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Review

Adaptive Automation: status of research and future challenge

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ABSTRACT

Automation modifies workplaces, tools, and production activities, leading to new modalities of human-machine interaction. Traditionally, the allocation of functions in automated systems is static over time, i.e., functions are assigned to humans or machines. Adaptive Automation (AA) makes functions allocation dynamic, resulting from system conditions, performance, and human attributes to face emerging or unpredictable contingencies, and to cope with traditional automation challenges and limits. Tracing the evolutionary stages of the topic, the paper provides an extensive literature review. First, the review details the current definition of AA, the starting motivations for AA, and the temporal evolution of the topic considering the pioneers' theories. Then, the paper presents the design elements involved in AA systems, i.e., the Level Of Automation (LOA), the Human-Machine Interfaces (HMIs), and the different approaches than can guide the adaptive shift. Finally, the practical applications of AA in manufacturing are reported. In such a way, the research offers the state of the art of the topic, providing the main distinguishing features between static and AA, also outlining the open challenges and the future developments in manufacturing.

1. Introduction

Adaptive Automation (AA) changes how functions are allocated between man and machine and how they interact [1–4]. Traditionally, the static allocation of system functions and activities defines who is doing what. Here, the Level Of Automation (LOA) is unchanged over time, as it identifies functions involving humans and machines. Instead, the adaptive rationale defines who is doing what, and when [5]. As a result, the tasks assigned to humans or machines can change dynamically over time, adapting the LOA to contextual conditions. Through AA, the allocation of functions results from system conditions, performance, and human attributes to cope with emerging and unpredictable contingencies [6,7]. However, these adaptations require a careful design of the system [8,9]. In literature, the topic of AA is not novel. In industries other than manufacturing, it is established as a successful logic, e.g., in aeronautics, automotive, and aviation [10,11]. In manufacturing concrete applications are still residual, despite the research showing efforts in this field as well, and some test cases are emerging [12–16]. Several authors addressed the AA topic, formalizing theoretical models to guide the design of adaptive environments. Despite this evidence, a lack of extensive research that presents the state of the art on the topic arises. The research presented in the literature features practical or theoretical aspects, with a narrow focus and an absence of cross-sectional vision. For instance, some papers focus on very specific design aspects, like interfaces, or they present applied case studies, without this cross-sectional vision. This paper aims to fill this gap through a systematic literature review, answering the following Research Questions (RQs):

RQ1: *What is the definition of AA?*

RQ2: *Why was AA introduced?*

RQ3: *From an historical perspective, who has addressed the AA topic, with what purpose, and what theories emerged?*

RQ4: *What design elements are involved in an AA system?*

RQ5. *Which applications of AA emerged in manufacturing?*

By answering these questions, the paper presents theoretical and practical aspects. Moving from the *Definitions* (Section 3), which frame what adaptive automation is, the evolution of the topic over time is traced by the *Motivations for AA* (Section 4), and the *Historical Evolution, and the pioneers' theories* (Section 5). A further section defines the specific *Design Elements* (Section 6) involved in implementing AA. Finally, the *Practical Applications* in manufacturing (Section 7) are presented. A comprehensive analysis of such results maps the *State of the art* of the topic (Section 8) as well as the *Open challenges and future developments*, focusing on the manufacturing field (Section 9).

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2. Materials and methods

This review investigates documents following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, given by Moher et al. (2009) [17]. PRISMA enables the identification of AA definitions (RQ1), the extraction of the motivations behind the establishment of AA (RQ2), the analysis of the papers in a temporal evolution (RQ3), the retrieval of the design elements of AA systems (RQ4), and the collection of applications of AA emerging in manufacturing (RQ5). PRISMA guidelines define a systematic literature review strategy, which is described in Fig. 1.

