LLM-Assisted Augmented Intelligence for Context-Aware Decision Support: Current Trends and Integrated Approach

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Abstract: The growing complexity of technical, social, and business systems created and managed by humans determine the need for effective decision support. Recent advancements in AI push the boundary of what can be accomplished using AI tools and what are possible modes of human-AI interaction, bringing a concept of augmented intelligence, extending intellectual capabilities of human by variety of AI-based tools, while leaving final decision-making (as well as some other operations, e.g., goal-setting, coordination, control) to a human. This paper explores possibilities of using augmented intelligence for decision support. Starting with a general structure of decision-making process, it highlights and reviews current trends in several branches of AI, that are most important for decision support. Then, it proposes an integrated approach combining conversational, generative, and evaluative AI. Distinguishing features of the proposed approach are integration and mutual enrichment of data- and model-based techniques, as well as using modern LLMs as a basis for human-AI interaction during decision-making.

1 INTRODUCTION

The growing complexity and number of tasks solved by humans determine the need for the design of effective decision support systems (DSSs). Over the last few decades, a variety of techniques and approaches powering DSSs have been proposed and explored (Megawaty and Ulfa 2020). Recently, the development of machine learning methods, and in particular, large language models (LLMs), has led to their introduction into various human activity processes, including decision-making processes. However, this trend is also associated with a number of problems, such as the complexity of interaction with such models, the low level of trust in them, the unpredictability of the results they generate. This highlights the relevance and global nature of the tasks considered in the paper.

Among the approaches aimed at addressing these issues, one can highlight the development of dialogue-based DSSs, which involve both the argumentation of alternative solutions presented to the user and their evaluation alongside the assessment of user-proposed solutions, ultimately aiding the user in reaching a final decision through step-by-step recommendations. Therefore, there is urge in the development of new methods that would allow both to synthesize new generation of DSSs and to use them, supplementing human intelligence with artificial intelligence to improve the effectiveness of decision-making processes by preserving the leading role of humans in the decision-making process and organizing constructive dialogue between the decision maker (DM) and AI.

Context awareness is critical for effectiveness of decision support, as decisions inherently depend on situational factors, user constraints, and domain-specific knowledge. Without proper context integration, even technically optimal solutions may

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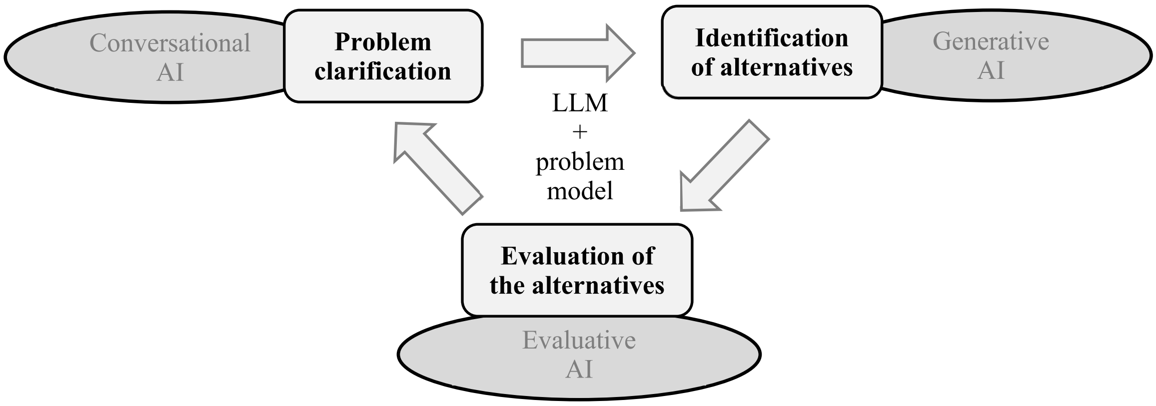

Figure 1: Decision-making cycle and relevant areas of AI.

prove impractical. Thus, context awareness serves not as an enhancement but as a core requirement for DSS in complex, real-world environments. Context-dependent decision support focuses on formulating solutions based on context (the task status, the situation of the DM, as well as her/his preferences), and a DSS implementing this approach should include the following stages: (1) clarifying the current task's formulation, (2) generating solutions feasible within the current context, (3) evaluating these solutions, including explanations, and providing the DM with recommendations for making the final decision.

