Agentic AI: Understanding its Impact on Automation and Automaticity

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This position paper proposes a multiple viewpoint perspective on Agentic AI to discuss its possible impact on automation (process of automating behaviour inside a system) and on automaticity (how human behavior is automated inside the human). Beyond, the position paper proposes to identify how software agents (developed following the Agentic AI philosophy) will impact the collaboration between users and systems. More broadly, this position paper tries to shed new light on automation properties, drawbacks, and benefits when AI technologies are designed and deployed with an Agentic AI approach in mind.

Additional Key Words and Phrases: automation, automaticity, Agentic AI, agency

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1 Introduction

Workplaces across a wide range of domains have benefited from automation to reduce errors, avoid cumbersome and repetitive tasks, or even perform tasks that are impractical or impossible for humans (e.g. counting time). A significant step forward in that area is the use of Artificial Intelligence (AI) technologies to implement automation. The design of automation is deeply affected by the AI technologies that are used. Broad AI is used to replace a large number of tasks which were previously performed manually or interactively by the users (e.g. Generative AI technologies for writing stories). Agentic AI usually proposes a smaller number of tasks to be automated fitting simpler tasks grouped into a coherent activity. However, these tasks may be quite diverse, as Agentic AI goes beyond deterministic tools to become proactive entities capable of independently initiating actions, making decisions, and solving complex problems with minimal human intervention [1].

However, the successful implementation of agentic AI faces critical ethical, technical, and societal risks [14]. Beyond the "black box" opacity and technical complexities, agentic AI introduces broader societal challenges such as workforce disruption and loss-of-control scenarios. In the context of Industry 5.0, placing the well-being of the worker at the center of the production process is fundamental to avoiding boredom and ensuring professional fulfillment [7]. As Gershon and Lynch [9] noted, "sometimes automation replaces interactions that do so much more than simply the

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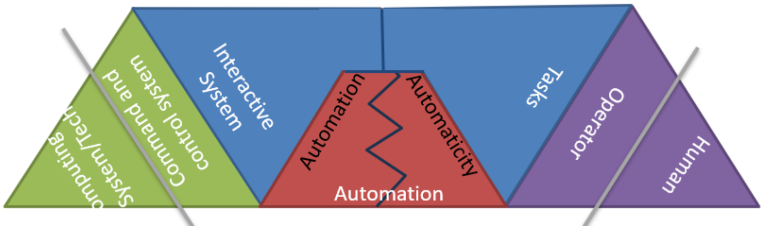

Fig. 1. Modified POISE framework illustrating the connection between the human operator and the computing system through automation.

action that is being automated". The negative impact of automation on arousal and ability to react has been studied for a long time [26] and Agentic AI might be a way, if well designed, to reduce this drawback.

To better understand these positive and negative impacts, we must distinguish between automation within the system and automaticity within the human. Although system automation aims to reduce immediate workload and resource consumption (e.g. water in dishwashers or time in data processing), human automaticity is a cognitive state in which tasks are performed rapidly and without conscious effort through practice [19]. This relationship is modeled in the POISE framework (see Figure 1 reworked from [16]), which illustrates how the human and the computing system are connected through automation. By automating specific functions, we aim to get benefits as, for instance, to save time for the user or to increase throughput. However, if not designed carefully, this can lead to multiple drawbacks on the user side such as "deskilling" [21] or complacency [17]. On the system side, the dependability of a system with high automation is likely to be low (due to the number of lines of code) [**?**] and the "Lumberjack Problem", where a high level of automation results in a more catastrophic failure when the system eventually breaks [24] is likely to be present.

Effective design must therefore move beyond mere efficiency to address core issues of explainability (system side), intelligibility (user side), transparency [**?**], and congruence between human expectations and system behavior [3, 13, 22]. This position paper explores how agentic AI affects these dynamics, particularly focusing on how non-deterministic interfaces may interfere with the consistent mapping required for human tool mastery.

2 Automation in the context of Agentic AI

The migration of user tasks to automated systems occurs across three distinct levels of human performance: perceptive, cognitive, and motor. Perceptive automation includes aids such as auto-zooming to support reading; cognitive automation handles complex tasks like object detection, recognition, and everyday utilities such as spell checkers. Motor automation involves the refinement of physical interactions, such as mouse acceleration, to improve users' performance in target selection. In order to explain how automation can vary, multiple levels of automation can be established, shown in Figure 2 [18]. The scale spans from manual control (L1) and decision support (L2-4) to supervised execution (L5-6), culminating in proactive autonomous control (L7-10) where the system acts independently or informs the human post-execution.

