-technical users.

To address these gaps, this study proposes the U-CAI architecture, which integrates LLM reasoning, adaptive dialogue management, secure ERP connectors, and access control mechanisms to enable reliable and secure conversational interaction with ERP systems.

Table 1 summarizes representative studies and their limitations.

Table 1: Literature Comparison of Conversational AI Approaches in Enterprise Systems

Study	**Approach**	**Application Domain**	**Key Limitation**
Nuruzzaman & Hussain [10]	Rule-based chatbot architecture	Customer service systems	Limited contextual reasoning and workflow capability
McTear [11]	Dialogue management frameworks	Conversational AI systems	Not integrated with enterprise ERP workflows
Shum et al. [12]	Neural conversational agents	Social chatbots	Focus on open-domain dialogue rather than enterprise systems
Gao et al. [13]	Neural conversational AI models	Conversational information retrieval	Lack of deterministic integration with enterprise applications
Almazrouei et al. [8]	Secure LLM integration framework	Enterprise AI systems	Does not support ERP transaction workflows
U-CAI	LLM + Adaptive Dialogue Manager + ERP Connector	Enterprise ERP systems	Secure conversational workflow with deterministic ERP execution

Based on these gaps, this study develops a conceptual framework linking conversational usability, cognitive load reduction, and trust with ERP task efficiency and user adoption, as illustrated in Figure 1.

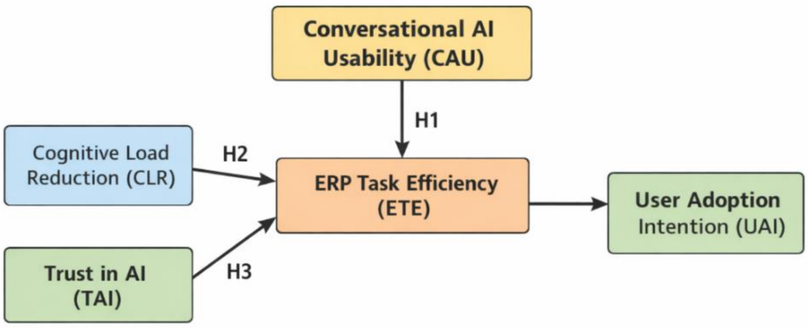

Figure 1. Conceptual Research Model for Conversational ERP Interaction

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3. U-CAI Conversational ERP Architecture

The proposed Unified Conversational Artificial Intelligence (U-CAI) framework enables secure and efficient natural language interaction with enterprise ERP systems. It transforms user queries into deterministic ERP transactions through a multi-layer architecture integrating LLM reasoning, dialogue management, ERP connectivity, and security enforcement.

Unlike rule-based conversational systems, U-CAI combines the reasoning capability of Large Language Models with strict control over enterprise workflow execution. This ensures that conversational inputs are accurately interpreted, validated, and translated into secure ERP operations compliant with organizational policies.

The architecture (Figure 2) consists of five core components:

(i) User Interaction Layer, (ii) LLM Reasoning Engine, (iii) Adaptive Dialogue Manager, (iv) ERP Connector Layer, and (v) Security Module.