Integrating the DM's intelligence with AI models and methods can significantly improve the effectiveness of context-dependent decision support. Such integration, including the development of AI models designed to support and enhance human capabilities (as opposed to autonomous AI decision-making), is referred to as augmented intelligence.

Implementation of the aforementioned stages of context-dependent decision support requires: (1) dialogue with the DM to clarify the task (since the user's preferences and task conditions are rarely fully known initially), (2) generation of possible solutions (alternatives), and (3) their evaluation while ensuring trust between the DM and the decision-supporting AI. This trust is achieved, in particular, through explainable reasoning. To meet these requirements, it is advisable to use methods from conversational, generative, and evaluative AI, respectively (Fig. 1). This can be viewed as a natural elaboration of existing trends in human-AI collaborative decision support and (Smirnov, Shilov, and Ponomarev 2022).

Thus, the approach proposed in the paper focuses on the three aforementioned types of AI (conversational, generative, and evaluative) in terms of developing models and methods necessary for their effective use by DMs within the framework of augmented intelligence. Application of LLMs appears promising for implementing these.

The rest of the paper is organized as follows. Section 2 provides a brief review of existing research in areas, relevant to the proposed approach. Based on this review, Section 3 summarizes key principles of the approach, which is presented in more detail in Section 4.

2 RELATED WORK

This section is structured according to the four main research directions indicated above, namely: LLM-based decision support, conversational, generative, and evaluative AI.

2.1 LLM-Based Decision Support

In recent years, with the rapid advancement of LLMs, a variety of general (and sufficiently universal) approaches have been proposed to support decision-making through natural language interaction with users.

There are several approaches trying to integrate different types of AI. For example, the integrated methodology proposed in (Ramaul, Ritala, and Ruokonen 2024) emphasizes the combined use of generative and conversational AI in chatbots like ChatGPT. The methodology is based on cyclic bidirectional interactions between these two AI types: the human initiates the generative AI, which then engages the conversational AI for further dialogue. This allows users to maintain continuous conversation with the system, initiating new queries, receiving responses, requesting clarifications or refinements, and obtaining updated answers. Similar methodologies, integrating several types of AI are Ask Grapho (Gutierrez de Esteban 2023), DeLLMa (Liu et al. 2024) and mPulse methodology (Danzer 2024).

From the technical perspective, using LLM for decision support is typically done by enriching LLM with additional modules and tools (sometimes, this is referred to as LLM-based agents). For example, RAGADA architecture (Pitkäranta and Pitkäranta 2024) integrates a library of specialized methods and algorithms with the generative capabilities of LLMs, enhanced by Retrieval-Augmented Generation (RAG) technology, providing means to select appropriate problem-specific algorithms and present their outputs in natural language.

Beyond general-purpose DSS architectures employing LLMs for user interaction (among other functions), there are also specialized frameworks for particular DSS categories, e.g., recommender systems, and conversational recommender systems (Feng et al. 2023).

A distinctive feature of the approach proposed in this paper is bidirectional integration of LLMs and conceptual modeling – leveraging conceptual models to enhance decision support quality while simultaneously employing LLMs for conceptual model construction during DSS development. Initial attempts to apply LLMs for building domain conceptual models have already emerged. For instance, (Kommineni, König-Ries, and Samuel 2024) presents an automated approach to knowledge graph construction using LLMs. Similar efforts appear in (Caufield et al. 2023; Babaei Giglou, D'Souza, and Auer 2023; Lam et al. 2024).

