The Role of Modeling and Analysis Techniques in Designing Joint Cognitive Systems

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The goal of Cognitive Systems Engineering (CSE) is to develop systems that effectively support cognitive work in complex environments where humans and technology interact, thereby enhancing performance, mitigating errors, and increasing resiliency. In a joint cognitive system (JCS), humans and machines are a unified system collaborating to accomplish a shared goal. While computers are programmed to make decisions using binary operations, humans are guided by individual mental models that shape how information is processed and interpreted (Hoffman & Smith, 2017). This can create a coherence problem when system representations fail to align with the human's expectations, potentially leading to errors and catastrophic failures. CSE uses modeling and analysis techniques to mitigate these misrepresentation problems by understanding cognitive processes, identifying potential usability problems, and designing systems with intuitive and efficient interfaces. The process of developing a JCS includes modeling the work domain, analyzing cognitive tasks, designing support systems, and evaluating joint performance.

Modeling is used in CSE to develop JCSs by capturing the cognitive work being performed under variable and uncertain conditions, and simulating how JCSs could behave under various scenarios. Modeling can also support design and evaluation by illustrating how cognitive functions are distributed, while identifying efficient methods to allocate functions between humans and machines that support joint performance. The modeling process can identify affordances and limitations within the operational environment, and characterize the system's purpose, functions, and constraints (Cormier et al., 2014).

Cognitive Performance Models (CCPMs) in JCS development

Computational Cognitive Performance Models (CCPMs) are computational representations of human cognitive processes such as perception, memory, decision-making, and problem-solving

(Kim & Nam, 2020). They serve as tools to simulate, predict, and evaluate human performance and cognitive workload as humans interact with a machine interface (Fortino et al., 2023). CCPMs model how humans are likely to perform cognitive tasks under stress, uncertainty, and different workloads. This allows system designers to predict joint system behavior in various operational contexts, while identifying bottlenecks, errors, or conditions leading to cognitive overload. CCPMS can optimize the division of labor between human and machine agents, and evaluate the impact of different automation levels or interface designs on human performance (Zahabi & Park., 2023). CCPMs can be applied at various stages of JCS design such as design prototyping and evaluation, workload performance prediction, human-automation interaction modeling, and training and skill development. The various cognitive performance models (GOMS, ACT-R, EPIC, SOAR, and QN-MHP) all aim to estimate task performance and cognitive workload, but they have distinct characteristics, limitations, applications, and tools.

GOMS (Goals, Operators, Methods, and Selection Rules)

GOMS (Goals, Operators, Methods, and Selection Rules) is a task analysis technique developed by the human-computer interaction field to model routine, well-learned user behaviors. Goals represent what the human agent wants to accomplish, operators represent the actions that must be performed, methods are the order of operations to achieve the goals, and selection rules are criteria for choosing among methods (Kieras, 2004). Application of GOMS has been valuable for analyzing and predicting user performance and learning, evaluating the efficiency of user interactions with interfaces, comparing alternative interface designs based on predicted task completion times, and identifying cognitive bottlenecks in workflows (John & Kieras, 1996). While GOMS is appropriate for highly procedural tasks, it is less suitable for modeling learning, error recovery, or dynamic decisions.

Adaptive Control of Thought-Rational (ACT-R)

Adaptive Control of Thought-Rational (ACT-R) was developed as a high-level simulation of human cognition with the goal of predicting human performance in the real-world (Kim & Nam, 2020). ACT-R represents cognition as an interaction between components of declarative memory, procedural memory, perceptual-motor modules, and goal modules. Declarative memory stores facts as chunks, with activation processes controlling access to this information, and guiding behavior based on learned facts (Anderson et al., 2004). The procedural memory system is composed of production rules (if-then statements) that determine how and when knowledge is applied. Perceptual-motor modules simulate how sensory information is processed and used to control motor actions, such as interfaces requiring vision, hearing, and hand movement. Goal modules manage current intentions and goals, including managing transitions between subgoals. ACT-R is utilized in JCS development to simulate cognitive workload within various interface designs or automation levels, predict task performance, model multitasking and attention allocation, and evaluate decision support systems (Byrne, 2001). However, ACT-R is less suited for modeling social interaction or team-level coordination, requires detailed task analysis and significant effort to develop, and its simulation output is sensitive to cognitive assumptions.

