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Mini Review

Evaluation and Adaptive Complexity of Cognitive Information Systems

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Abstract: Contemporary business Decision-Making (DM) requires adaptive systems capable of aligning Artificial Intelligence (AI) with human cognitive reasoning. Traditional Decision-Support Systems (DSS) struggle to address the multidimensional and subjective nature of modern decisions. Cognitive Information Systems (CIS) aim to bridge this gap by enabling continuous, adaptive interaction between human (Carbon) and system (Silicon) agents. By leveraging AI, Generative AI (GenAI), and automation, CIS can enhance cognitive alignment, support personalized decision environments, and sustain system-user trust even in dynamic, uncertain conditions. Cognitive Resonance is a measurable attribute of CIS that reflects the degree of alignment between system outputs and user cognitive feedback during dynamic interaction. It captures how the reasoning structures of Carbon and Silicon agents become synchronized through iterative DM. The Cognitive and Artificial Intelligence Evaluation (CAIE) model offers a structured framework to assess cognitive system maturity across six key domains. These components enable CIS to sustain cognitive alignment and effective decision support, even under evolving and unpredictable organizational conditions.

Keywords: Artificial Intelligence; Cognitive Information Systems; Cognitive Resonance; Personalization; Decision-Making; Human-Computer Interaction

I. INTRODUCTION

In today's complex, rapidly changing, and uncertain business environment, improvements in how data are managed in Decision-Making (DM) must be achieved by incorporating diverse information sources and by responding to strategic, tactical, operational, and contextual demands. While traditional Decision-Support Systems (DSS) are used to automate and streamline data collection and processing for managers, the cognitive processes involved in managerial decision-making are often insufficiently supported. Managers frequently struggle to reconcile the outputs of their DSS with their cognitive models, thereby diminishing trust and transparency, and applying a level of consistency with their decisions. To meet this challenge, Cognitive Information Systems (CIS) have evolved to create adaptive cognitive systems where human (Carbon agents) and machine (Silicon agents) constantly interact through continuous cognitive interaction in a dynamic environment to facilitate their decision-making process. Rather than simply automating tasks and providing outputs, CIS actively engages with human cognition by aligning system-generated representations with the user's reasoning structures, preferences, and decision environments [1]. The purpose of this synchronization is to decrease cognitive load, increase transparency, and enable the integration of both objective data and subjective organizational priorities in the coherent cognitive processes employed by users for decision-making. Although incredible advances have been enabled in educational and predictive systems through Artificial Intelligence (AI) technologies, the levels of active and dynamic cognitive alignment have consistently been lacking. Conventional AI models tend to focus on the task-specific optimization of outputs and do not engage in the complexity of managerial reasoning or subjective assessments. CIS integrates learning, reasoning, interaction, memory, personalisation, and optimisation into a cohesive cognitive system that negotiates the whole cognitive processing for the decider by being sensitive to the decider's mental models. Cognitive Resonance can only be achieved while retaining the relationship between system outputs and user reasoning patterns, which enhances user trust, transparency, and confidence in decisions [1]. This resonance is typically achieved by composite system environments, including adaptive user interfaces, cognitive evaluation models, personalized interaction, and complex AI.

This paper outlines a consolidated framework for Cognitive Information Systems, bringing together the components into a single comprehensive decision-support structure. In doing so, the paper considers how Artificial Intelligence, Generative AI (GenAI), and Robotic Process Automation (RPA) have increased the adaptive capabilities of systems by learning about the interaction, generating exploratory scenarios, and carrying out workflows through automation. In addition, the paper examines how Cognitive Resonance and Human-Computer Interaction (HCI) facilitate an iterative process of cognitive infocommunication through realistic synchronizing between system behaviors and human cognition. Moreover, the paper also examines how cognitive system maturity can be partially examined using the Cognitive and Artificial Intelligence Evaluation (CAIE) model, comprising six cognitive domains required for achieving continuous alignment. Lastly, the paper appraises how hyperpersonalization can dynamically adapt system interactions based on user preferences, enhancing decision-making transparency and reducing cognitive load. By assessing and bringing together the components, Cognitive Information Systems become adaptive, cognitively aligned contexts which can support the complexities of multi-dimensional managerial reasoning and organizational learning.