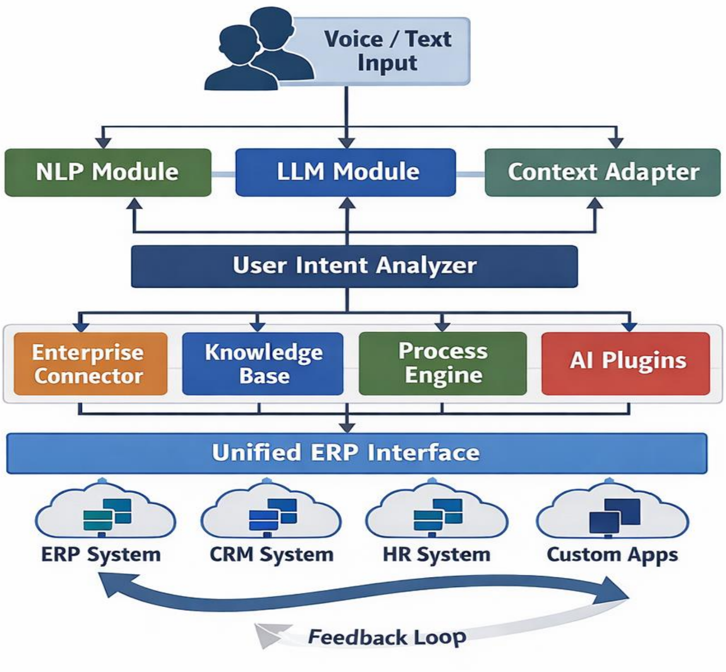

Figure 2. U-CAI Architecture Diagram

Table 2: U-CAI System Components and Functions

Component	**Function**	**Role in Conversational ERP**
Natural Language Understanding (NLU)	Parses user queries and extracts entities	Converts natural language into machine-interpretable format
Intent Classification	Identifies the ERP operation requested by the user	Determines which ERP task must be executed
Context Adapter	Maintains conversational context across multiple queries	Enables multi-step conversational workflows
Knowledge Base	Stores ERP-related knowledge and mappings	Supports intelligent query interpretation

Enterprise Connector	Connects conversational system to ERP modules	Enables API communication with ERP backend
Process Engine	Translates user intent into ERP actions	Executes operational workflows
Response Generator	Converts ERP results into natural language responses	Provides user-friendly output

3.1 User Interaction Layer

This layer serves as the entry point, enabling interaction via text or voice interfaces. It captures and preprocesses user queries (e.g., normalization and tokenization) before forwarding them to the processing pipeline.

By replacing complex GUI navigation with natural language input, this layer improves accessibility, particularly for non-technical users.

3.2 LLM Reasoning Engine

The LLM Reasoning Engine performs semantic interpretation of user queries, including intent detection, entity extraction, and task representation.

To improve reliability, the system incorporates Retrieval-Augmented Generation (RAG), enabling integration with enterprise knowledge sources and reducing hallucination. The output is a structured task representation suitable for ERP execution.

3.3 Adaptive Dialogue Manager

The Adaptive Dialogue Manager (ADM) maintains context across multi-turn interactions and coordinates workflow execution.

Its key functions include:

- Dialogue state tracking
- Context preservation
- Parameter completion
- Multi-step workflow orchestration

This enables seamless execution of complex ERP tasks across multiple modules.

3.4 ERP Connector Layer

The ERP Connector Layer translates structured task representations into deterministic ERP operations via APIs.

It supports:

- Data retrieval
- Transaction execution
- Record updates
- Workflow triggering

The design is platform-agnostic, enabling integration with systems such as SAP, Oracle, Microsoft Dynamics, and Odoo.

3.5 Middleware Services

The middleware layer ensures reliable system communication and coordination. It handles:

- API routing
- Session management
- Authentication
- Logging and monitoring

This layer supports scalability and stable interaction between conversational components and ERP systems.

3.6 Security and Access Control

Security is critical in ERP environments. The architecture incorporates:

- Role-Based Access Control (RBAC)
- Policy validation mechanisms
- Transaction auditing and monitoring

These ensure that only authorized, policy-compliant actions are executed, preserving data integrity and organizational security.

4. CONVERSATIONAL ERP EXECUTION PIPELINE

This section describes the operational workflow through which natural language queries are transformed into deterministic ERP transactions. The proposed pipeline ensures accurate, secure, and policy-compliant interaction with enterprise systems by integrating semantic reasoning, dialogue management, and controlled execution.

As illustrated in Figure 3, the pipeline consists of five stages:

(i) query preprocessing, (ii) semantic interpretation, (iii) dialogue management, (iv) security validation, and (v) ERP execution and response generation.