Contextual Control Model (COCOM) and the Extended Control Model

The Contextual Control Model (COCOM) and the Extended Control Model (ECOM) are frameworks for understanding and modeling human control in sociotechnical systems. While COCOM focuses on the influence of context and control levels, ECOM proposes an examination of control processes using four concurrent loops. COCOM describes how human operators exercise control within complex systems in response to contextual factors such as changes in task demands, environment regularity, and time availability. COCOM was built on three main concepts of competence, control, and constructs. ECOM describes the performance of JCS through different but concurrent control loops (targeting, monitoring, regulating, tracking), operating simultaneously to maintain performance parameters within acceptable bounds, while tracking progress toward overarching objectives (Son et al., 2018). Both models acknowledge the necessary understanding of control in complex sociotechnical systems, the role of human factors in system performance, and the importance of utilizing this information to design operationally efficient systems.

Contextual Control Model (COCOM)

COCOM prescribes a functional approach to human performance, focusing on performance existing within a given context and determined by the current needs and constraints, as opposed to inherent properties of action elements. The concept of constructs refers to the knowledge and assumptions held by the human regarding the situation, which provide the basis for interpreting information and action selection (Hollnagel, 1998). Planning is an essential component of control, influenced by the context and expectations of the situational outcome. A human's actions rely on their understanding or construct, influenced by events (feedback) and the actions that are executed. The concept of control describes the order of performance and the application of possible actions. COCOM describes control as a set of four control modes including scrambled, opportunistic, tactical, and strategic. Scrambled controls are random actions that can be seen as trial-and-error, typically occurring when the system is overwhelmed and situational assessment is paralyzed. Opportunistic control mode describes heuristic actions with minimal forward planning, originating when constructs are inadequate or the context is difficult to understand (Hollnagel, 2000). Tactical control is a sequence of short-term actions influenced by immediate needs and limited planning. Strategic control considers high-level goals and long-term planning, in addition to goal decomposition and resource allocation (Leecaster et al., 2017).

An example of a JCS under COCOM is an air traffic control tower where controllers must shift control modes in response to changing circumstances. In strategic mode, controllers can plan traffic flow minutes in advance. Tactical mode is activated when traffic density increases and they must sequence arrivals and departures. In situations when unexpected weather forces reroutes, controllers are in opportunistic mode as they select the next best available route dependent on salient cues. Air traffic controllers can reach scrambled mode when faced with extreme overload and system outages, leading to ad-hoc trial responses. The air traffic control towers must manage complex situations involving human controllers, radar displays, and communication systems. This system is dependent on the controller's understanding and interpretation of the situation, the flow of information, and actions that must follow the guidelines of air traffic control and constraints of the physical environment.

Extended Control Model (ECOM)

ECOM was introduced by Hollnagel and Woods to capture how a JCS maintains control over its goals across multiple time-scales and levels of abstraction. Targeting is the highest level of control, which involves defining and prioritizing goals, and planning the sequence of actions. Performance at the targeting level is an open-loop type (proactive) requiring high concentration and attention, focusing on information regarding the past, present, and future, along with the potential for re-targeting and revision of criteria for the regulating loop (Langhanns et al., 2022). The monitoring level is responsible for evaluating system state against long-term objectives, in addition to activating plans according to feedback from lower level loops, and expectations from the targeting level. Performance at the monitoring level is open-loop, demanding low and intermittent attention, while focusing on the past and present. The regulating loop provides input (new goals and criteria) to the tracking control type, while activities at this level originate from plans at the monitoring level. Performance at the regulating level is a closed-loop type (reactive), as well as anticipatory control, requiring the human to predict subsequent events by combining feedforward and feedback. The tracking level is responsible for monitoring moment-to-moment performance, focusing on information from the present, and demanding little attention. Performance at the tracking level is closed-loop relying on sensory feedback processing. However, tracking with closed-loop control mostly applies to experienced users who require minimal effort and attention to the task, as they have lower needs for high-level conscious attention and working memory processing (Langhanns et al., 2022).

An example of a JCS under ECOM would be a driver and their car interacting with the road and other drivers. In the target level, the driver sets the goal of driving to a vacation destination using GPS navigation, route planning, weather and traffic apps. The driver selects the fastest route, plans to stop for fuel or breaks, or reroutes due to road closures. Achieving these goals may result in changes for the lower loops as the driver makes adjustments to speed and driving style. At the monitoring level, the driver must maintain awareness of the vehicle's location relative to the environment, while watching traffic signs and fuel level. The regulating level is activated as the driver manipulates the vehicle in response to traffic conditions, potentially leading to changes in target speed, lane position, and movement around other cars. In the tracking level, driving includes maintaining the intended speed and distance as the driver reacts to changes in traffic conditions and disturbances from other cars. An experienced driver may perform tracking activities instinctively, while a student driver will need to dedicate more attention and effort to monitoring their location.