While LLMs may compete with ontologies in certain applications, their combined use shows significant potential. Moreover, complete automation of high-quality ontology development through LLMs remains unachievable (Neuhaus 2023), necessitating human-AI collaboration (through dialogue and DM involvement).

2.2 Generative AI

Generative Adversarial Networks (GANs) (Kusiak 2025; Chakraborty et al. 2024) represent one of the most powerful deep learning methods for artifact generation. Contemporary generative models are capable of producing diverse artifacts including text, images, videos, tabular data, and parameterized graphs (Fan and Huang 2019; Fan, Tech, and Huang 2019; Zhou et al. 2019; Jia et al. 2023). These models can be enhanced through conditional architectures that incorporate additional input parameters (conditional GAN), e.g, (Fan, Tech, and Huang 2019), and specialized modules that optimize training efficiency for domain-specific constraints (De Cao and Kipf 2018). Such capabilities make them potentially suitable for generating feasible solutions in DSSs, where outputs must satisfy both explicit requirements and implicit patterns learned from training data.

Notably, generative AI extends beyond neural network implementations. Alternative approaches include knowledge-based systems employing symbolic knowledge representations (dynamic modeling, metaheuristics, constraint satisfaction) and evolutionary algorithms (genetic, swarm intelligence, cellular automata) (Liao et al. 2024; Jiang et al. 2024). Hybrid methodologies also show promise, such as the integrated approach combining metaheuristics with question generation to create educationally balanced assignments with comprehensive topic coverage (Láng and Dömsödi 2024).

2.3 Conversational AI for Decision Support

Within the domain of conversational AI for context-aware DSS, two key challenges merit particular attention: model-oriented dialogue management using LLMs for situation modeling and requirement refinement, and LLM adaptation for domain-specific dialogues.

The refinement of user requirements through dialogue represents a critical application of LLMs in DSS. Here, the primary function of LLMs involves interpreting user inputs and mapping them to elements of the task model, including their potential values (Lawless et al. 2024; Han et al. 2023). However, in most implementations, the task model is predefined, with LLM integration designed accordingly. Extending these approaches to work with generalized structural models could significantly streamline DSS development.

Domain adaptation of LLMs aims to enhance response accuracy and reduce hallucinations. Widely applied adaptation methods fall into two broad categories: parametric and non-parametric. Parametric adaptation involves fine-tuning model parameters using domain-specific training samples. This process not only improves the model's grasp of specialized terminology and conceptual relationships but also optimizes dialogue performance for specific tasks (Tu et al. 2025). The complexity of parametric adaptation, coupled with the inherent optimization of many LLMs for general dialogue and instruction-following, has led to widespread adoption of non-parametric methods. These techniques, collectively termed “prompt engineering”, augment queries with relevant information unavailable during initial training (e.g., post-training updates or proprietary knowledge). Dozens of prompt engineering techniques now exist, serving not only for domain adaptation but also for generating step-by-step reasoning, reducing hallucinations and other tasks (Sahoo et al. 2024). Such methods have proven particularly effective in medical DSS prototypes, where they incorporate clinical guidelines (unavailable during model training) into physician recommendations (Zhao, Wang, and Peng 2024).

2.4 Evaluative AI

The role of evaluative AI within the proposed approach lies in assessing both human-proposed and AI-generated solutions, subsequently presenting these evaluations to DMs alongside explanatory rationale to facilitate more informed final decisions.

The evaluative AI embodies a paradigm shift from recommendation-driven to hypothesis-driven (Le, Miller, Zhang, et al. 2024; Miller 2023), where the AI system enhances rather than dictates decision-making processes. Specifically, it aims to strengthen decision-maker autonomy (Le, Miller, Sonenberg, et al. 2024), contextual awareness (Le 2023; Le, Miller, Sonenberg, et al. 2024), and DM’s procedural control through her/his hypothesis incorporation. While implementation approaches vary significantly, a defining characteristic of such evaluative AI systems is their capacity to present balanced arguments supporting and opposing each alternative.