II. AI, Generative AI, and Robotic Process Automation

The progress of Artificial Intelligence has led Cognitive Information Systems to evolve from traditional data processing systems to adaptive, cognitively enhanced systems. The evolution of these systems from rule-based approaches to machine learning and deep learning has resulted in systems and architectures that can generalize, model the future, and act adaptively to both structured and unstructured data [2- 4]. For CIS, AI provides the infrastructure needed to identify complex relationships, anticipate developments, and facilitate managerial decision-making within fluid and dynamic business conditions [5]. This capacity allows these systems to respond to organizational complexity, external condition change, and changes in the strategic matrix.

AI technologies now offer the means to build systems that can adapt and improve on an ongoing basis, thereby facilitating higher-order cognitive functions such as personalization [6]. Generative AI is the next step in cognitive system evolution as it expands the scope of AI capabilities beyond classification and anticipation. GenAI allows these systems to generate new contextually appropriate content in various modalities, including text, simulations, and synthesized knowledge. For cognitive systems, GenAI allows systems to generate scenarios, narrate occurrences, and communicate interactively, informed by human cognitive models [7]. Systems with natural language generation capabilities can also recommend, justify, and forecast in a manner understandable to the end user, which improves their trust and comprehension. While AI and GenAI address the cognitive layers of analysis and communication, Robotic Process Automation and Intelligent Process Automation (IPA) address the operational layer by automating routine processes [8, 9]. These technologies can automate repetitive tasks, manage workflows flexibly, and integrate AI-based logic into routine enterprise operations. This situation allows organizations to leverage RPA and IPA to shift cognitive efforts toward higher-order reasoning, which continues to reinforce the explicit cognitive intent, consistent with CIS [10, 11].

Nevertheless, the rapid expansion of AI, GenAI, and RPA integration into CIS comes with ethical issues. Specifically, how an organization handles issues such as data privacy, algorithmic bias, decision transparency, and accountability will have impacts on organizational trust and regulatory compliance. Robust governance systems, explainability protocols, and transparency in the audit trail of these interconnected technologies must be in place as effective safeguards to protect the integrity of the systems and confidence of the users [12, 13]. In addition, these governance dimensions will also support Cognitive Resonance, through increased system transparency, congruence in system outputs and user expectations [1]. By supporting continuous learning, real-time adaptation, scalable automation, and narrative explanation capacity, AI, GenAI, and RPA provide the technical foundation for enterprise-level Cognitive Resonance.

III. Cognitive Resonance and Human-Computer Interaction

According to the design foundation of the CAIE framework, Cognitive Information Systems are integrated decision-support environments that possess all of the key cognitive functions. Based on Hurwitz’s definition, CIS has three main components: contextual awareness from underlying models, hypothesis generation (i.e., developing explanations for observed events), and continual adaptation through learning from data over time [14]. While static algorithmic outputs are not directly provided by these systems, adaptive cognitive processes are still performed within complex contexts, allowing for integration and dynamic processing of knowledge in a decision-making environment. In the case of CAIE, these systems are expected to enhance the cognitive processes of the Carbon agent by creating understandability, interpretability, and reasoning capacity [1]. This interaction enables synergic engagement between Carbon and Silicon agents through cognitive feedback mechanisms. The resulting operational efficiency is governed by mechanisms that ensure semantic alignment and adaptive cognitive support during iterative decision interaction [15].

