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Vienna, Austria, August 28-30, 2024

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FOREWORD

Twin transformation aims at synergetic interaction and mutual reinforcement of the digital and sustainable transformation of manufacturing enterprises and associated value-added chains. This introduces several challenges and opportunities for cross- and interdisciplinary research on establishing sustainable, smart, resilient and human-centered manufacturing and supply chain of the future.

Information Control Problems in Manufacturing (INCOM) is a triennial symposium organized by the International Federation on Automatic Control (IFAC). The IFAC Coordinating Committee on Cyber-Physical Manufacturing Enterprises (CC 5) sponsors INCOM, which equally involves Technical Committees on Manufacturing Plant Control (TC 5.1), Management and Control in Manufacturing and Logistics (TC 5.2), Integration and Interoperability of Enterprise Systems (TC 5.3), and Large Scale Complex Systems (TC 5.4).

Technische Universität Wien (TU Wien) and Fraunhofer Austria are delighted to organize the 18th edition of INCOM in Vienna, Austria in August 28-30, 2024. Hosted by the Austrian Federal Economic Chamber (WKÖ), INCOM 2024 has provided a great forum and unique opportunity for exchanging knowledge and discussing theoretical advances, emerging topics and industrial experiences under the **flagship** topic of "**sustainable transformation towards autonomous manufacturing systems**".

Academic and industrial experts joined the event and shared their research results and empirical insights focusing among others on: digital twin, green factories and logistic networks, federated manufacturing platforms, virtualization, global manufacturing, autonomous and self-learnable systems, data-driven industrial engineering, Industry 4.0/5.0's strategies, models, and technologies, human interaction in robotics and cyber-physical systems as well as new advances in additive manufacturing, Physical internet, predictive maintenance, robotics and conversational AI applications in manufacturing and supply chain. At INCOM 2024, five outstanding keynote talks were delivered:

- Prof. Torbjørn H. Netland, ETH Zürich, Switzerland, "Augmented Intelligence for Next-Level Manufacturing Excellence"
- Prof. Dmitry Ivanov, Berlin School of Economics and Law, Germany, "The Future of Supply Chain Simulation and Digital Twins"
- Prof. Alexandre Dolgui, IMT Atlantique, France, "Information Control Problems in Manufacturing: History of IFAC INCOM Symposium"
- Prof. Andreas Kugi, TU Wien and AIT Austrian Institute of Technology, Austria, "Advanced Control for Sustainable Autonomous Manufacturing"
- Caroline Viarouge, EIT Manufacturing, France, "How European Manufacturing is shaping our Greener and Digital Future?"

INCOM 2024 intended to foster synergies among all participants and establish dialogues. To this end, two panels have been organized. The first panel focused on "Smart and Sustainable Manufacturing", with participation of academic experts from IFAC community, and also industrial experts from UNIDO, Infineon Technologies Austria, and EIT Manufacturing. The second panel was dedicated to CC5 involving TC chairs, where the discussion focused on "Resilient, Digital and Sustainable Manufacturing and Supply Chain". Offering a Doctoral Workshop on "Advances in Manufacturing and Logistics Management and Control Problems" as a pre-conference event on August 27, 2024, INCOM 2024 also highly acknowledged the value of next generation scientists and industrial experts. This is also reinforced by delivering Young Author Awards and Best Paper Awards.

To sum up, 360 submissions were reviewed, out of which 218 were accepted and presented at the symposium (acceptance rate: 60.5%). The paper were presented from 39 nations in front of the audience of 340 people. The conference received 42 session proposals, out of which 28 proposals with at least five accepted papers have been appeared on the symposium program. Further, the Doctoral Workshop involved 31 PhD candidates presenting their research proposals and progress to 10 senior advisors.