Application of evaluative AI in DSS is a promising research direction, necessitating further work in three key areas: task model specification, solution evaluation, and their presentation to DMs.

2.5 Summary

1. The development of augmented intelligence-based DSS necessitates a comprehensive methodology that combines: natural language contextual interaction with users, generation of appropriate responses or solutions aligned with user requests, and justification & evaluation of proposed solutions preserving the final decision authority with human DMs. The most promising AI components for such methodology appear to be generative AI, conversational AI, and evaluative AI. Currently, no existing methodology integrates all three AI types for augmented decision support. While some approaches combine generative and conversational AI - where generative AI utilizes LLMs to formulate responses derived from logical inference or computational problem-solving, and conversational AI manages user interaction through LLMs and NLP techniques. The proposed in this paper approach aims to incorporate all three AI types to implement Simon's decision-making model (Simon 1979).
2. General-purpose LLMs, which form the foundation of conversational AI implementations, exhibit several inherent limitations. These limitations can be effectively addressed by employing LLMs as components within integrated solutions supplemented by decision-making methodologies and specialized reasoning tools.
3. Current research notably underrepresents the integration of conceptual modeling with LLMs, making this an exceptionally promising direction for advancing conversational AI techniques.
4. The predominant specialization of existing artifact generation methods (generative AI) similarly suggests the value of developing more universal solutions grounded in domain conceptual models, which would enable broader applicability with minimal adaptation.
5. The incorporation of evaluative AI into DSS represents another promising research avenue demanding development of task model specification methods, solution evaluation frameworks, and presentation models for DMs.

3 FOUNDATIONAL PRINCIPLES

This section summarizes key principles that shape the integrated approach, proposed in the paper. These principles are based on the literature review, in particular, on the identification of open issues and their potential solutions. The principles are structured along three dimensions: 1) the role of the prospective DSSs in management activities, their scope and functionality, 2) mode of interaction with the user (decision-maker), 3) problem representation and processing. These dimensions capture both “external” image of the DSS in its location among other tools available to the decision-maker, and its “internal” organization.

Scope and Role

1. DSS is aimed at helping decision-maker to understand situation in detail, it may propose solutions, help to evaluate solutions (proposed either by decision-maker, or by itself), but the final decision is made by human and human is responsible for it. Hence, it is an exemplar of augmented intelligence, when decision-makers competency and understanding of the problem situation is extended by external information and reasoning capabilities of AI.
2. DSS memorizes the scenarios, results of their executions, and decisions made and can use this knowledge to make recommendations in the future.

Interaction with the User

1. DSS interprets problems presented in natural language. This interface can be supplemented with other suitable forms of information presentation and input (depending on the problem domain of the DSS), but interface in natural language is obligatory. Despite the ambiguity immanent to natural language, the support of it as a main communication media obviates the need for creating problem-specific user interfaces and simplifies the adoption of the DSS.
2. DSS interacts with human, when necessary, e.g., to refine the query, to agree on the problem model, etc. In particular, it can help to resolve ambiguities unavoidable when using natural language communication. But moreover, problem is rarely clearly specified in advance, often even decision-maker *a priori* doesn't know all the details and preferences.
3. AI provides explanations of recommendations (proposed decisions) and evaluations (of the decisions proposed by itself or by decision-maker), giving a traceable critique, allowing to check whether these results can be trusted.
4. AI infers, manages, and takes into account decision-makers' preferences (explicit and implicit).