Identification

The review investigates the Scopus database, i.e., the largest abstract and citation database of peer-reviewed literature. The choice of this database is based on its relevance in academia. At the end of 2022, the RELX Annual Report [18] addresses Scopus as a leading source, an expertly curated abstract and citated database with content from over 27,000 journals from more than 7000 publishers to help researchers track and discover global knowledge in all fields. The first step of the review defines the scope of the search query. The search query looks for every document that addresses the so-called “adaptive, or adaptable, or dynamic automation” to broadly collect all the contributions that explore this topic from different points of view. Since the topic is strongly human centered, the research performed a multi-disciplinary analysis including the field of engineering, management, psychology, social sciences, neuroscience, and decision sciences, which, as hereafter discussed, formalized theories that became real triggers for all the studies in other research areas. To have broader inclusion criteria, quotation marks are used to ensure that terms composed of multiple words are searched together, as well as asterisks are used to include both singular and plurals terms, and derived terms. The scope of the research is limited to contributions published in English. The search query for the database is: TITLE-ABS-KEY (“adaptive automation*” OR “adaptable automation*” OR “dynamic automation*”)) AND (LIMIT-TO (SUBJAREA, “ENGI”) OR LIMIT-TO (SUBJAREA, “SOCI”) OR LIMIT-TO (SUBJAREA, “PSYC”) OR LIMIT TO (SUBJAREA, “DECI”) OR LIMIT TO (SUBJAREA, “BUSI”) OR LIMIT TO (SUBJAREA, “NEUR”)) AND (LIMIT-TO (LANGUAGE, “English”)). The query retrieved 344 contributions. Specifically, 156 conference proceedings, 152 journal articles, 18 book chapters, 10 conference reviews, 6 reviews, 1 book, and 1 short review. 15 contributions were eliminated because duplicated. Then, the 46 contributions for which the extended abstract or the full text was not available were excluded. Therefore, the identification phase is concluded with 283 contributions selected.

Screening

In the screening phase, each contribution is screened in the title, abstract, and keywords to evaluate if its research is adherent to the objective of the review. Among 283 articles, 50 were excluded due to Exclusion Criteria 1 (EC1) and Exclusion Criteria 2 (EC2). Specifically, 30 are excluded since they ascribed to the concept of Adaptive Automation a different meaning than the one of interest (EC1), and 20 because they dealt with Adaptive Automation, but the adaptive subjects were not man and machine (EC2).

Eligibility

During this phase, 233 documents are analyzed. The authors reviewed the full texts and 62 were rejected as they do not meet the Inclusion Criteria (IC). The IC1 requires the paper to cover Adaptive Automation broadly, presenting high-level aspects. The IC2 requires that papers present specific aspects related to Adaptive Automation, such as the design of specific parts of the system. The IC3 requires that papers contain an application of Adaptive Automation in a specific context and finally the IC4 that the papers feature a hands-on experiment of Adaptive Automation.

Inclusion

A total of 171 documents are included for analysis. Further references, i.e., 10 documents, were included in the sample through the backward and forward snowball sampling technique [19]. A final sample of 181 documents was reviewed thoroughly, to allow data extraction and to synthesize the information pertinent to the scope of this review. Data are organized to categorize information concerning citation information, abstract and keywords, domains of application, and information concerning theories, models, methods, and frameworks that emerged. The fields reported are the following: authors, the title of the paper, year, source title, number of citations, DOI, abstract, keywords,

