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The Effectiveness of Adaptive Automation in Human-Technology Interaction

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This paper focuses on the design and effectiveness of adaptive automation in Safety-critical systems. Our perspective is to focus on the human agent in the system as part of the Meaningful Human Control (MAS) project, pivoting on how humans will be accounted for in system design to enhance human performance. The division of tasks, decision authority, and the extent of automation are among the challenges introduced by new systems. Adaptive automation could balance function allocation between humans and machines to improve performance. It is therefore important to know if and how adaptive automation can be effective. This review paper aims to (1) define adaptive automation, (2) highlight important factors in adaptive automation design and application in interactive systems, (3) show when adaptive automation can be effective, and (4) highlight the design implications and gaps identified. This is part of a broader systematic literature review on the successful design principles in automation in the past 10 years. Following the PRISMA model and applying exclusion criteria, 14 articles were selected and thematically analyzed. The results showed that adaptive automation could potentially improve performance depending on the specific context and design boundaries that are discussed in this paper.

Keywords: Adaptive automation, Adaptable automation, Human-machine interaction, Human factors, Trust.

1. Introduction

Technology evolves rapidly but we are not always prepared to deal with unexpected challenges of complex technologies (Dekker 2011) which creates a paradox in technology use. One of such advancements in automation is adaptive automation. It is a ‘double-edged sword’ (Miller and Parasuraman 2007) with both benefits and risks. It is beneficial in enhancing performance but simultaneously degrades expertise as the system takes over routine tasks and automatically corrects mistakes (Leva et al. 2018). This results in deskilling of the operator due to lack of enough practice, but the adverse effects expand to operator’s compromised Situation Awareness (SA), complacency and overreliance on automation (Endsley 2017; Sauer et al. 2013). If the automation fails to respond to unexpected occurrences and the deskilled, out-of-the-loop operators are pushed beyond their limited resources to take over control, disaster strikes (Endsley and Kiris 1995; Leva et al. 2018). To avoid that, the design of human-machine interactive systems must tackle the challenges of adverse automation impact on SA and workload (Coster 2017; Park et al. 2018; Yerkes and Dodson 1908). This is possible through a better understanding of such systems. Therefore, in this paper we aim to understand (1) the concept adaptive automation, (2) how it is applied in system design (3) how it affects performance and (4) the gaps and implications based on the current literature. In addition, we (5) discuss the important considerations for the design of these systems.

2. Method

A systematic literature review was conducted to identify the relevant literature about ‘which design principles lead to success in automation and remote operation', as part of the project *Meaningful Human Control* (MAS). The search was conducted in Web of Science, Scopus, Dimensions, Compendex, and IEEE in November 2022. The search terms and a search string were developed by the research group using an iterative process, where the search string was extensively tested and modified before the final search was conducted. The inclusion criteria included: English language articles, from 2013-2023, which coincided with the onset of booming research in Industry 4.0 and advancements in digitalization (Culot et al. 2020) setting the foundation for and transitioning into Industry 5.0. The resulting articles, book chapters, and conference proceedings amounted to 14001, from which 6410 duplicates were removed using the AI tool Deduklick. The remaining 7591 articles were uploaded to the Rayyan platform. For this paper, articles with key term "adaptive automation" mentioned in the papers were filtered. This resulted in 44 articles. After full-text screening and filtering for empirical findings, 14 resulting articles (Figure 1) were analyzed using thematic analysis (Braun and Clark, 2006).

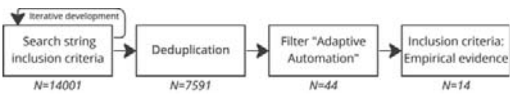

Fig. 1. Overview of the literature review process.

The analysis was an iterative coding process to ensure that the themes were consistent and reliably derived from their constituent codes, while highlighting their connection to each other. The articles are presented in Table 1.

3. Results

In this section the major automation concepts and themes derived from the analysis of the 14 articles are presented. The articles analyzed represented the automotive sector (N=6), followed by aerospace (N=5), maritime (N=1), and unspecified target sector (N=2).