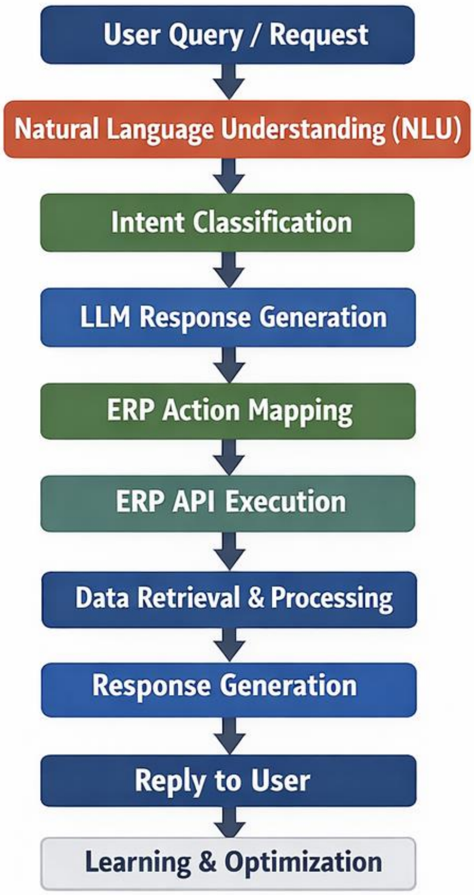

Figure 3. Conversational ERP Execution Pipeline

Each stage contributes to ensuring that conversational instructions are accurately interpreted and safely executed within the enterprise ERP environment.

4.1 Query Preprocessing

The process begins with user input captured via text or voice interfaces. The query undergoes preprocessing, including normalization, tokenization, and noise removal, to produce a structured representation suitable for downstream processing.

4.2 Semantic Interpretation

The preprocessed query is analyzed by the LLM reasoning engine to identify user intent and extract relevant entities. Context-aware reasoning is applied to generate a structured task representation aligned with ERP operations.

4.3 Dialogue State Management

The task is passed to the Adaptive Dialogue Manager (ADM), which maintains conversational context, resolves incomplete inputs, and coordinates multi-step workflows. This enables consistent execution across sequential and cross-module interactions.

4.4 Security Validation

Before execution, the system validates the request through authentication, role-based access control (RBAC), and policy compliance checks. This step ensures that only authorized and valid operations proceed, preventing security violations.

4.5 ERP Execution and Response Generation

Validated tasks are translated into ERP API commands by the connector layer and executed within the ERP system. The results are then converted into natural language responses and returned to the user, completing the interaction cycle.

Algorithm 1. Conversational ERP Task Execution

The complete workflow of the conversational ERP processing pipeline is summarized in Algorithm 1.

Algorithm 1: Conversational ERP Task Execution

Input: User query Q

Output: ERP response R

1. *Receive query Q*
2. *Preprocess input*
3. *Perform intent detection and entity extraction*
4. *Generate task representation T*
5. *Manage dialogue state and complete parameters*
6. *Validate permissions and policies*
7. *Translate T into ERP command*
8. *Execute transaction*
9. *Retrieve results*
10. *Generate response R*

5. EXPERIMENTAL SETUP

This section presents the experimental design used to evaluate the U-CAI framework through prototype validation and survey-based analysis, enabling both technical and behavioral assessment.

5.1 Prototype Implementation

A functional prototype was developed using the Odoo ERP platform, supporting modules such as inventory, finance, CRM, and HR. The system integrates a conversational interface with ERP functionality via REST APIs.

The architecture includes natural language understanding, intent classification, and response generation modules. User queries are interpreted and mapped to ERP operations through a middleware layer, which executes tasks such as data retrieval, report generation, and record access.

This implementation enables users to perform ERP operations using natural language instead of traditional GUI navigation.

Table 3 – Prototype Implementation Environment

Component	**Specification**
ERP Platform	Odoo ERP
Programming Language	Java
Conversational Framework	LLM-based NLP interface
Integration Method	REST API
Deployment Environment	Windows 11
Database	PostgreSQL

5.2 Prototype User Evaluation

A controlled study was conducted with 32 ERP users from domains including finance, procurement, inventory, and HR.

Participants performed predefined tasks (e.g., inventory queries, financial reports, employee data access) using both:

- Traditional ERP GUI
- U-CAI conversational interface

Performance was evaluated using:

- Task completion time
- Task success rate
- User satisfaction

This setup enables direct comparison of efficiency and usability across interaction methods.