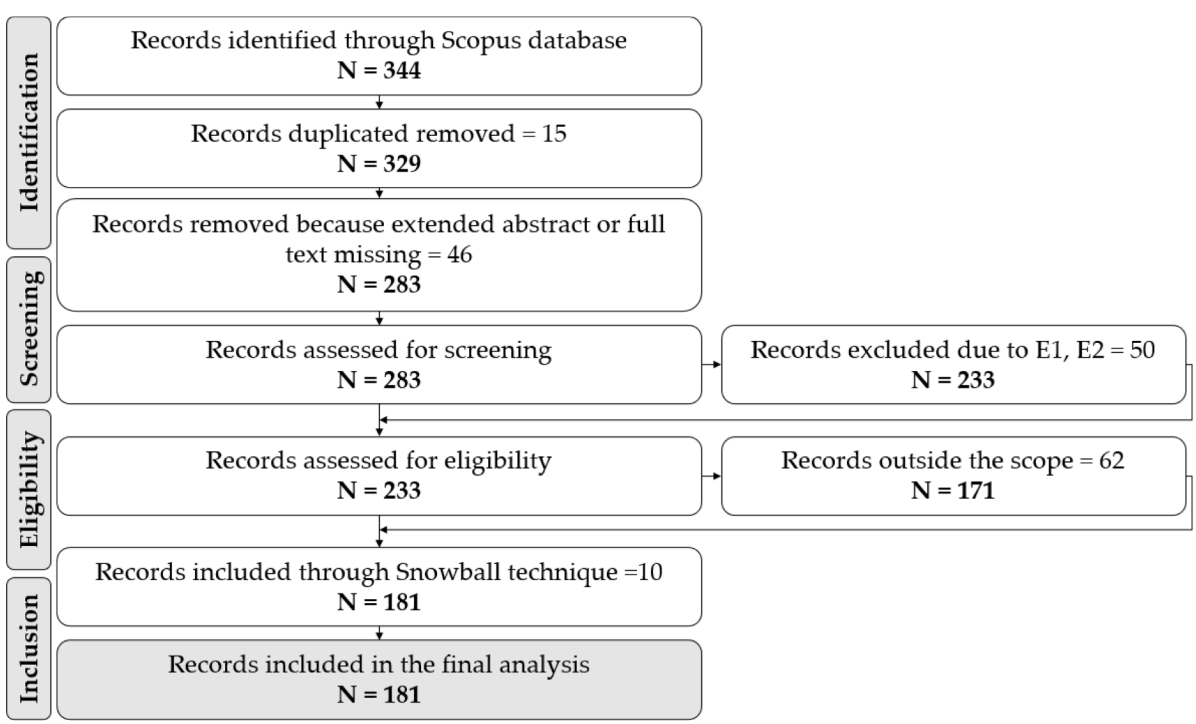

Fig. 1. Literature review strategy.

document type, and domain.

3. Definitions

RQ1: What is the definition of AA?

Differentiated definitions regarding AA emerged in the literature. More than one author highlighted a variety of forms of adaptability, with the main goal to compare system performance as it varies. Namely, [20] compares practical adaptive scenarios to benchmark their costs and benefits, trust-related issues, and it highlights how the design of human interfaces depends on them. In [21] the authors focused on operator performance, like [22]. In this latest research, experiments are presented to highlight which solutions improve performance for the operator and ensure a less perceived workload. In [23] the research presented the most suitable allocation strategies and triggers that should drive the allocation and other systemic aspects, as the adaptation possibilities vary. So, it emerges how the topic is mainly discussed from a practical point of view, lacking shared theoretical and homogeneous definitions and illustrations. Reviewing the scientific contributions, the findings revealed how AA encompasses several logics that need to be considered and differentiated. First, highlighting the difference between static and dynamic automation, and then differentiating the types of dynamic automation, i.e., adaptive, adaptable and hybrid, by formalizing the differences also on a graphical basis (Fig. 2). If the Level Of Automation (LOA) does not change over time and it's fixed if human or machine perform the task, the allocation is static, i.e., the design choices remain unchanged over time [24]. This involves two agents within the system, the human, and the machine. However, if the LOA is not fixed but can change over time during the operations, the allocation is dynamic [25], i.e., the division of work between human and machine agents is not fixed but flexible, and context-dependent [26]. The possibility to dynamically initiate LOA or function assignment, whenever one or more triggers are met [27,22], can reflect different dynamic criteria, adaptive or adaptable. The difference lies in the authority that initiates the dynamic shift, which can be considered as a third agent of the system. The agent with this authority was defined by Sheridan as an Allocation Authority Agent (AAA) [28]. If the authority belongs to the human operator, the dynamic allocation is called adaptable automation [26]. If the authority belongs