3.1. *Definition of automation*

This section describes how adaptive automation is understood. In addition, the *why*, *what*, *how* and *when* of adaptive automation are explained, followed by *who* has control in automation, based on the literature analysis.

Table 1. The overview of concepts in references

	Reference													
Automation concept	[1] Wang, Z. et al., 2021	[2] Rehman et al., 2021	[3] Thropp et al., 2018	[4] Park et al., 2018	[5] Zhang et al., 2017	[6] Rusnock & Geiger, 2016	[7] Sauer et al., 2013	[8] Muslim & Itoh, 2018	[9] Grabbe et al., 2022	[10] Sauer & Chavaillaz, 2018	[11] Muslim & Itoh, 2021	[12] Benloucif et al., 2019	[13] Chen et al., 2017	[14] Yang et al., 2021
Adaptive automation	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Adaptable automation			•	•			•	•		•			•	
Implicit automation							•							
Explicit automation							•							
Static automation			•			•	•		•	•			•	
Dynamic automation								•						
Continous automation													•	
Intermittent automation													•	
Deciding factors	•		•	•	•	•	•	•	•			•	•	
Effectiveness	•		•	•	•	•	•	•	•	•	•	•	•	
Levels of automation			•	•			•			•		•		
Workload and SA	•		•	•	•	•	•	•			•	•	•	
Personalization		•	•		•			•						
Implications of design	•	•	•	•	•	•	•	•	•			•		
Gaps and limitations	•	•	•	•	•	•	•	•	•		•			
Trust and acceptance		•				•	•	•			•			•

Adaptive automation refers to dynamically changing the Level of Automation (LoA) based on the environment, user, and tasks to ensure optimal operation and performance. Adaptive automation was described to be a mean to create a positive tradeoff between the costs and benefits of automation so that a balance can be created between the system's agents (the human and the machine) and their abilities to process information under hazardous conditions (Sauer et al. 2013). The aim of adaptive automation is to find out the best way to dynamically balance the LoA to the needs of the system agents (Park et al. 2018). While Muslim and Itoh (2018, 2021) believed that the aim of automation is to "prevent inappropriate human action" and take control to avoid risk, others believed that automation should aim to "augment human abilities" (Thropp et al. 2018). This is achieved by adapting to users' preferences in controlling the non-critical functions (Rehman et al. 2021). Adaptive automation is ultimately about sharing control and reducing operator's workload (Wang et al, 2020), through changes in LoA, based on real-time data gathered on the operator, the situation, and the performance measures. This implies a certain level of consideration for organizational and environmental variables interacting with humans and technology. However, there was no explicit application of a systemic perspective such as the (hu)Man-Technology-Organization (MTO) for designing safer automated systems. By automating tasks during cognitively demanding conditions, an adaptive system takes on more tasks from the operator, thus moderating workload while aiming to increase SA. Under less demanding conditions, adaptive systems return tasks to the operator to prevent boredom, complacency, and skill degradation (Rusnock and Geiger 2016). Regarding what to automate, it was a task or a function that was automated, which was either routine and continuous, or dangerous for humans to perform. Regarding how to automate, the focus is on function reallocation (Sauer et al. 2013) and the decisions is based on the risk level, cognitive and workload, agents' capabilities, LoA based on agents' needs, and the system goals (Muslim and Itoh 2018; Park et al. 2018; Rusnock and Geiger 2016) to achieve an optimal level of system performance (Zhang et al. 2017). Regarding when to automate, it is most useful when there is a wide variation in human cognitive ability and workload, and in high-risk situations with possible hazardous encounters (Muslim and Itoh 2021). There are four criteria that signal an appropriate time for automation to engage: occurrence of critical events, deviations in operator's real-time psychophysiological measures, performance degradation, and system malfunction (Kaber and Endsley 2004, Sauer et al. 2013). Furthermore, when there is a secondary task that can intervene with primary task performance, adaptive automation can be useful in taking over the secondary task and to relieve the operator of added workload. Regarding the 'who' in adaptive automation and its design implications, the next section will further elaborate on this topic.