In these adaptive cognitive interactions, as discussed, Cognitive Resonance (r) is the primary factor that helps to realize a dynamic fit between system reasoning processes and human decision-making structures. It helps align system-based decision recommendations with the cognitive expectations, reasoning practices, and subjective preferences of human decision-makers [16-19]. In complex decision environments, decisions are rarely based on objectivity alone. Strategic decisions require attention to subjective aspects such as organizational priorities, market uncertainties, or risk preferences. Cognitive Resonance incorporates these subjective dimensions into the decision-making process and facilitates consistent alignment of system-generated outputs with areas of analytical focus and the implicit reasoning of managers. As Cognitive Resonance increases, managers are more likely to develop trust, transparency, and confidence in the outcomes that can be supported by the system. Cognitive Resonance (r) is formally defined as the degree of correspondence between system recommendations and the evolving preferences and expectations of the decision-maker, conceptually ranging from 0 (no alignment) to 1 (perfect alignment), indicating how well the reasoning of the system aligns with the cognitive evaluation of the manager. The adaptive development of Cognitive Resonance depends on the ongoing collaborative and dynamic interactions between Carbon agents and Silicon agents through Human-Computer Interaction. HCI is a dynamic process of cognitive infocommunication, where content, context, and reasoning structures are continuously exchanged, adapted, and optimized across both agents [20]. Both the system and the decision-maker derive cognitive information iteratively, interpreting that information and gradually developing resonance. During this adaptive process of Cognitive Resonance development, different cognitive elements evolve at the same time: adaptations to content, context, convergence of expectations, and feedback of preferences, which all serve to develop resonance. With increasing decision complexity, the system can adapt its reasoning structures to strengthen and stabilize Cognitive Resonance, albeit under changing decision parameters. The process of hyperpersonalization further supports this type of adaptive alignment by encompassing user-specific cognitive styles, task characteristics, and behavioral patterns, thereby allowing the system to provide the content in a form or format that reduces cognitive effort and enhances clarity of decision-making.

IV. Cognitive System Evaluation

As Cognitive Information Systems transform into dynamic, learning-based environments, CIS confront a new level of cognitive complexity, which introduces challenges beyond the scope of traditional system assessment approaches. Commonly used performance measures – such as processing time, task accuracy, or algorithmic precision – do not provide an adequate characterization of the abilities of systems designed to align with human cognition and support complex managerial thinking and reasoning. Without a structured evaluation of the cognitive dimensions, organizations risk deploying technically advanced systems that fail to deliver meaningful Cognitive Resonance, user trust, or long-term decision support. To address this multidimensional evaluation challenge, the Cognitive and Artificial Intelligence Evaluation framework was developed. Rather than focusing on isolated technical functions, CAIE provides a structured taxonomy for assessing the completeness, depth, and cognitive maturity of decision support, allowing for the systematic identification of both existing strengths and functional gaps that may affect cognitive alignment, decision clarity, or personalization [21-24].

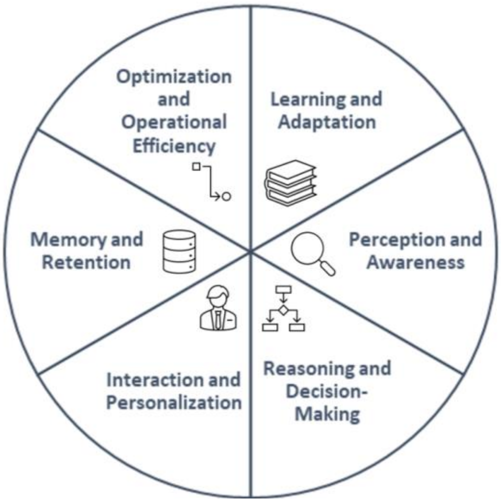

Figure 1. *CAIE Framework dimensions*

The CAIE framework divides system capabilities into six interrelated cognitive dimensions-zones [25-27] – as presented in **Fig. 1** – each representing a fundamental aspect of cognitive functioning:

- **Learning and Adaptation:** The system's ability to acquire new knowledge, extract patterns from dynamic data streams, generalize across varying decision contexts, and continuously adjust reasoning models as business environments evolve.