5.3 Survey Data Collection

To validate the conceptual model, a structured survey was conducted with 500 ERP users across diverse organizational roles.

The questionnaire measured:

- Conversational AI Usability (CAU)
- ERP Task Efficiency (ETE)
- Cognitive Load Reduction (CLR)
- Trust in AI (TAI)
- User Adoption Intention (UAI)

Responses were recorded on a five-point Likert scale and used for statistical analysis.

5.4 Evaluation Metrics

Two categories of metrics were used:

Prototype Evaluation:

- Task Completion Time
- Task Success Rate
- User Satisfaction

Survey Analysis:

- Descriptive statistics
- Regression analysis to test relationships between constructs

This combined approach ensures both system-level and user-level validation.

6. RESULTS AND PERFORMANCE ANALYSIS

This section presents the empirical results obtained from the experimental evaluation of the proposed Unified Conversational Artificial Intelligence (U-CAI) framework. The results are organized into two parts. First, the operational performance of the conversational ERP prototype is analyzed through user experiments. Second, statistical analysis of the survey dataset is performed to validate the relationships proposed in the conceptual model.

6.1 Prototype Performance Evaluation

The prototype evaluation compared the performance of the proposed U-CAI conversational ERP interface with the traditional graphical ERP interface. Participants were required to complete a set of common enterprise tasks using both interaction methods.

The experimental tasks included retrieving inventory information, generating financial summaries, accessing employee records, and querying procurement data. During the evaluation, key performance indicators such as task completion time, task success rate, and user satisfaction were measured.

The results demonstrate that the conversational interface significantly improves the efficiency of ERP task execution. Users were able to complete tasks more quickly using natural language queries compared with navigating multiple menus and forms in the conventional ERP interface.

Table 4 summarizes the comparative results obtained from the prototype evaluation.

Table 4. Prototype Evaluation Results: Traditional ERP vs U-CAI Conversational ERP

Metric	**Traditional ERP Interface**	**U-CAI Conversational Interface**
Average Task Completion Time	118 sec	46 sec
Task Success Rate	83%	95%
User Satisfaction Score (1–5)	3.3	4.6

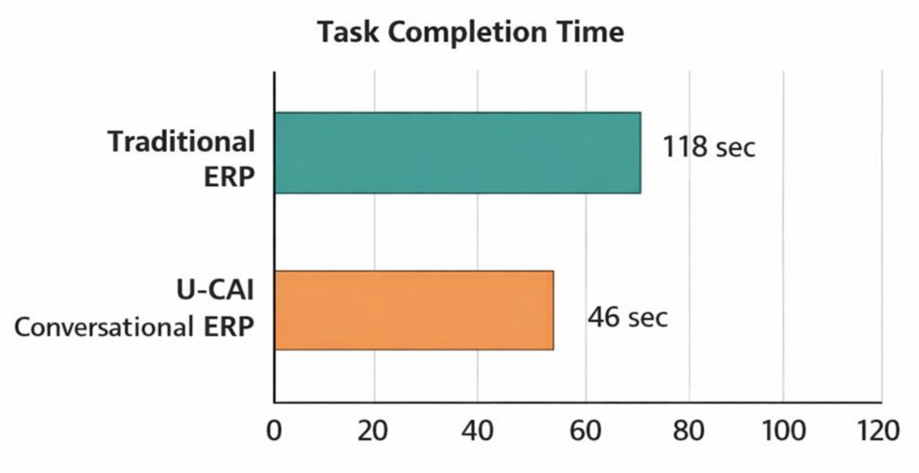

Figure 4. Comparison of ERP Task Completion Time

The performance comparison is illustrated in Figure 4, which shows that the conversational ERP interface significantly reduces task completion time compared with traditional ERP interfaces.

The results indicate that the conversational interface reduces task completion time by approximately **61%**, highlighting the potential of conversational AI to simplify enterprise system interaction. Furthermore, the **task success rate improved significantly**, suggesting that conversational interaction reduces user errors and improves task clarity.