3.1.1. *Adaptive versus adaptable automation*

The 'who' of adaptive automation, is a matter of authority and control. Adaptive automation is when the machine decides when and how much to automate, while adaptable automation is when the human decides (Park et al. 2018; Sauer and Chavaillaz, 2018). In adaptive automation, LoA changes based on the obtained real-time data on the operator, task performance and events (Rusnock and Geiger 2016). Adaptive automation uses intermittent automation based on the objective demands in the task while adaptable automation uses intermittent automation based on the perceived, subjective task demands (Chen et al. 2017). Although adaptive automation can be best applied to systems with variable task loads (Rusnock and Geiger 2016), it still requires human judgement (Moray et al. 2000; Parasuraman et al. 2007), which is contradictory with the distinction made between adaptive and adaptable automation. This shows inconsistency in distinction between these types of automation.

3.1.2. *Implicit versus explicit automation*

Explicit automation is when the human oversees operation, (s)he is in-the-loop and decides on the function allocation. This was named adaptable automation by Miller and Parasuraman (2007). Implicit automation is when the machine oversees operation and makes decisions. Although it seems that explicit automation is in line with adaptable automation and implicit automation is in line with adaptive automation, the literature is not consistent in this matter. Explicit and implicit automation are also framed as two forms of adaptive automation (Sauer et al. 2013). This shows an inconsistency in the literature.

3.1.3. *Static versus dynamic automation*

In static automation the automated task and LoA are fixed. In dynamic automation, including both adaptable and adaptive automation, the task allocation and LoA can be adjusted during operations. Adaptive automation is stated to be the evolution of static automation (Thropp et al. 2018).

3.2. *Automation system design factors*

This section takes a closer look at factors that are the building blocks of automation and how they are affected across automation modes. These factors range from concrete to more abstract factors and concepts, including performance measures, objective and subjective workload and stressors, SA, trust, and LOA.