- **Perception and Awareness:** The processing of diverse external data inputs, including multimodal sensory information, unstructured text, real-time environmental signals. This dimension also includes situational awareness, anomaly detection, and temporal context interpretation.
- **Reasoning and Decision-Making:** Logical problem-solving, multicriteria evaluation, trade-off handling, ethical reasoning, and support for both tactical decisions (short-term optimization) and strategic decisions (long-term goal alignment), incorporating subjective managerial priorities.
- **Interaction and Personalization:** Support the adaptive communication, convey behavioral feedback, integrate user-specific preferences, and realign cognition through Hyperpersonalization.
- **Memory and Retention:** Management of Short-Term Working Memory, maintaining knowledge for the Long-Term Memory, and managing Advanced Memory, World Model Memory.
- **Optimization and Operational Efficiency:** Managing use of computational resources needed to provide an effective governance framework, scaling the system based on usage, speed of decision-cycle, risk-efficient trade-offs, and ensuring cognitive systems can sustainably integrate with complex business domains.

The CAIE framework allows organizations to assess cognitive system maturity in a structured and flexible manner, facilitating both horizontal benchmarking across different industries and vertical assessment of internal system progress over time. The alterable weighting of the CAIE framework allows organizations to structure assessment according to their specific internal priorities related to dimension, resources for governance, and complexity of decision-making in sectors as varied as manufacturing, healthcare, logistics, and financial services. Further evaluation concepts may include a structured, quantitative research method, whereby cognitive functions could be assessed along three axes: implementation presence, performance, and contextual relevance. These inputs – collected from developers, users, and stakeholders – could support the generation of weighted scores at the zonal level, contributing to composite indicators. The evaluation may be supported by mathematical techniques such as multi-criteria aggregation, weight normalization, and matrix-based structuring to enable systematic comparison and tracking of cognitive maturity across systems. When CAIE is embedded in system design and development, the assessment of cognitive system maturity has transitioned from a fixed technical audit (as is still the norm) to an ongoing strategic diagnostic process that supports various manifestations of Cognitive Information Systems towards greater cognitive completeness and productive human-aligned decision support. Furthermore, the implementation and ongoing sustainability of these cognitive systems are fully enabled by Artificial Intelligence technologies because they are the core functional components represented by the CAIE framework [14].

V. HYPERPERSONALIZATION

As Cognitive Information Systems aim to facilitate long-term Cognitive Resonance, it is increasingly essential that the system can dynamically align outputs with each decision maker's cognitive structures. Hyperpersonalization is the technical mechanism of CIS enabling the system-level resonance of outputs to be personalized cognitive synchronization to each decision maker by allowing individual system outputs to adapt to changing rational structures, underlying subjective preferences, and dependent situational business contexts [28, 29]. A key operational domain for hyperpersonalization lies in the design of visual decision interfaces. Dashboards, as primary cognitive interaction points, are configured to minimize cognitive load and optimize information processing through scientifically grounded design principles. Color theory is employed to manage arousal levels and direct attention: warmer colors (e.g., red, orange) enhance alertness for critical indicators, while cooler tones (e.g., blue, green) promote cognitive stability. Layout models such as Z-pattern eye-scanning paths are used to guide attention toward priority elements, while white space, typography, and visual contrast are carefully balanced to reduce unnecessary cognitive effort and improve decision clarity [30, 31].

Beyond visual adaptation, hyperpersonalization enables CIS to integrate subjective and strategic factors directly into the decision-making process. These may include organizational priorities, evolving risk tolerance, the market-specific considerations, or user-specific evaluation criteria that would not otherwise emerge from strictly data-driven optimization models. By integrating these multidimensional cognitive factors, Cognitive Information Systems function as adaptive cognitive systems and architectures actively support structured reasoning, preference alignment, and context-sensitive decision-making across uncertain and dynamically evolving organizational environments. By continuously adapting in real time, hyperpersonalized outputs stabilize Cognitive Resonance in the ever-increasing variability of decision environments. This, in turn, supports trust-building, continued system usage, and more consistent decision accuracy as a business context and user expectations evolve.