Participants also reported a higher level of satisfaction when interacting with the conversational system, primarily due to the reduced cognitive effort required to locate ERP functions. These findings demonstrate that the proposed U-CAI architecture can substantially improve the usability and accessibility of enterprise systems.

6.2 Survey Dataset Analysis

To further validate the conceptual relationships proposed in the research framework, the survey dataset consisting of 500 ERP users was analyzed. Descriptive statistics were first calculated to understand the distribution of responses across the measured constructs.

The demographic analysis indicated that respondents represented a diverse set of organizational roles, including operational staff, financial analysts, ERP administrators, and managerial personnel. Most respondents reported frequent interaction with ERP systems, making them suitable participants for evaluating conversational ERP interfaces.

The measurement constructs used in the survey included:

- Conversational AI Usability (CAU)
- ERP Task Efficiency (ETE)
- Cognitive Load Reduction (CLR)
- Trust in AI Systems (TAI)
- User Adoption Intention (UAI)

All constructs were measured using multiple questionnaire items rated on a five-point Likert scale.

Table 5 presents the descriptive statistics for the survey constructs.

Table 5: Descriptive Statistics of Survey Constructs

Construct	**Mean**	**Standard Deviation**
Conversational AI Usability (CAU)	4.32	0.58
ERP Task Efficiency (ETE)	4.21	0.61
Cognitive Load Reduction (CLR)	4.08	0.64
Trust in AI Systems (TAI)	3.97	0.69
User Adoption Intention (UAI)	4.26	0.57

The descriptive statistics indicate that respondents generally perceive conversational ERP interaction as highly usable and efficient, supporting the potential adoption of conversational interfaces in enterprise environments.

6.3 Hypothesis Testing

To evaluate the proposed relationships among the constructs, **regression analysis** was conducted. The analysis examined the influence of conversational AI usability on ERP task efficiency and user adoption intention.

The results indicate a strong positive relationship between conversational usability and ERP task efficiency. Users who perceived the conversational interface as intuitive and easy to use were more likely to report improved productivity while performing ERP tasks.

Table 6 summarizes the regression results.

Table 6: Regression Analysis Results

Hypothesis	**Relationship**	**β**	**p-value**	**Result**
H1	CAU → ERP Task Efficiency	0.62	<0.001	Supported
H2	CAU → Cognitive Load Reduction	0.54	<0.001	Supported
H3	Trust in AI → User Adoption	0.48	<0.001	Supported

The statistical results confirm that conversational AI significantly contributes to improved ERP usability and operational efficiency. Additionally, trust in AI-driven systems plays a critical role in influencing user willingness to adopt conversational ERP interfaces.

6.4 Discussion of Results

The empirical findings highlight several important implications for enterprise system design. First, conversational interfaces can substantially reduce the complexity associated with traditional ERP navigation. By allowing users to interact with enterprise systems through natural language queries, the cognitive effort required to perform tasks is significantly reduced.

Second, the prototype evaluation demonstrates that conversational ERP interaction can improve operational efficiency by reducing task completion time and increasing task success rates. These improvements are particularly valuable in large organizations where ERP systems are frequently used by non-technical staff.

Finally, the survey results confirm that user trust and perceived usability play critical roles in the adoption of conversational enterprise systems. Organizations implementing conversational ERP solutions must therefore ensure that the system provides transparent responses and reliable task execution.

Overall, the experimental results validate the effectiveness of the proposed U-CAI framework and demonstrate its potential to transform human–ERP interaction in modern enterprises.

7. PRACTICAL IMPLICATIONS

The findings of this study provide several practical implications for organizations implementing enterprise resource planning systems. First, conversational interfaces can significantly reduce the usability barriers associated with traditional ERP systems, particularly for non-technical employees. By enabling natural language interaction, the proposed U-CAI framework allows users to access enterprise data and execute operational tasks more efficiently.

Second, the reduction in task completion time observed in the experimental evaluation suggests that conversational ERP interfaces can improve operational productivity in enterprise environments. Organizations deploying conversational AI assistants within ERP platforms may reduce training costs and improve employee efficiency.