The current proceeding stores all the papers presented during the INCOM 2024 symposium, representing the current trends and evolution in twin transformation of manufacturing and supply chain. The INCOM 2024's editors would like to acknowledge the efforts of all contributors, namely authors, reviewers, technical associate editors, session organizers and chairs, as well as all IPC and NOC members. During the review process and planning the symposium program, we have been committed and humbly put efforts to assure scientific quality and significant contributions of the IFAC community to the body of knowledge in manufacturing and supply chain.

We, on behalf of all contributors of INCOM 2024, sincerely hope that the present proceedings inspires you on creating, sharing and implementing new ideas towards shaping manufacturing and supply chain of the future. We wish you a pleasant reading.

Vienna, August 2024

Fazel Ansari (AT)
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INCOM 2024's Editor and NOC Co-Chair

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A Conversationally Enabled Decision Support System for Supply Chain Management: A Conceptual Framework

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Abstract: This paper introduces a conceptual framework for integrating Conversational AI (CAI), specifically conversational agents (CAs), with Decision Support Systems (DSS) to enhance Supply Chain Management (SCM) decision-making processes. In today's complex supply chain environment, characterized by diverse processes and entities operating across different geographic locations, the effective use of AI in DSS is crucial. The proposed framework envisions a Conversationally Enabled Supply Chain (CESC) where decision-makers interact with the DSS using natural language through a CA, facilitating tasks such as data analysis, scenario analysis, and simulation. The choice of a conceptual framework as a research tool provides a systematic approach to collect and organize elements, offering a clear reference structure and a common language. This framework aims to enhance understanding, guide research and analysis, and integrate knowledge from diverse sources, contributing to a holistic understanding of the proposed CA-empowered DSS for SCM. The paper emphasizes the significance of CESC and sets the stage for future research and development in the domain, providing a foundation for ongoing work.

Keywords: Conversational Agents; Decision Support System; Functional Architecture; Supply Chain Management; Human-AI interaction

1. INTRODUCTION

A supply chain (SC) is typically described as a highly complex system, encompassing numerous processes (from the procurement of raw materials to the distribution of finished products to consumers) and entities (i.e., the different companies with their peculiar roles involved in the abovementioned processes), often extending across different geographic locations. The effective management of such a complex system – operating in an even more complex environment composed of different customers, global markets, competitors, and legal systems – necessitates a focalized effort for planning, execution, and control. Decision Support Systems (DSS) emerge as an essential tool in this context. A DSS is an information system intended to support business or organizational decision-making processes merging human intuition judgement and computer systems (Eom & Lee, 1990). A DSS offers a mix of data, analytical tools, and computational capabilities to support the decision-maker in selecting the best course of action to increase efficiency, profit, and customer satisfaction (Teniwut & Hasyim, 2020). Integrating Artificial intelligence (AI) in DSS may offer significant opportunities for supply chain management (SCM) enhancement (Dwivedi et al., 2021; Pournader et al., 2021; Tirkolaee et al., 2021; Toorajipour et al., 2021): Machine Learning (ML), Deep Learning (DL) and other methods can support the detection of patterns and the generation of new insights to direct the user in the decision-making process (e.g. demand forecasting, quality control, suppliers risks management, dynamic pricing, collaborative decision-making). Further, AI-enhanced or AI-empowered DSS can continuously learn from new data, adapt to changes, and proactively address complex challenges. However, not all of the possible factors behind an optimal decision can be algorithmically implemented due to the complexity or the nature of the factors. In the SCM decision-making processes, a DSS must be able to deal with highly complex environments where both qualitative and quantitative criteria play a substantial role. This aspect emphasizes the role and contribution of a human expert in integrating qualitative knowledge into the decision process and highlights the critical role of human specialists in bringing qualitative understanding to the decision-making table (Pinto et al., 2013). Indeed, traditional decision support tools leave the initiative to the users to choose the elements they want to observe or analyze (Ltifi et al., 2013). Thus, the interaction between the DSS and the decision-maker is a critical factor to be addressed. In this respect, a specific form of AI growing in relevance in practice and research is *conversational AI* (CAI) (Mariani et al., 2023). CAI is "*the study of techniques for creating software agents that can engage in natural conversational interactions with humans*" (Khatri et al., 2018), allowing humans to interact with computers using text and voice. Conversational AI enables AI-empowered conversational agents (CAs), which are "*software systems that mimic interactions with real people*" (Radziwill & Benton, 2017). One of the most common examples of – relatively simple – CAs is represented by chatbots (Dilmegani, 2024), which exploit the potential of