Problem Representation and Processing

1. DSS is context-aware, it infers and takes into account environment of the problem, decision-makers perspective and other transient information related to the problem.
2. DSS builds a model of the problem (or several semantically interoperable models). Specifics of these models may vary depending on the problem domain and problem itself, however, model building on the one hand, allows clarifying intricacies of the problem at hand and its relations to other elements of the domain, on the other hand, it sometimes allows employing efficient and explainable techniques, fulfilling the explainability principle. This is one of the most important principles and in severely influences several other.
3. DSS decomposes complex problems into simpler ones. Such decomposition is often made based on the model of the problem and on some process-based representation of similar problems.
4. Multi-aspect semantically consistent representation of the proposed solution. A potential solution sometimes has to address the requirements of several stakeholders, who may deal with the problem on different levels of abstraction or from different perspectives. Solution representation should allow such multiple views, ensuring that they are consistent.
5. Utilization of existing knowledge. Such utilization can take two forms: on a meta-level, domain models can be viewed as a refined representation of domain knowledge. On the factual level, domain knowledge is represented in variety of structured and unstructured resources that can be interpreted and leveraged.

4 THE PROPOSED APPROACH

The article primarily examines support in solving complex tasks that cannot be fully delegated to AI. Accordingly, the main operational scenarios of the decision support system (DSS) are those in which AI generates recommendations, provides the necessary information for decision-making (including explanations), and evaluates possible solutions, while humans use the AI's outputs to form their own decisions and select the final solution.

The central element of the proposed approach (see Fig. 2) for developing context-dependent decision support systems is the process of model specification using conceptual modeling techniques, as well as information extraction and generalization methods to systematize knowledge about the problem domain.

Thus, according to the proposed methodology, during the DSS development phase, two closely interconnected parallel processes are carried out in a dialog mode: (a) the analysis of unstructured (textual) and structured (database) information sources about the problem domain; (b) the construction and refinement of a conceptual model of the problem domain, which includes the main object classes, their relationships, the decision-maker's (DM) task models, their possible decomposition into subtasks, and the anticipated solution scenarios.

During the DSS operation phase, the DM's goal is identified, and the model of the current task is specified (populated with concrete attributes). This refined task model is then used to generate and evaluate solutions using developed generative and evaluative AI methods, respectively.

As it was already noted, the proposed concept amalgamates several branches (or, flavors) of AI, here, the roles of different types of AI in the proposed framework are summarized:

1. Generative AI. Within the proposed approach, the objective of generative AI methods is to construct solutions aligned with the decision-maker's (DM) task. A common feature of the generative AI methods considered here is that they take as input a task model constructed through user interaction using an LLM (Large Language Model), along with elements of the problem domain model. Two key directions in generative AI are deemed relevant: a) optimization-based approaches (potentially constraint-aware), primarily relying on metaheuristics; b) generative neural network models. To select appropriate solution-generation methods, it is necessary to develop a method for determining dependencies between problem domain models and the corresponding solution-generation techniques. When considering solution generation directly via LLMs, attention should be given to investigating their analogy with crowd computing. In both cases, solutions are obtained through unreliable agents, and crowd computing has developed various techniques to process such results and enhance their reliability.

2. Conversational AI. The role of conversational AI methods in the proposed approach is to construct and refine the problem domain model (during DSS development) and the specific task model (during DSS operation) through natural language dialogue with the user. The proposed approach centers conversational AI around LLMs, which currently represent the most promising tool for natural language interaction. Specifically, LLMs are used for: a) acquiring domain knowledge, context, and user preferences through dialogue; b) providing the user with information (e.g., solution evaluations) in natural language. However, generic LLMs are not always suitable for decision support in specific domains. Therefore, one of two kinds of adaptation of LLM to the domain can be used:

- parametric adaptation, which involves fine-tuning the LLM to optimize dialogue behavior for the given task. The most demanded here are resource-efficient techniques allowing to reduce computational complexity of the LLM fine-tuning (e.g., Quantized Low-Rank Adaptation – QLoRA).