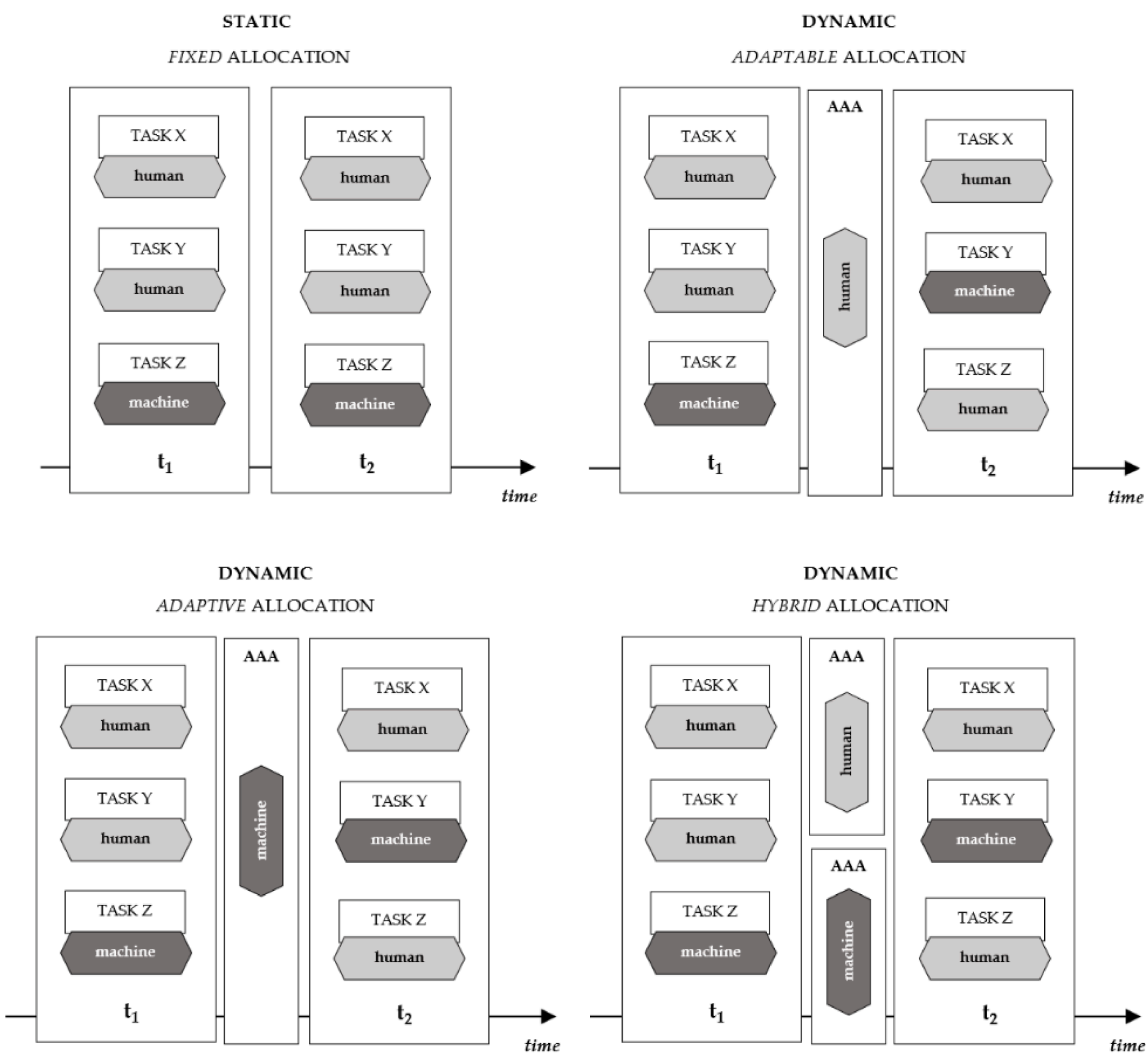

Fig. 2. Graphical representation of different automation scenarios, considering the allocation of function between human and machine and the Allocation Authority Agent (AAA): static allocation (top left), adaptable allocation (top right), adaptive allocation (bottom left), and hybrid allocation (bottom right).

to the machine, it is referred to as adaptive automation. Hybrid automation occurs when the allocation authority is variable. Adaptable automation has been found to result in greater human operator acceptance, in appropriate levels of trust in automation, and in greater situational awareness [29]. On the other hand, considerable skepticism emerges about the applicability of adaptable automation in high-complexity and criticality domains [22,30]. Several experiments comparing adaptive, adaptable and hybrid automation emerged in the literature with a low replicability in industry [23,31–33]. That is, some experiments imposed a limit on the duration of the automated task [31,32]. Others imposed that humans guide the modifications of the LOA. In the experiments comparing adaptive automation with adaptable automation [23,33], the adaptable scenarios revealed lower levels of operators' workload, fatigue, and anxiety, and higher confidence. Other experiments [22,33,34], show that hybrid automation presents advantages over the others (adaptable or adaptive) since it generates better humans' performance and lower mental and physical workload.

Since it is the most common label in the literature, including both adaptive and adaptable automation, the paper will refer to all dynamic modes as "AA", i.e., "Adaptive Automation, as other authors have already done in different contexts [35].

4. Motivations for AA

RQ2: Why was AA introduced?