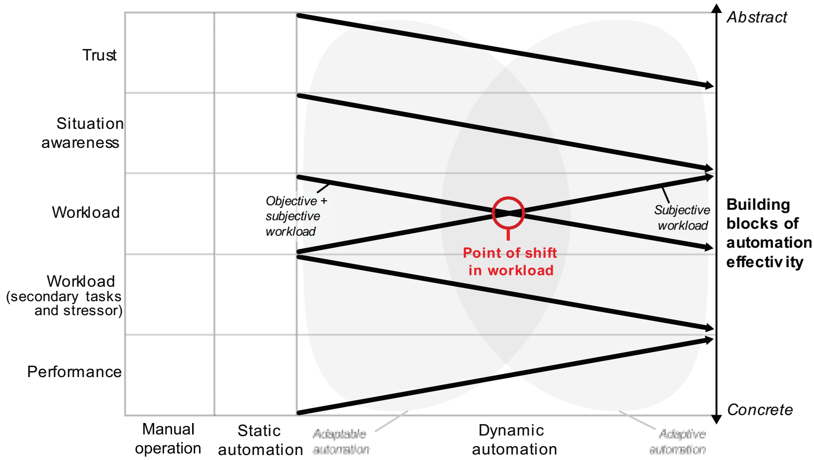

Fig. 2. Automation modes and important criteria in automation design

The changes in these factors across automation modes are shown in Figure 2. Operation can be performed manually, or in a fixed automation mode (static automation) or dynamically. Focusing on dynamic automation, a general and simplified overview of how performance, workload, workload in presence of secondary task demands and stressors, SA and trust vary across adaptable to adaptive automation is shown. This is not an all-encompassing overview nor a statistically drawn correlations. This is simply a visual aid to present the general patterns and tendencies reported in the articles that are thematically analyzed. Thus, caution must be taken to apply it to specific experimental settings, sectors, and contexts. For example, SA is generally reported to be higher in adaptable automation and is lower in adaptive automation. Trust follows the same pattern. The overall system performance tends to be superior in adaptive automation compared to adaptable automation (Rusnock and Geiger, 2016) under normal conditions (Sauer et al. 2013). However, workload seems to be difficult to regulate in both adaptable and adaptive automation. Workload is highest when there is a need for information processing and function reallocation. This is the point of shift in workload. This authority in function reallocation, based on information processing, is consistent with what the literature proposes to be the major distinction between adaptable and adaptive automation. The main measurement methods in the literature included psychophysiological measures such as muscular activity levels, electroencephalogram (EEG), electrocardiogram (ECG), task performance, and behavior metrics. The subjective measures included workload self-report (NASA-TLX and RTLX) and the subjective acceptance questionnaire, risk perception, perceived control, and interference detection during task performance.

3.3. *Automation in complex systems*

Sauer et al. (2013) reported that under implicit control, the overall system performance is higher than under explicit control. However, explicit control resulted in lower workload, higher SA and higher trust in the system. The overall findings, however, showed a more complex picture. In addition to these major criteria that are often referred to in the automation literature, the effect of different LoAs, within and outside design boundary occurrences, automation failure and recovery, operator's preference were considered as well. The effectiveness of adaptive automation is context dependent, where context includes normal versus abnormal conditions, automation failure, and within versus outside design boundaries (Muslim and Itoh 2018).

3.3.1. *Adaptive automation effectiveness*

Determining the effectiveness of adaptive automation across all contexts is still not plausible. Grabbe et al. (2022) claimed that adaptive automation is better than full automation in using the strengths of both human and technology for overall system performance. According to Park et al. (2018), performance is significantly superior in adaptive condition than adaptable condition. Adaptive automation increases human work capacity, and it is particularly effective when it is well-understood by the operator and is more customized to the operator's needs. Adaptive automation is superior to manual operation, static and adaptable automation in lowering subjective and objective workload/task load (Park et al. 2018; Wang et al. 2020). However, while overall system performance in adaptive automation is better than other modes of automation, Rusnock and Geiger (2016) stated that a few studies did not show statistically significant differences in performance between adaptive and non-adaptive systems. Adaptive automation is effective in handling demanding secondary tasks (Benloucif et al. 2019) and certain types of stressors (Thropp et al. 2018). It was found that different stressors can have different effects on task performance. When stressor coincides with demanding tasks such as fault detection, the interaction could lead to failure. Stressors are perceived through different sensory modalities at different rates. For example, audio input is processed faster than visual input. This means that in the presence of stressors, such as noise or visual alarms, and especially when this demands for a secondary task performance, adaptive automation could be effective in handling a sensory input that requires more cognitive effort, such as visual processing (Thropp et al. 2018). Adaptive automation is effective for within design boundary fault detection and correction. A human operator is more effective in dealing with unexpected incidents. Nevertheless, human operators can be prone to overestimating automation's capability in dealing with incidents. This overreliance could be hazardous.

3.3.2. *Adaptable automation effectiveness*

Adaptable automation showed mixed effects. When the objective and subjective workload increased, operators were more likely to engage adaptable automation. In general, operators prefer explicit adaptable automation because they have control over LoA. The benefit of adaptable automation is that it supports retention of manual skills and results in higher SA, being in-the-loop and lower workload, leading to more trust (Sauer et al. 2013). The operators may choose lower LoA to maintain and exercise more control. Operators tend to be conservative in utilizing automation (Sauer et al. 2013; Sauer and Chavaillaz 2018) and they only change the LoA at a minimum level. This means that they also fail to develop a comprehensive mental model of the system. Sauer et al. (2013) suggested that adaptable automation could be designed in a way that it would prompt the operator of the availability of more automatic support, either through performance-based feedback or physiological indicators. However, the risk of adaptable automation is that the operator could either fail to see the need for assistance from automation until it is too late or the operator is too pre-occupied with other tasks to determine the appropriate LoA (Thropp et al. 2018). As a result, adaptable automation could become counterproductive. Furthermore, operators' overreliance on automation to deal with hazardous situations and sudden realization that they need to take over, may result in a struggle to regain control. This could lead to further loss of SA (Muslim and Itoh 2018). Thus, control can be shifted from human to the system if the human is always able to smoothly retake control when necessary. This may reduce the effects of misunderstanding the automation assistance (Muslim and Itoh 2018). Chen et al. (2017) reported that empirical evidence regarding the effectiveness of adaptable and adaptive automation is limited, and they did not find that adaptable or adaptive automation could maximize performance while maintaining SA.