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Natural Language Processing (NLP) in marketing campaigns, online advertisement, brand management, customer relationship management and data collection (Toorajipour et al., 2021).

1.1 Research contribution

In this paper, we envision the integration of CAIs – and CAs in particular – with DSS to support SCM decision-making processes. Through a CA that provides a *conversational interface*, the decision-maker interacts with the DSS using natural language (textual or voice) to harness the computational power of the underlying system. The CA mediates between the decision-maker and the DSS, translating the users' queries into computational tasks – i.e., data collection, statistical analysis, data exploration, reporting, scenario analysis and simulation – that can be executed on the DSS. In this respect, the system operates as a *decision-maker companion* (or a *copilot*) that dialogue with the user and provides answers based on the available data and the exploration of the solution space using the analytical tools provided by the DSS. Such a CA would exploit the computational capabilities of the DSS, enhancing the effectiveness of the user experience in interacting with the system. We propose a conceptual framework of a high-level functional architecture for a CA-empowered DSS. The framework outlines the core components and main functionalities, with our approach focusing on key processes such as data analysis, user interaction, and decision-making facilitation. In this initial framework, we intentionally omit technical and specific implementation details to focus on the broader operational processes, ensuring the framework's adaptability across various industrial applications. The paper is structured as follows: Section 2 describes the basic requirements defining a conversationally enabled supply chain. Section 3 provides the methodology for this research. Then, Section 4 provides a detailed description of the proposed conceptual framework. Finally, Section 5 concludes the paper by delineating future work directions.

2. CONVERSATIONALLY ENABLED SUPPLY CHAINS

Paraphrasing (Cui et al., 2023), "*the future of autonomous supply chains lies in the convergence of human-centric design and advanced AI capabilities*". Human decision-makers grappling with the growing complexity of modern supply chains must interact with tailored SCM-DSS that leverage AI and other digital technologies to navigate an overwhelming amount of data and information effectively. In this respect, a *Conversationally Enabled Supply Chain* (CESC) is a supply chain in which decision-making activities (and, potentially, operational activities) can be managed through natural language interactions between the decision-maker and the SCM-DSS, where the latter has to provide detailed information on various aspects of the supply chain, as well as to identify, understand and solve problems and implement corrective actions. To this end, a CA-empowered SCM-DSS must be capable of: 1) engaging in natural language dialogue with the human decision-makers, understanding their specific requests and inquiries, and interpreting their underlying needs or intentions; 2) understanding the business context in which the analysis should be performed, which includes understanding industry-specific nuances, market dynamics, and organizational goals that influence decision-making; 3) conducting suitable data analysis and/or scenario optimization/simulation to identify the best answers to the decision-makers requests by processing large data sets and model potential outcomes; 4) detecting problems (i.e., deviations from expected performance) proactively from data, and autonomously alert the decision-makers to initiate an interaction with them; 5) learning from previous interactions, mistakes, and feedback provided by the decision-makers, thereby ensuring the system's evolution and adaptation; and 6) managing exceptions and unforeseen events to guarantee a safe and reliable process execution. These capabilities also delineate the boundaries of possible use cases for the CA-empowered DSS: cases in which the decision-maker needs to interact with data and systems to make informed SCM decisions. The following sections provide a conceptual framework that could guide the definition of a functional architecture of a CA-empowered DSS with the abovementioned capabilities.