The concerns that static automation introduced are not a recent issue. About half a century ago, Bainbridge reflected on the "irony of automation" [36]. Her referenced paper discusses how machines work more precisely and reliably than operators, even if, as she stated: "*the more advanced a control system is, the more crucial may be the contribution of the human operator, in case of anomalies*". Automation of industrial processes, despite bringing shared benefits, generates significant problems [1,3,22,37–46]. Here, the relationship between humans and machines brings increasingly questionable challenges [47].

As articulated by Gartenberg et al. [48], the central objective of AA is to address and rectify the criticalities that arise from static automation. This involves a multifaceted approach that encompasses both the human and machine perspectives, as illustrated in Fig. 3. What follows is an in-depth exploration of both perspectives.

In literature, the main concerns for humans operating in static automated systems refer to the out-of-the-loop condition, and to the degradation of skills and knowledge, which lead to a decrease in situation awareness, behavioral adaptation, automated induced errors, job dissatisfaction, and distrust in automation [45]. The out-of-the-loop condition refers to the difficulty for operators to know and govern automated processes. This condition arises since automation mostly leaves the operator the task to monitor the system, generating a marginalization from practical activities [49]. Automation can also cause a degradation of operators' skills and knowledge, both considering long- and short-term expertise and capabilities [3,38,44]. As an example, pervasive automation diminishes the opportunity to train manual skills, which are ineffective when an urgent manual control of the system is needed. Additionally, in automated systems, operators may become unaware of automation's inherent changes, experiencing unexpected mode transitions that can be traced back to the decrease of situation awareness [22,50–53]. This entails a decreased ability to detect automation failures and resume manual control [22,37].

Moreover, automation may increase perceptions of safety and operators may adapt their behavior and encounter new risks; this phenomenon is known as behavioral adaptation [44]. While automation compensates for or reduces some human errors, it also generates new forms of human errors, and new types of human mistakes related to unexpected system transitions, i.e., automation-induced errors [45]. These arise from the difficulty in understanding and interpreting the system.

Automation can also result in job dissatisfaction, since it could be perceived as a threat to workers, especially when inadequate training or retraining processes arise [45,54]. Distrust in automation arise when operators perceive the system unreliable [45], and when they are not be able to predict the machine's behavior and future performance, nor be sure the machine will work in his or her interest [55–58]. Complacency, i.e., the belief in and reliance on automated systems is highly relevant in automated processes [44].