3.3.3. *Level of Automation considerations*

Operators generally preferred to have a low to intermediate LoA (Sauer et al. 2013). However, people may respond to LoAs differently based on their ability in directing and shifting attention without getting distracted (attentional control). Higher LoA improved performance in people with high and low attentional control. However, while people with low attentional control preferred higher LoAs, people with high attentional control preferred lower LoA so that they can have more control (Thropp et al. 2018). It was found that higher LoA results in faster fault detection within the system design, but for novel situations and in automation failure, the reverse occurs. Intermediate LoA is "the golden standard" to avoid over automation risks (Sauer et al. 2013).

3.3.4. *Workload and SA considerations*

Workload was reported to be lower in adaptive automation compared to the manual operation and static automation (Wang et al. 2020). Sauer et al. (2013) stated that workload is lower in explicit automation, based on subjectively perceived workload. However, when both objective and subjective workload was measured, adaptive automation was better than adaptable automation in lowering workload (Park et al. 2018). Furthermore, there was a non-linear relationship between workload and performance (Rusnock and Geiger 2016). Intermediate workload is desired for optimal performance and when workload expands beyond this range, performance is compromised (Yerkes and Dodson 1908; Park et al. 2018). Regarding SA, it was found that it is higher in explicit automation compared to implicit automation and it is lowest in static automation (Sauer et al, 2013). However, the relationship between SA and workload is dynamic. Adaptive automation is activated upon reaching a selected threshold in the design of the system. When this threshold is reached, a trade-off between performance, workload, and SA takes place. It is important to know about this trade-off, when it takes place and how it impacts SA, workload, and performance at that specific threshold. Design of automation systems should be based on an informed trade-off between these competing priorities. (Muslim and Itoh 2018; Rusnock and Geiger 2016).

3.3.5. *Personalization considerations*

When accounting for the cognitive ability of operators and improving design in a more personalized and natural way, the operator's understanding of the system improves (Zhang et al. 2017). Personalization is based on individual traits and differences, preferences, motivation, emotions, and anticipated error (Thropp et al. 2018). To personalize adaptive task allocation using physiological and task performance data, past performance measures are integrated into real-time performance data to better allocate tasks between humans and machines. However, if the system makes too many adjustments, the operator feels disrupted, and performance will suffer (Zhang et al. 2017).

3.4. *Implication of automation design*

The automation system design pivoted on enhancing human performance, and takeover the 4D tasks (dull, dirty, dangerous, and delicate) (Valori et al. 2021). This is done by deploying (predictive) risk assessment, and accounting for possible trade-offs while realizing the system goals (Zhang et al. 2017). If in the early design process, the performance variables goals are clarified, it will be easier for designers to trigger the appropriate LoA, and yet make sure that the trade-off between performance measures are kept in check (Rusnock and Geiger 2016). However, this will still be bound to closed-loop systems and within-design issues. Human response is needed to deal with complexities of open-loop systems and outside-design issues. A human operator should have a very clear mental model of the system, its capabilities, and limitations, under normal operation conditions. (Muslim and Itoh 2018; Sauer et al. 2013). It is only then that the operator can take over when the unexpected occurs and navigate through hazardous situations.