3. METHODOLOGY

A conceptual framework is a research tool supporting the understanding of a concept or system by systematically collecting and organising its underlying elements. It enhances understanding of a concept or system by providing a clear reference structure, a common reference language, and clarifying relationships among the different elements. It could be helpful to guide research and analysis by providing a systematic interpretation of the concept or system under consideration, thereby enabling the integration of knowledge from different sources or disciplines, leading to a more holistic understanding. This is particularly important when the concept or system is new. Additionally, a conceptual framework may facilitate longitudinal analysis by documenting changes to the initial reference structure and relationships among elements over time. From a scientific viewpoint, the framework structure and contents may serve to analyze the existing literature, thus enabling the identification of each work's strong points and weaknesses concerning the different aspects indicated in the conceptual framework (Alarcón et al., 2009). By developing a conceptual framework, new knowledge is created by building on selected sources of information not derived from data in the traditional sense but through the assimilation and combination of evidence in the form of previously developed concepts and theories (Hirschheim, 2008; Jaakkola, 2020). The purpose is thus to develop logical and complete arguments about these associations rather than testing them empirically (Gilson & Goldberg, 2015). A conceptual framework gives a broad overview, which cannot usually be achieved by applying other traditional methods (Tirkolaee et al., 2021). It must contain the principal concepts and elements characterizing the subject to be studied and allow the identification, description, organization and understanding of these aspects. Figure 1 depicts the overall architecture of the proposed system, where the *Core Computational System (CCS)* (Section 4.3) represents where most data analysis activities (including understanding the input/problem) occur. The CCS is fed through the *User Interface* (Section 4.1) or by *Contextual Inputs* provided by the system itself and the external environment (Section 4.2). The CCS generates the *Outputs* to be provided to the user (Section 4.4) and information about the *System Status* (e.g., request for feedback, exception) (Section 4.5). This architecture is further detailed in Figure 2 and the subsequent Section 4.

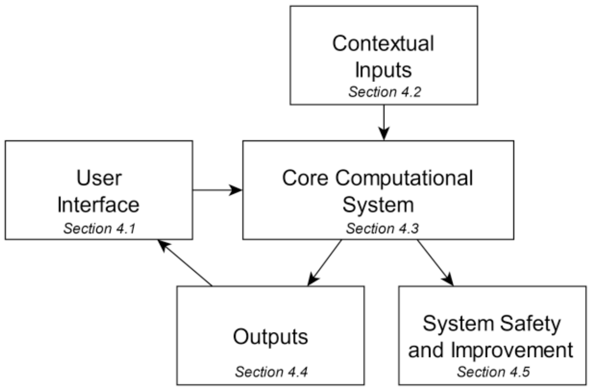

Figure 1. Conceptual framework structure

4. A CONCEPTUAL FRAMEWORK FOR A CA-EMPOWERED DSS

The proposed conceptual framework structure is composed of *manager modules* (Figure 2). Each module manages a specific aspect of the overall process and interacts with other modules to answer the user's input or respond to external stimuli related to external events, disturbances, or deviation from expected performance. Within these manager modules, processes and resources are orchestrated – that is, arranged, coordinated, and directed – to gather, generate, process, and organize data, information, and knowledge to support the decision-making process. We provide an abridged description of each manager module's scope, role, and main functions.

4.1 User Interface

In a conversationally empowered DSS, efficient and effective user interaction is pivotal. The *User interface manager* manages the two-way interaction with the users (also referred to as *episode*, which is a single, continuous conversation between the user and the DSS) getting the input – either in voice or textual form using Natural Language Processing (NLP) and Understanding (NLU) or Automatic Speech Recognition (ASR) tools – and converting the output in conversation form through the use of generative AI and Large Language Models (LLM). Unlike traditional autonomous systems, which generally lack the capacity for language understanding, LLMs can handle complex requests, offer real-time feedback and comprehensive explanations, and assist in decision-making (Cui et al., 2023).