The Law of Requisite Variety and Mental Models

In Cognitive Systems Engineering, the Law of Requisite Variety and mental models are foundational to understanding and designing for the complexity of sociotechnical systems, providing fundamental theories for analyzing system adaptability and ensuring effective control in dynamic environments. The Law of Requisite Variety ensures that the system of people, tools, and processes are capable of adapting to the demands of their complex environment, while mental models determine how individual agents perceive and interact with the system. CSE emphasizes that a human agent's mental model must be aligned with the system, asserting that incomplete mental models can lead to errors, misdiagnoses, or poor decisions. The Law of Requisite Variety asserts that for a system to maintain stability and achieve effective control, the controller must be capable of handling at least as many states of variability as the environment can produce (Heylighen & Joslyn, 2001). Applied to CSE in a JCS, human and machine agents must collectively possess sufficient flexibility and responsiveness to perform within the complexity of their operational environment. Both concepts support system design by enhancing representational richness to increase perceived variety, support the flexibility of mental models in real time, and enable distributed agents to aggregate their cognitive resources for performance that is adaptive and resilient (Heylighen & Joslyn, 2001).

Cognitive Work Analysis And Cognitive Task Analysis In Developing JCSs

Cognitive Work Analysis (CWA) and Cognitive Task Analysis (CTA) are prominent analytical frameworks used to understand and support human performance in complex sociotechnical systems. Although both approaches share a common focus on cognition in context, they differ significantly in terms of their analytical focus, scope, methodologies, and application in various stages of system development.

Cognitive Work Analysis (CWA)

CWA is a formative procedure in analyzing work, focusing on evaluating the constraints that influence work rather than dictating the methods to accomplish the task, or describing how work should be done under specific conditions (Naikar, 2017). CWA's ability to focus on constraints allows workers to adapt behavior when confronted with unforeseen events while maintaining safety and performance, while highlighting the importance of human workers managing these threats to system safety (Naikar et al., 2006). CWA can be applied to the design of an air traffic management system to model the functional objectives and constraints of the airspace system. This allows designers to identify affordances and areas needing additional guidance, thereby promoting the development of interfaces and tools that are context-sensitive and resilient to variability in task demands (Naikar, 2017).

CWA is composed of five interrelated phases including work domain analysis, control task analysis, strategies analysis, social-organizational analysis, and worker competency analysis. Work domain analysis models the functional structure of the system using abstraction hierarchies, while analyzing constraints from the physical, social, and cultural environment. Control task analysis analyzes the constraints placed on agents while attempting to achieve the system's purpose and functions. Strategies analysis explores multiple ways to perform control tasks, while analyzing the constraints imposed from the available cognitive strategies. Social–Organizational analysis examines how functions are allocated, distributed, and coordinated across agents. Worker competency analysis characterizes the skills and capabilities of human agents, while analyzing the constraints of human cognitive abilities and limitations. These phases collectively support the design of systems that are flexible, robust, and aligned with human cognitive capabilities.

Cognitive Task Analysis (CTA)

CTA encompasses a family of methods used to elicit the knowledge, strategies, and decision-making processes used by experts in successfully performing cognitive tasks, with a focus on documenting the micro-cognitive processes that underpin expert performance (Schraagen et al., 2000). The process of CTA can include methods such as the Critical Decision Method (CDM), structured interviews, observation, and think-aloud protocol. In time-sensitive environments where agents must make informed decisions, CTA is particularly useful for revealing the tacit knowledge that supports expertise, including pattern recognition, cue utilization, and mental simulation (Knisely et al., 2021). CTA can inform JCS development by designing training programs, automation aids, and procedural supports that align with the thought process and coordinated actions of subject matter experts. An example of CTA in practice could evaluate a surgical team to identify how an anesthesiologist anticipates and responds to complications during induction. The insights collected can then be translated into simulation training scenarios or real-time decision support systems that reinforce expert strategies. The goal is to both diminish unnecessary cognitive demands and support human cognitive work (Pfaff et al., 2021). While CWA is often utilized in the early stages of system design, CTA is more frequently applied during later stages to refine interfaces, develop procedures, or train new operators (Roth et al., 2013).

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