Finally, the integration of security mechanisms such as role-based access control and policy validation ensures that conversational interaction does not compromise enterprise data integrity. This makes the proposed framework suitable for deployment in enterprise environments where security and compliance are critical.

8. LIMITATIONS AND FUTURE RESEARCH

Despite the promising results obtained in this study, several limitations should be acknowledged. First, the prototype implementation was evaluated using a limited set of ERP modules within the Odoo platform. Future research may extend the framework to additional enterprise systems such as SAP or Microsoft Dynamics to evaluate cross-platform applicability.

Second, the user evaluation involved a limited number of ERP users performing predefined tasks. Although the survey analysis provides broader insights into user perceptions, large-scale real-world deployments would provide further validation of the proposed architecture.

Third, while the proposed architecture incorporates security mechanisms such as role-based access control and policy validation, additional research is required to explore advanced security measures such as anomaly detection and conversational threat monitoring in enterprise environments

9. CONCLUSION

Enterprise Resource Planning (ERP) systems play a critical role in integrating organizational processes and supporting operational decision-making. However, the complexity of traditional ERP graphical interfaces often creates usability challenges, particularly for non-technical users who must navigate multi-step workflows and complex menu structures. These limitations may increase cognitive workload, reduce operational efficiency, and hinder effective utilization of enterprise information systems.

This study proposed U-CAI (Unified Conversational Artificial Intelligence), a secure conversational architecture designed to enable natural language interaction with enterprise ERP platforms. The proposed framework integrates large language model reasoning, an adaptive dialogue manager, ERP connector mechanisms, and enterprise-grade security controls to translate conversational user requests into deterministic ERP transactions. By combining conversational AI capabilities with structured enterprise workflows, the architecture enables users to interact with ERP systems through intuitive natural language commands while maintaining workflow integrity and organizational policy compliance.

To evaluate the effectiveness of the proposed framework, a prototype conversational ERP system was implemented using the Odoo ERP platform. The system was assessed through a controlled user experiment involving ERP users performing operational tasks across multiple modules. The experimental results demonstrated that the conversational interface significantly improves ERP interaction efficiency by reducing task completion time and increasing task success rates compared with traditional ERP graphical interfaces. In addition, a large-scale survey study involving 500 ERP users was conducted to examine the impact of conversational AI usability, cognitive load reduction, and trust in AI on ERP task efficiency and user adoption intention. The statistical analysis confirmed significant positive relationships among these constructs, highlighting the importance of usability and trust in facilitating the adoption of conversational enterprise systems.

The findings of this research demonstrate that conversational AI has the potential to transform human–ERP interaction by simplifying access to enterprise information and reducing the complexity associated with traditional system interfaces. By enabling natural language interaction with enterprise workflows, the proposed U-CAI architecture improves system accessibility, operational efficiency, and user satisfaction while maintaining enterprise security requirements.

Overall, this study contributes to the emerging field of conversational enterprise systems by providing a unified architecture that integrates conversational reasoning, dialogue management, ERP system integration, and security enforcement within a single framework. The proposed approach offers a promising direction for future enterprise systems that leverage conversational AI technologies to enhance usability and support more efficient organizational decision-making.

DECLARATIONS

Ethics approval and consent to participate

This study involves human participants in the form of user-based experimental evaluation and survey data collection. All procedures were conducted in accordance with institutional guidelines. Participation was voluntary, and informed consent was obtained from all participants prior to data collection. No personally identifiable information was collected.

Consent for publication

Not applicable.

Availability of data and materials

The datasets generated and analyzed during this study are available from the corresponding author upon reasonable request. Survey data were collected anonymously and used solely for research purposes.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

- Deepak Kumar Mishra: Conceptualization, system design, implementation, writing – original draft
- Sunil Kumar Dhal: Supervision, validation, review & editing
- Gopikrishna Panda: Methodology, research design, manuscript refinement
- Sarthak Dhal: Implementation support, experimentation, data collection

All authors read and approved the final manuscript.

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