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Teaming Models with Intelligent Systems at the Workplace

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Teaming Models with Intelligent Systems in the Workplace

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Abstract. To study how organizational users team up with intelligent systems to make business decisions, we interviewed different users of supply chain planning tools on how they incorporate the intelligent system into their daily planning process. In an autonomous mode, an intelligent agent will perform all planning steps without any intervention by a user. In a distributed mode, both the user and the intelligent agent either handle or contribute in a subset of the steps. Using an extended version of the Endsley's Situational Awareness Model as a theoretical framework, we modeled planning activities as a sequence of cognitive task types: *detect, comprehend, predict, decide, and execute*. We observed different teaming models depending on which cognitive task type a user delegated to the intelligent agent.

Keywords: situational awareness, intelligent systems, autonomous business process, distributed cognition

1 Introduction

To study how organizational users team up with Intelligent Systems (ISs) to make business decisions, we interviewed transport planners, shifts schedulers, promotions planners, and demand planners on how they incorporate the intelligent system into their supply chain management (SCM) daily planning process. The interviews aimed to understand the entire user journey from learning, using, and optimizing the intelligent system and identify the driving forces influencing trust and acceptance of using the intelligent agent during the planning process.

Our research approach was multi-grounded in the sense that we used established theoretical frameworks as heuristics for the workplace interviews and interpretation. Our focus was on how human users and IS agents accomplish the shared goal of business planning and what factors influence the users' confidence in autonomous ISs.

2 Theoretical Framework

Planning entails multi-step tasks that follow a *sense-respond-act* schema, in which a planner first must understand the current or future reality (*sense*), then make planning decisions (*respond*), and ultimately enact the action plan (*act*).

To guide our research, we used a distributed cognition framework to explain the teaming between human (user) and intelligent agent (system). To model the planning process as a sequence of cognitive task types, we combined the three levels of Endsley's Situational Awareness model [1] with a decision-making step followed by the actual enactment step (execute) [2, 3].

2.1 Situational Awareness

Situational Awareness (SA) is an established concept originated from aviation research to describe cognitive demands of pilots when flying jets and their cooperation with intelligent autonomous systems in the cockpit. With the emerging trend of self-driving cars and broader human-centered Artificial Intelligence (HCAI) considerations, the SA concept is more relevant than ever. In our work, the premise is that the SA levels apply to human planning and business decision making similar to cockpit-based decision-making. We will explain each of the three levels via the example of self-driving cars:

Detect (Perceive). A driver must visually process the physical environment to understand the position of the car relative to the street, other cars, and objects. This is primarily an unconscious ongoing sensory process that may become compromised if environmental factors such as poor visibility or auditory distractions (e.g., noise) impede the driver from processing external signals. Self-driving systems use many sensors to sense the environment, some augmenting and enhancing human perception, e.g., an infra-red camera that can help the driver detect warm objects at night.

Comprehend. The above-mentioned perceived signals must then be translated into higher-level features and meaningful concepts such as streets, cars, and pedestrians; and dimensions and the relationships between them, such as speed and distance. For example, if a warm surface is detected at night, the intelligent system might map this data to the concept of a pedestrian being near the street.

Project. At the third level of situational awareness, the driver can project the future state along with any potential risks or factors affecting their ability to achieve or not the desired outcome. For example, a warm object detected by the infra-red camera classified as a pedestrian might be compared with the projected movements on the road and make the driver use the brakes.

2.2 Decision Making

According to the Decision Ladder model by Rasmussen [2], decisions are made on different levels of cognitive complexity. For example, to keep a car in the lane, an autonomous control loop must only establish low-level features defining the lane boundaries and make adjustments via the car's steering system. On the contrary, to make decisions on how to react to the pedestrian approaching the street, a high-impact decision must be made based on the projection of the future state of all relevant objects.

Similarly, in business there are also decisions of different complexity demanding different information qualities from an SA system. Decisions may be simple rule-based decisions based on heuristics informed by current reality. Such a reality can be a simple fact detected by an SA system, or a complex relationship inferred by the comprehension of many data points and relationships. Many planning decisions are complex knowledge-based decisions that need to be made considering a longer time horizon which requires the capability to project future reality as part of establishing situational awareness.

Those examples demonstrate that decision making is highly influenced by the capabilities of the situational awareness stage. The 'heuristics and biases' research stream of Tversky and Kahneman [4] has shown that people are prone to several cognitive biases that lead to suboptimal decisions [5]. Most of these biases occur due to a combination of limited information, time, and cognitive resources [6].

In addition, there are human limitations with respect to the decision-making task itself including the ability to predict. The body of research on behavioral economics provides an overview of the differences between human decision-making that is irrational and biased, and system decision-making that follows a set of rational, predetermined, and economically-optimized rules.

Considering these significant differences between human and system decision making, our research project aims to understand and describe how these differences influence the teaming model(s) between human planners and intelligent system agents.