However, large-scale automation introduces significant systemic risks, particularly when datasets contain erroneous data or are subject to external attacks [2, 11]. This leads to the "Lumberjack Problem," which posits that the higher the level of automation, the more catastrophic the failure when the system eventually breaks [24]. As automated systems become more reliable, human operators tend to drift "out-of-the-loop," losing the situational awareness and technical judgment necessary for manual intervention [10]. This detachment creates a dangerous scenario where the scale of the

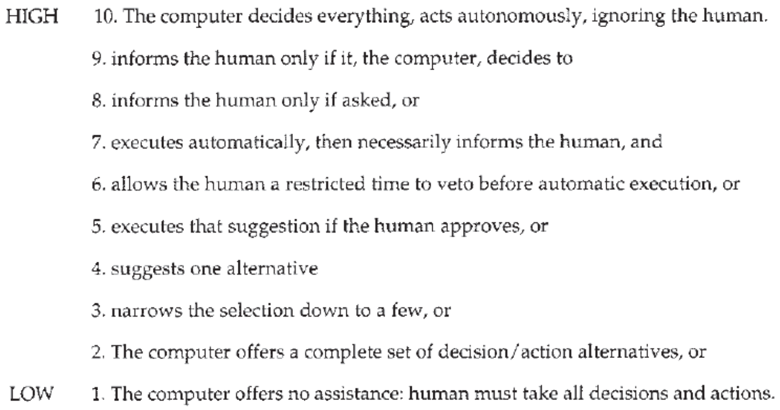
HIGH 10. The computer decides everything, acts autonomously, ignoring the human.
9. informs the human only if it, the computer, decides to
8. informs the human only if asked, or
7. executes automatically, then necessarily informs the human, and
6. allows the human a restricted time to veto before automatic execution, or
5. executes that suggestion if the human approves, or
4. suggests one alternative
3. narrows the selection down to a few, or
2. The computer offers a complete set of decision/action alternatives, or
LOW 1. The computer offers no assistance: human must take all decisions and actions.

Fig. 2. Levels of automation of decision and action selection (from Parasuraman et al. [17])

automation conceals underlying vulnerabilities, resulting in a performance crash during unforeseen failures that the operator is no longer equipped to handle.

To solve this, agentic AI can leverage a multi-agent approach where specialized, independent entities perform small, discrete tasks rather than relying on a single monolithic process. By decomposing complex problems into these smaller, autonomous functions, the system can potentially avoid fatal execution errors. Nevertheless, while this modularity offers a safeguard against total system collapse, it requires higher transparency in agent coordination to ensure that human operators do not lose control over these distributed outcomes.

3 Automaticity in the context of Agentic AI

3.1 Automation aspects inside the human

Human performance can be categorized using the Rasmussen model [19] into Skill-based, Rule-based, and Knowledge-based behaviors. As illustrated in Figure 3, these levels interact to determine how an operator processes information based on their level of expertise. At the base, Skill-based behavior represents automated sensori-motor patterns triggered by continuous “signals”. Mastery here requires consistent mapping, allowing the brain to “chunk” information and bypass conscious effort for high-speed performance [20, 23]. The intermediate Rule-based behavior involves applying stored procedures triggered by “signs” in the environment. Finally, Knowledge-based behavior is engaged in unfamiliar situations, requiring conscious “Identification,” “Decision,” and “Planning” through the use of “symbols”. This mode is serial, slow, and effortful.

Agentic AI often forces users back into the serial and effortful Knowledge-based level because the system’s adaptive responses are too variable to be internalized into habits. This disruption is particularly visible in professional workflows. For instance, software engineers using AI assistants score 17% lower on mastery tests than those who code manually, as the AI offloads the active “writing” phase and prevents the deep analytical processing required for debugging and logical understanding [25].

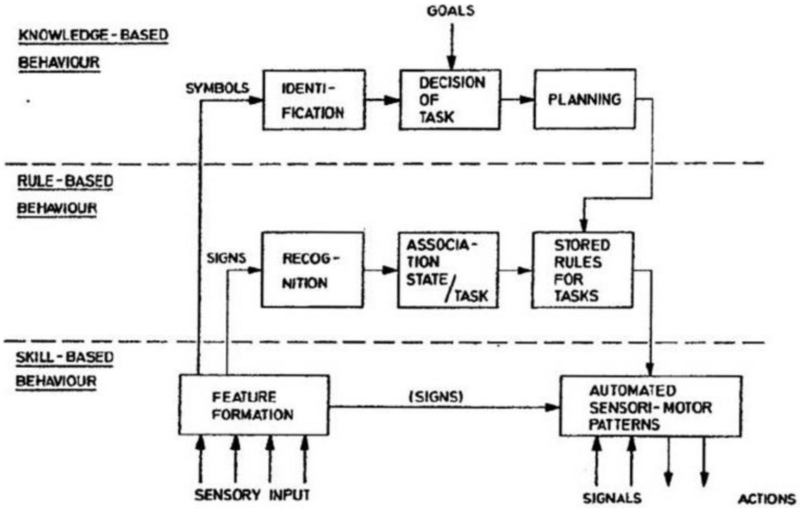

Fig. 3. Simplified illustration of three levels of performance of skilled human operators (from Rasmussen et al. [19]).

3.2 Agentic AI aspects on automaticity

The integration of agentic AI into professional workflows introduces significant cognitive risks, primarily driven by a lack of explainability and the resulting automation complacency [17]. Because AI systems often operate as "black boxes," [6] they obscure the relationship between human input and system outcomes, preventing users from developing the stable mental models necessary for tool mastery. This lack of transparency frequently leads to over-reliance, where users blindly accept AI suggestions/answers without engaging in the critical verification required for oversight [17].