4.2 Contextual Inputs

Contextual inputs refer to inputs coming from the context (i.e., the supply chain) rather than the users. In this respect, the *Event and context manager* modules allows to achieve situational or situation awareness, which requires a system capable of sensing the operational environment, including supply chain participants and objects, their interactions and changes in their state. In this respect, Complex Event Processing (CEP) and Supply Chain Event Management (SCEM) systems aim to recognize interesting situations when they occur (Flouris et al., 2017). This is a rather complex task, and most existing approaches lack the capability of handling events that originate not only from within the supply chain itself but also from the entire operational environment of the supply chain (Vlahakis et al., 2018). The *Performance manager*, instead, is devoted to problem detection. In our context, a problem is a (measurable) deviation from an expectation that prevents achieving a goal; therefore, the *Performance manager* is responsible for monitoring the supply chain's performance and detecting deviations concerning the targets and the overall company's objectives to define the problem to be tackled. Current performance and well-defined objectives and targets are crucial elements to be formalized and quantified.

4.3 Core Computational System

The *Core Computational System* comprises multiple modules devoted to analysis and data management. The *Goals manager* aims to define the goal to achieve given the input from the user or a stimulus from an external event. In other words, the goals manager determines the problem to be addressed and identifies the goal to pursue. It requires decoding the input (i.e., converting the external input to a format the system can understand) and may imply its decomposition in smaller sub-problems. In this respect, approaches such as Chain of Thought (Wei et al., 2023) or Tree of Thoughts (Yao et al., 2023) can decompose long and complex input into smaller and simpler steps. The output of this manager feeds the *Task manager* that organizes and supervises the actual execution. In our context, a task is a work that should be completed to generate a usable result. The system should be able to generate, plan, prioritize, and complete tasks in order to achieve the goal. The task may involve the use of data (through the *Knowledge and data manager*), external services (via the *External API manager*) as well as the interaction with computational models (via the *Models manager*) or existing software applications through the *Enterprise software portfolio manager*. In particular, the *Models manager* orchestrates the interaction between computational models and the *Task manager* to provide relevant data. In this context, meta-modelling can provide the rules and constraints to build models addressing the specific problem under consideration in the specific (sub)field of supply chain management and operations management. A relevant tool encompassed in this manager module is the Supply Chain Digital Twin (Ivanov, 2023), a digital replica of the physical supply chain network that emulates the flows and interactions among the involved actors to detect issues in advances and test alternative courses of action. Finally, this manager may also encompass Machine Learning (ML) models to analyse the data and identify patterns or clusters in the data. The *Knowledge and data manager* represents the memory of the system. Managing data and knowledge – i.e., efficiently retrieving existing information and storing new pieces of knowledge to be recalled in the future – represents a critical element of the system. The system's memory can be differentiated into *short-term memory* that allows the system to maintain a context of the episode, which in turn allows reasoning and to provide coherent and relevant responses based on the ongoing conversation with the users, and *long-*

term memory to store information over a significant period. In general, conversational systems are characterized by statelessness between episodes (i.e., new episodes do not have memory of previous episodes). Long-term memory allows us to overcome this limitation to support long-term context and improvement through self-reflection (see *Feedback and alert manager*). The *External API manager* is responsible for interacting with systems external to the company, usually through API calls. For example, it allows searching the Internet for data or information or interacting autonomously with external data sources and service providers. The external API calls must be orchestrated according to the goals, and the responses must be reconciled and integrated. This is an important capability that should be contextualised concerning the intended use of the system (i.e., the APIs to be used may depend on the intended scope of the system). Finally, *Enterprise software portfolio manager* orchestrates interactions with software applications and tools an organization uses for business operations. It typically includes applications for ERP, CRM, data analysis, and the like, each tailored to specific business functions. Like the *External API manager*, this manager requires contextualisation and tailored interfaces to communicate with existing in-house software applications in the company's portfolio.