3.5. *Gaps and limitations in the literature*

There is still a bias towards seeing humans as the source of error and automation as the solution (Grabbe et al. 2022). Although some aim for full automation, this is still not possible. Instead, predictive performance measures are used to allow automation to detect risky operator function (Zhang et al. 2017). This is aligned with 'human error' approach which ignores the role of system dynamics in modern safety science. In addition to this bias, the literature lacks empirical evidence that automation can maximize performance, regulate SA and workload (Chen et al. 2017). There is also inconsistent evidence that adaptive mechanisms are needed for performance enhancement compared to non-adaptive mechanisms. Furthermore, there is still a lack of sufficient end-user input in the system design (Rehman et al. 2021). There is not enough investment in training the operators to improve their understanding and use of automation. In the design of authority and control allocation, more research is needed to design how the authority of shared steering control should be adjusted. Finally, an important gap is that most research on automation effect is done under 'normal' operational conditions and not under system breakdowns (Sauer et al. 2013).

3.5.1. *Design for realistic level of trust*

One important factor affecting human-automation interaction is trust, which is believing that one can rely on automation, while distrust is believing that automation is unreliable (Itoh and Tanaka 2000). Mistrust can be either trusting the automation when it is not reliable, or distrusting automation when it works fine (Muir 1994; Itoh and Tanaka 2000). People develop trust over time, and on a continuous basis while interacting with the system. Trust-building is not a linear process and system failures can destroy trust (Rusnock and Geiger 2016; Yang et al. 2021). Developing an accurate mental model, getting training, and having ethical and legal readiness, could eventually foster trust and acceptance. However, "realistic" trust may take years to build. Anthropomorphism was also mentioned to enhance trust in design (Muslim and Itoh 2018; Muslim and Itoh 2021; Rehman et al. 2021).

4. Discussion and Conclusion

The aim of this literature review was to find out if and how adaptive automation is effective. For the scope of this paper, the focus was on empirical articles that explicitly mentioned the term 'adaptive automation', meaning that some relevant articles might have been inadvertently excluded. The findings showed a lack of consistent empirical evidence across different contexts to show the effectiveness of adaptive and adaptable automation as mentioned by Chen et al. (2017). It was found that adaptive automation can enhance system performance more than other automation modes, but trade-offs occur that need to be accounted for based on the specific context of the system design. More research is needed to determine if adaptive is truly superior to adaptable automation, assuming that trust and acceptance in the latter is higher. Calhoun (2022) states that direct comparisons of adaptive to adaptable automation studies show that adaptable automation is better in task performance and perceived workload. There is also inconsistency in the literature in the concepts, definition, and the spectrum of static to dynamic automation. Although we focused on adaptive automation, the concept of adaptable automation was inevitably intertwined with adaptive automation. Future research can take a closer look at adaptable automation literature. Furthermore, it seems that explicit automation is aligned with adaptable automation while implicit automation is aligned with adaptive automation. However, adaptive automation can be made explicit if there is well designed automation transparency in the system. This requires further research to see how adaptive automation can become more transparent and keep the human in-the-loop, while maintaining its objectivity in task allocation between human and the machine. Adaptive automation is effective in overall system performance, but the context, the design boundaries and the transition of authority and control based on performance measures and the operator, play a role in how effective automation is. The balance between important performance-related variables such as workload and SA and system goal realization still needs further research. Adaptable automation is meant to keep the human-in-the-loop. However, when the system is not well understood, detecting faults and failures becomes more difficult for humans. Therefore, there are mixed findings on its effectiveness. Regarding trust and acceptance, transparency and smooth control takeover by the operators are important to build a realistic level of trust. A training in the functionalities of the system in handling dangerous situations could improve trust. The occurrence of emergency situations increases workload regardless of automation type. This is the main area of overlap between adaptable and adaptive automation. When the unexpected occurs, workload peaks, SA is compromised and either of the agents must take control. If this is made transparent, workload and SA can be quickly restored, and there will be a shared understanding between system agents. This helps to make the right decision. Thus, transparency can improve automation design.

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