This detachment from the underlying task leads directly to deskilling, as the "cognitive offloading" provided by AI bypasses the effortful engagement required for skill internalization [21]. By delegating the active execution phase to an agent, professionals fail to engage in the task, resulting in the atrophy of their own technical judgment. In the medical field, for example, endoscopists who routinely use AI for assistance in lesion detection have been found to perform significantly worse (22.4% detection rate vs. 28.4%) if the technology is suddenly removed [5].

4 Agentic AI and Users Collaboration aspects

Effective collaboration between humans and agentic AI is a multi-dimensional construct that requires a shift from simple tool usage to complex partnership. According to the Clover model [12], successful collaboration is predicated on the integration of production, cooperation, and communication. While agentic systems often maximize production through autonomous task execution, their "black box" nature can undermine the cooperation and communication layers. This dynamic is visualized in the GUSPATO framework shown in Figure 4 [1], which maps the spectrum of interaction from human-driven to system-driven automation [4]. This model illustrates how the human's role evolves from "User" in low-automation settings to "Supervisor" or "Partner" as the system assumes greater automation. Achieving sustainable collaboration requires maintaining a balance where the system serves as a "Partner" rather than ascending to a "Supervisor" role that renders the human a passive "Assistant".

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[1] Originally published in Eurocontrol Hindsight magazine https://skybrary.aero/articles/hindsight-36, available here https://skybrary.aero/sites/default/files/bookshelf/hs36/HS36-Drogoul-and-Palanque.pdf

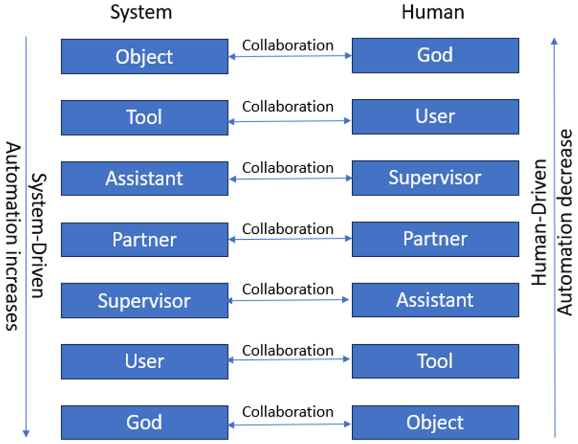

Fig. 4. GUSPATO: A seven-level classification of Human-System Collaboration

5 Lessons learnt

To ensure that agentic automation supports rather than erodes human expertise, design must transition from opaque "black box" systems to human-centered frameworks. A foundational strategy is the development of small, modular systems where specialized agents handle discrete sub-tasks; this approach prevents the "lumberjack problem" by ensuring that failures remain localized and easier for the operator to manage. Furthermore, human competence is sustained by interleaving AI-driven actions with manual tasks, requiring the operator to remain actively engaged in the workflow. This deliberate integration ensures that the human remains a "Partner" or "Supervisor" in the GUSPATO hierarchy rather than a passive observer.

The effectiveness of this collaboration depends on four critical design principles:

- **Explainability:** The system must provide the underlying reasoning and logic for its actions, which allows the user to build a robust mental model and guards against blind trust [3].
- **Intelligibility:** The AI's behavior and explanations should be easily understood by humans [8, 22].
- **Predictability:** Interfaces must maintain spatial and behavioral constancy, ensuring that identical stimuli always lead to expected responses to support tool internalization.
- **Transparency:** The mechanism by which the system works should be directly understandable [13].

6 Conclusion

The integration of Agentic AI technologies in interactive applications represents a fundamental shift in Human-Computer Interaction, creating a tension between immediate task efficiency and the long-term sustainability of human expertise. Although these systems, through automation, may successfully reduce immediate workload by automating perceptive, cognitive, and motoric tasks, their non-deterministic nature and "black box" opacity often disrupt the consistent mapping required for the transition towards skill-based behavior. As demonstrated in professional workflows, excessive cognitive offloading can lead to a significant erosion of mastery.

To mitigate the "Lumberjack Problem" and avoid leaving operators "out-of-the-loop," organizations must move toward a model of hybrid automation. By adopting human-centered design principles, specifically modularity, intelligibility, and the interleaving of manual and interactive tasks, Agentic systems can be designed to support rather than replace human agency. Ultimately, the goal of Agentic automation should not be the total delegation of decision-making, but the creation of collaborative partnerships that preserve the human's role as a strategic orchestrator and maintain professional mastery in an increasingly autonomous landscape. Future work aims at defining rules and objectives for designing Agentic AI technologies that fit the needs for Automaticity similar to the ones for automation [15] or the guidelines for Human AI interactions proposed in [**?**]. One key element to do so relates to the modeling and analysis of user tasks as this has been done when automation takes place on the interactive system side [**?**] by opposition to the human side (automaticity).

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