VI. Discussion

The proposed Cognitive Information Systems (CIS) framework highlights that facilitating dynamic cognitive alignment between system reasoning and human decision-making requires a multi-dimensional system design that involves AI, Cognitive Resonance, hyperpersonalisation, and structured cognitive appraisal. These interdependent components collectively address the increasing complexity and subjective nature of business Decision-Making (DM) contexts. Artificial Intelligence, Generative AI (GenAI), and Robotic Process Automation (RPA) build CIS's computational capability through adaptive learning, scenario development, dynamic data assessment, and scalable workflow automation. Each technology allows systems to handle vast amounts of heterogeneous data, analyze relevant patterns, and simulate decision paths through highly unpredictable organizational situations. Cognitive Resonance ensures that system outputs are not only computationally correct but also cognitively aligned with managerial reasoning that holds both considerations of subjective preferences and strategic intention.

The Cognitive and Artificial Intelligence Evaluation (CAIE) framework provides a structured mechanism for assessing system maturity across six key cognitive domains, offering both diagnostic and developmental insights. This multizonal evaluation approach supports systematic identification of functional gaps, guides system-level development, and ensures that technical enhancements directly contribute to cognitive completeness and user-aligned decision support. Hyperpersonalization operationalizes individualized cognitive alignment by adapting system outputs to user-specific reasoning patterns, decision contexts, and cognitive processing capacities. Through real-time adjustment of informational density, content sequencing, and adaptive visualization, hyperpersonalized CIS reduces cognitive fatigue, enhances decision clarity, and optimizes reasoning performance under varying cognitive demands.

Collectively, these integrated components establish Cognitive Information Systems as an adaptive cognitive framework that supports dynamic managerial reasoning, maintains sustained cognitive alignment, and enhances organizational decision quality in increasingly complex and volatile business environments.

VII. Conclusion

This study has presented a high-level unified Cognitive Information Systems framework that systematically integrates Artificial Intelligence, Cognitive Resonance, hyperpersonalization, and cognitive evaluation into an adaptive decision-support framework. By extending beyond conventional performance metrics, the framework addresses computational and cognitive challenges central to modern decision-making.

AI, GenAI, and RPA provide the necessary computational infrastructure for adaptive learning, data interpretation, and automation, while Cognitive Resonance ensures that system outputs remain aligned with the reasoning structures, preferences, and evolving priorities of decision-makers. Hyperpersonalization dynamically adjusts system behavior to individual cognitive patterns and situational demands, sustaining resonance across diverse operational contexts. The CAIE framework enables structured evaluation of cognitive maturity, offering organizations a systematic approach to monitor system development, identify functional gaps, and ensure cognitive completeness across six defined cognitive domains. The described framework is fully supported by Artificial Intelligence technologies, which serve as the functional enablers of Cognitive Information Systems and any complex AI-based architecture evaluated within the CAIE framework. By decomposing system capabilities into distinct cognitive domains and interrelated functionalities, CAIE enables a structured assessment of cognitive completeness and alignment across diverse decision-support systems.

The proposed framework provides a scalable and flexible basis for the creation of cognitively aligned decision environments that are capable of supporting complex managerial reasoning in rapidly changing business contexts. Additional research is still needed to improve the measurement of Cognitive Resonance, develop real-time adaptation algorithms, and systematically observe organizations with cognitive systems that are fully integrated under different levels of decision complexity. Future work will involve the use of structured, quantitative approaches to assess cognitive functions based on presence, performance, and contextual relevance, supporting maturity evaluation and system-level comparison.

AUTHOR CONTRIBUTIONS

Attila Márton Putnoki: Conceptualization, Writing, Review and editing.

Tamás Orosz: Writing, Supervision, Review and editing.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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