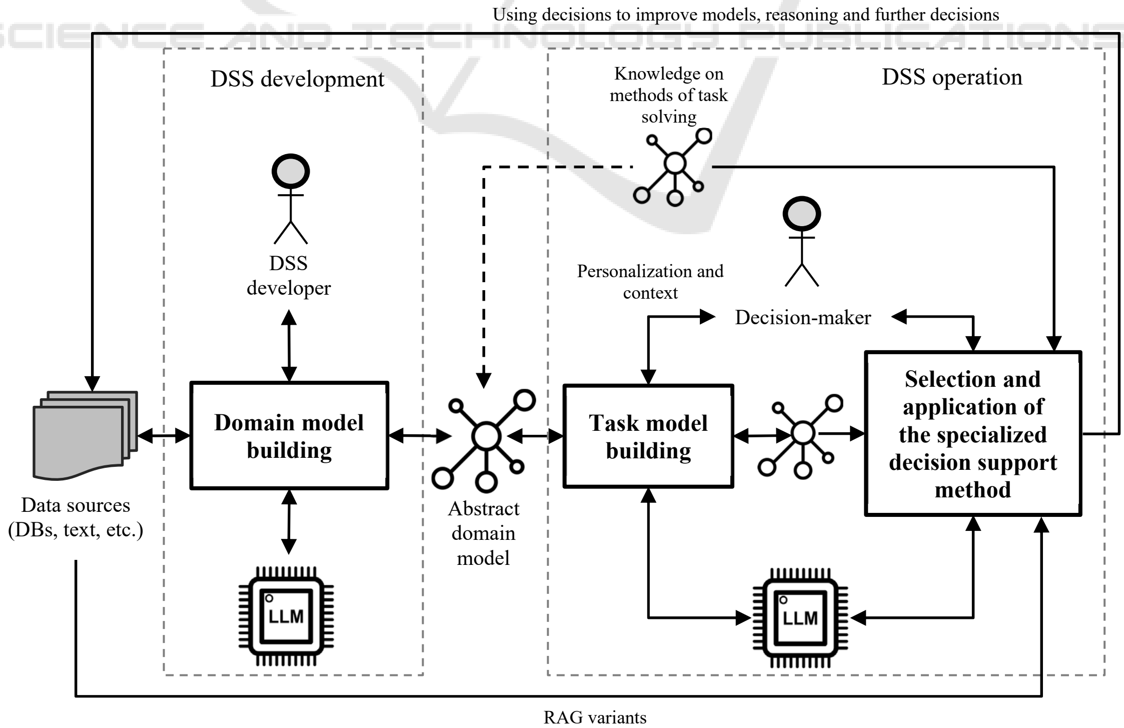

Figure 2: General scheme of the approach.

- non-parametric adaptation, which encompasses solutions implemented via LLM extensions (often termed LLM agents), including: prompt engineering methods for structured, goal-oriented dialogue; retrieval-Augmented Generation (RAG) to enhance responses with external knowledge, reducing hallucinations and improving answer quality and some other techniques.

3. Evaluative AI. The role of evaluative AI methods in the proposed approach is to assess solutions—whether proposed by the DM or generated by AI—and present these evaluations to the DM along with explanations to support more informed final decisions. Evaluations are performed using the task model and problem domain model, supplemented with pros and cons for each assessed solution.

5 CONCLUSIONS

The growing complexity of modern business and technical systems demands advanced decision-support methodologies that augment human intelligence rather than replace it. This paper has explored how conversational, generative, and evaluative AI—integrated into a unified framework—can enhance decision-making while preserving human agency in critical functions like goal setting and validation. By combining data-driven and model-based techniques with LLM-mediated interaction, the proposed approach enables adaptive, context-aware support that evolves alongside dynamic real-world challenges.

Key advantages include the system's ability to: (1) leverage structured and unstructured knowledge through hybrid AI methods, (2) provide explainable, auditable reasoning via evaluative components, and (3) maintain natural human oversight through conversational interfaces. Future work should address computational efficiency and domain-specific customization while maintaining ethical alignment. As AI capabilities progress, such augmented intelligence systems will become indispensable for balancing automation with human judgment in high-stakes decision environments.

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