2.3 Execution

Execution is about enactment of a plan or a decision being made. In our self-driving car example, the car may perform an automatic emergency break based on the autonomous decision that there is a risk of collision between the car and the pedestrian. In another case, the driver might have decided to park at a specific location, and manually triggers the parking assistant to maneuver the car into the available parking slot.

When a business decision is made either by an IS or by a human, the (human) planner can still choose to delegate execution to the IS or manually implement the plan by selecting, allocating, and scheduling resources. This enactment may include many micro-decisions for which a planner has to be comfortable to delegate to an intelligent system.

3 Findings

Overall, our interviews confirmed that the concept of Situational Awareness also applies to business planning with the difference that projection of future state may become its core task due to the complexity of long-term horizon forecasts. Concerning the question of how users accept and team up with Intelligent Systems, it became apparent that users are making conscious meta decisions to delegate a cognitive sub-task to the intelligent agent. In some cases, these meta decisions resulted in end-to-end autonomous business planning and execution. In other cases, they resulted in a hybrid model with mixed ownership of sub-tasks with human intervention along the decision-making and enactment process. The various teaming models that emerged from our multiple stakeholder user group interviews are presented in Table 1 below.

3.1 Teaming Models

We observed the following teaming models:

Table 1. Human-Intelligent System Teaming Models

Model	Description of Use Case
Autonomous	For short (~2 week) demand planning and replenishment of retail stores, planners fully relied on and trusted the intelligent system to come up with an accurate demand forecast and corresponding replenishment orders.
Complementing	For generating weekly shift schedules for hourly workers, schedulers accepted the system-generated schedule as a foundation, but put time and effort into fine tuning the schedule to reflect all preferences and quality criteria they had in mind
Framing	The output of the intelligent system was used as a baseline or generating best/worst-case scenarios as decision options/ This output was adjusted or overruled by the planner based on their knowledge about additional influencing factors, their job experience, and beliefs.
Recommending	Product prices were recommended but the planner could accept/reject/modify price of this suggestion per intervention

Three of the identified teaming models, namely complementing, framing, and recommending, are hybrid in that at least one of the five cognitive tasks is done manually by users. For the tasks delegated to the IS, users must see the value and be satisfied with their performance. Users often evaluate the benefits of ISs based on different measures for each cognitive task. These evaluations act as influencing factors of user acceptance of ISs.

These observations suggest that when designing intelligent systems that should be embedded into the practice of planners, the IS competes with the human planner on each cognitive sub-task. The acceptance will be influenced by how complete the situational awareness of the system is, how well aligned the decision-making is between human and IS, and how beneficial the delegation of execution is in terms of efficiency and effectiveness or outcome.

As illustrated in Figure 1, the teaming model for situational awareness, decision-making and execution may not necessarily be the same across the sub-tasks resulting in hybrid models when looking at the end-to-end planning process. The resulting usage patterns may change over time or at a per case basis if the user believes that the systems' situational awareness is incomplete, or the decision-making criteria or implementation of the execution plan are not fully aligned with the user's preferences.

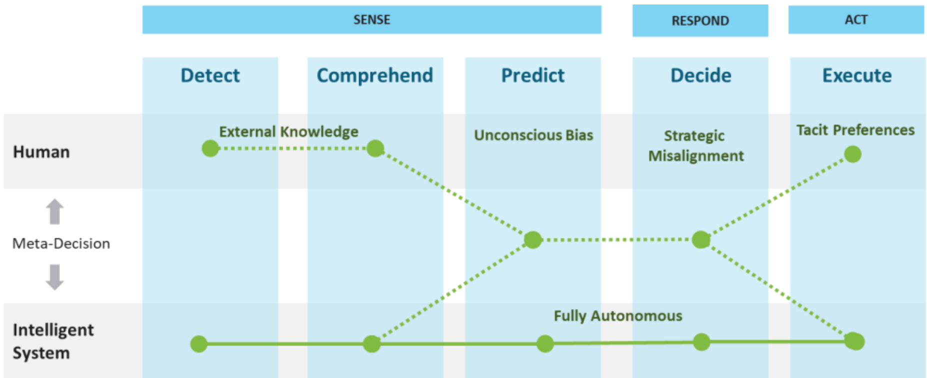

Figure 1. An illustration of the variation of human-system teaming models by cognitive tasks

4 Summary

Based on this improved understanding of usage patterns and underlying dynamics of shaping teaming models between human and IS over time, we propose an extension to the situational awareness model [1] by modeling the meta decisions that users make to determine how to interact (or team up) with the IS in each of the decision-making phases [7]. This extended theoretical framework allows us to identify factors that influence user engagement with intelligent systems on a more granular level. Moreover, it suggests that the design of future intelligent agents must ensure that user(s) develop adequate mental model(s) of the intelligent agent(s) and that users are empowered to interact with the agent(s) on a meta-level. Fostering this meta interaction will contribute to optimizing the teaming model between the user and the intelligent system.

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