4.4 Outputs

The main outputs are presented in the *Results manager* module. The execution of all the tasks may result in a set of outcomes from different sources (i.e., from the computational models, from the interaction with the other software in the portfolio, from the interaction with external services) that should be reconciled in order to provide a coherent answer to the user. In this respect, this manager plays the important role of "making sense" of all the data and results from other managers. This manager is quite challenging to be described exhaustively. However, the power of LLMs can be used to summarise the results coherently. The outcome of this manager is then transferred back to the *User interface manager,* who is in charge of communicating the results to the user in a conversational way.

4.5 System Safety and Improvement

A key aspect of the overall system is the integration of feedback loops that enable *self-reflection capabilitie*s to review past decisions and iteratively learn from prior mistakes to improve performance (Shinn et al., 2023). The *Feedback and alert manager* supports this aspect. In particular, feedbacks can be framed into two main categories: *user-provided* and *retrospective*. User-provided feedback is explicitly generated by the user during the conversation episode, therefore reflecting the user experience and representing a direct assessment from the user of the system's performance, relevance, and utility. This kind of feedback may also guide the next steps that the system should perform. Conversely, the retrospective feedback mechanism tracks the implementation and outcomes of the DSS recommendations over time. This long-term tracking is essential for assessing the real-world effectiveness of the advices provided, determining whether it led to successful outcomes, and facilitating the system's learning and adaptation processes. Such a dual feedback approach ensures system correction of errors, as well as stimulates evolution to meet user needs and expectations contributing to a dynamic and self-improving AI assistant. Although the system is meant to be autonomous in the definition, execution and summarization of all the tasks, sometimes it may require further input from the user to discern how to progress. The *Exception manager* is meant to safeguard against problems during the system operation, and to overcome stalling situations in which the system cannot progress autonomously. In this respect, an *exception* can be defined as an event or a situation occurring during the execution of a task that prevents the fulfilment of one or more tasks and the progress towards the goal. In this case, the interaction with the user may be necessary to solve inconsistencies or address specific problems encountered during the execution. Further, an alert system may determine the initiation of a conversation episode with the user when the system detects a problem through the *Performance manager*. Finally, the aim of the *Security manager* module is twofold: on one side, it should ensure that the output generated by the system complies with business, ethical and safety standards and guidelines, thereby reducing the risk of unintended consequences on the systems, its users, and the stakeholders. For instance, it could enforce data privacy regulations and operational safety checks. On the other hand, it aims to mitigate risks associated with data breaches and prevent malicious use of the system, such as unauthorized access or exploitation of system vulnerabilities. This element is critical in a broader cybersecurity strategy that extends beyond the immediate system.

5. CONCLUSION

The paper proposes integrating Conversational AI (CAI), specifically conversational agents (CAs), with Decision Support Systems (DSS) to enhance decision-making in SCM. CAs facilitate natural language interactions as mediators, translating queries into computational tasks. The framework envisions a Conversationally Enabled Supply Chain (CESC), emphasizing seamless CA, DSS, and external systems integration. The primary contribution of this research is the development of a high-level framework for a CA-empowered SCM-DSS, highlighting the potential of human-AI collaboration, and acknowledging the importance of user feedback and cybersecurity measures. One of the main limitations of this paper is the lack of an assessment of the current technology on the path to a real implementation. However, the proposed version of the framework should be considered a first attempt to systematize the required elements and factors; subsequent studies should investigate different aspects of the framework. In this respect, we highlight the following future research directions: i) develop use cases including the types of data that can be analysed, the algorithms used for scenario optimization/simulation, and the visualization tools used to present results; ii) develop the technical requirements of the functional architecture outlining the integration of the different components, referring to existing technologies; iii) explore the potentialities of existing LLM models and the requirements to implement local LLM specifically trained for the purpose of the CA-empowered SCM-DSS.

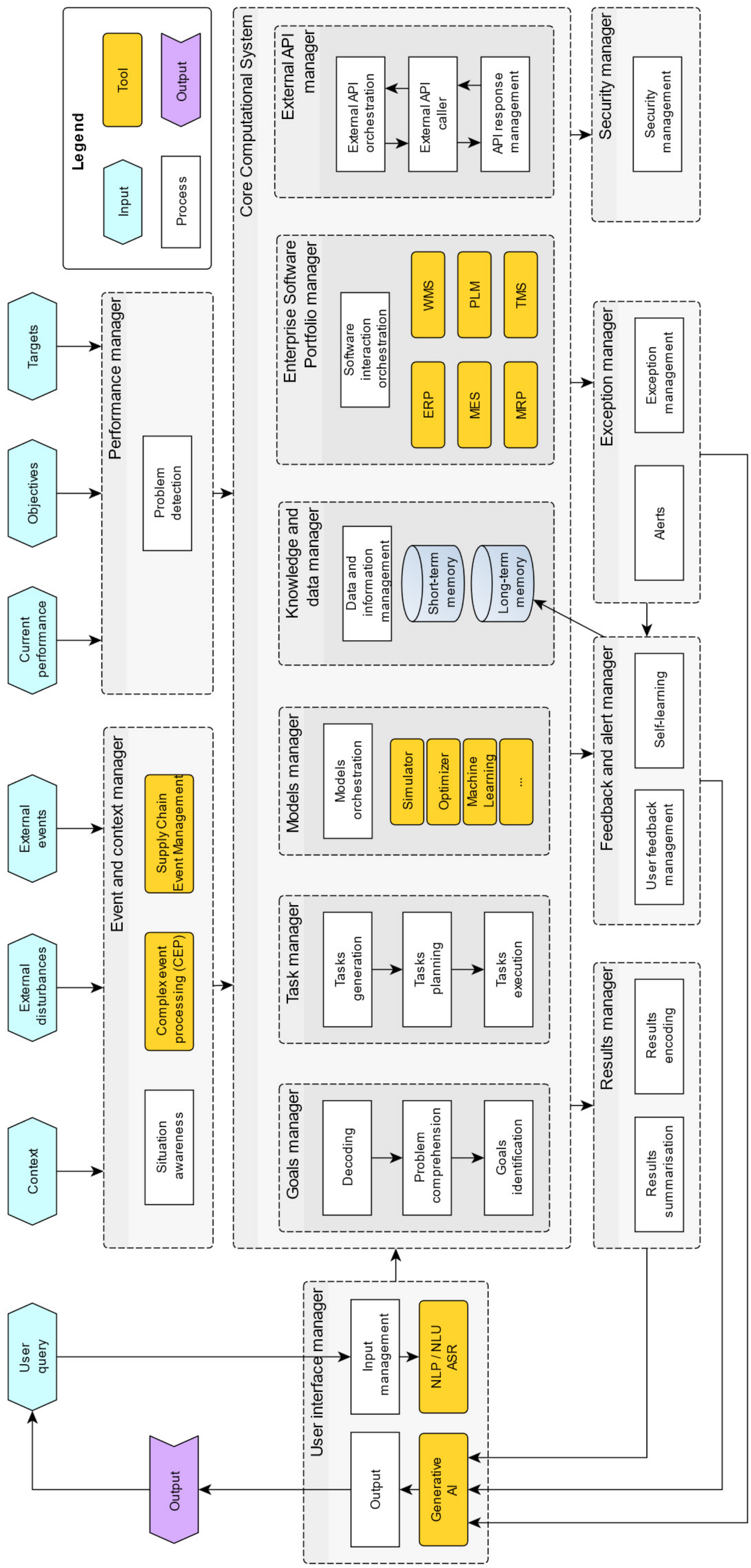

Figure 2. A conceptual framework for the design of a functional architecture of a CA-empowered DSS.

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