From a machine's point of view, the high specialization of automated

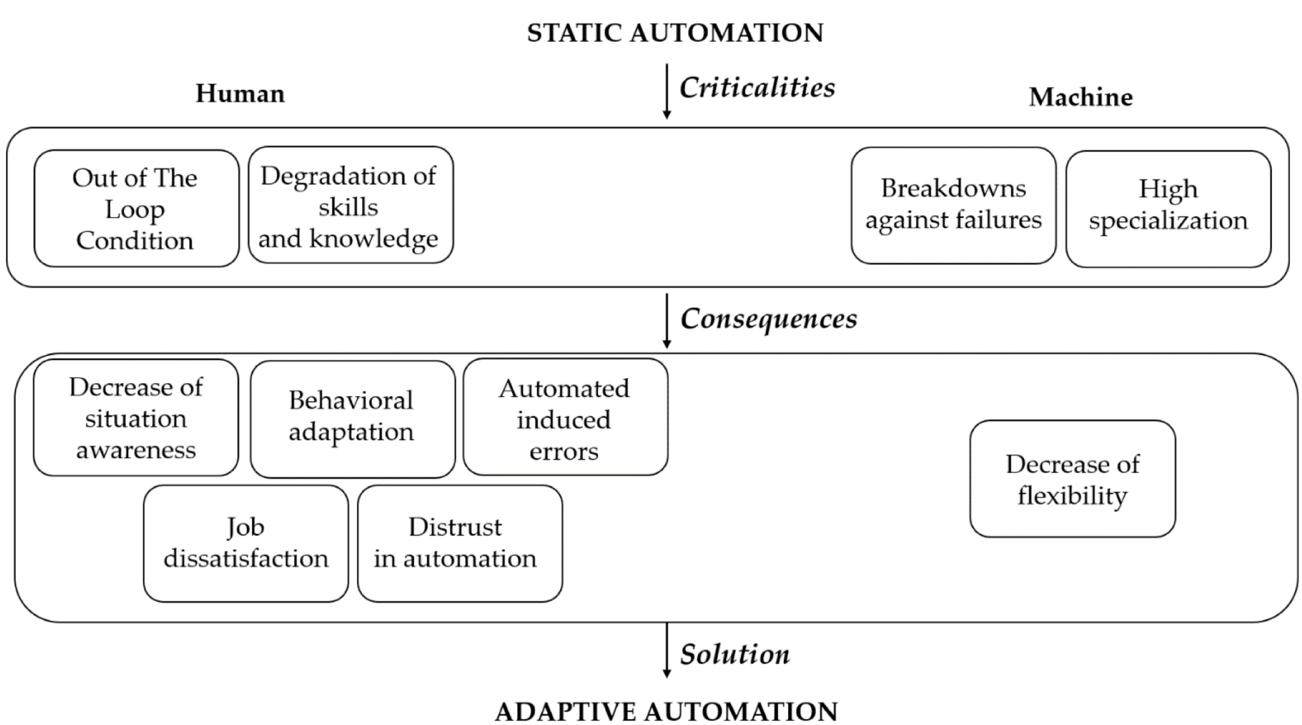

Fig. 3. From static to adaptive automation: motivations.

machines causes breakdowns against failures, i.e., some operations to stop in the face of failures or unforeseen events [38]. No other element in the system can fully replace the machines when they stop working. Moreover, the high specialization of the machines makes them highly efficient only on pre-set tasks [59]. These factors cause the decrease of flexibility, over the system's efficiency [60].

5. Historical evolution and pioneers' theories

RQ3: From an historical perspective, who has addressed the AA topic, with what purpose, and what theories emerged?

When analyzing the historical evolution of the AA, key authors emerge, i.e., Raja Parasuraman, David Kaber, Mark Scerbo, and Chris Miller [61]. The contribution of these authors is summarized in Fig. 4.

Raja Parasuraman retraced the history of AA and provided the background for the subsequent debate [62]. He discussed the main theoretical positions, and he pointed out that even though the topic of AA was proposed several years ago, extensive empirical studies were not conducted. Real-world applications reveal that there is a significant correlation between out-of-balance mental workload, impaired situational awareness, complacency, and cognitive skill degradation, all of which are found to reduce human performance and result in associated costs [63]. Such costs can be reduced with AA. Overall, empirical results have shown that AA can reduce the detrimental impacts of unfamiliarity. Another key figure in the historical evolution of AA research is David Kaber. He mapped out a program for applying AA methods to real-world assignments [64,65]. Furthermore, Mark Scerbo reviewed recent efforts to implement this topic [66]. He stated that AA relates to a single technology form in which both the user and the system can initiate changes in the system's operation. Emphasis was placed on how changes between system states are triggered [67]. He also presents research on performance-based and physiological triggers [68]. Chris Miller described how users demand to stay in charge of actions, despite their appreciation regarding the benefits AA provides them. A key factor is the explicit dialogue between user and machine, to fully understand their intentions and behaviors. Although such interaction somewhat increases the operator's workload, it has a payoff in terms of the operator's sense of control and, consequently, in terms of situational awareness, user acceptance, and human-machine performance [69].

To closely understand the origin of the idea that automation should be designed and implemented adaptively, a historical perspective is needed. First, by understanding the theories related to static automation, and then analyzing their modifications and evolutions. Reviewing the theories' temporal evolution, the main conceptual phases are summarized in Fig. 5.

Static view

The earliest automation theory dates to the 1950s, when the static function allocation was discussed by the pioneers of human factors and computer science. Referring to a posthumous classification drafted by Rouge in 1991, to allocate functions within a static automated system, three analyses can be made. The first analysis is called allocation by comparison. Such strategy compares the abilities of humans and machines for each function and allocate the function to the most capable agent (human or machine). The most famous "*MABA-MABA list*" (what "Men Are Better at Doing" and what "Machines Are Better at Doing") is the one compiled by Fitts in 1951 [20,70]. The second type of analysis is called leftover allocation. This strategy allocates to machines all functions that can be automated. Human operators are assigned the leftover functions for which automation technologies are not available. The third type of analysis is called economic allocation, i.e., an allocation that ensures economic efficiency. Even when technology is available to automate a function, if the costs of automation are higher than those of employing a human operator, the function is allocated to the operator. It should be noted that the static strategies just described "who does what" with a fixed function allocations perspective [37].

Static view questioning

The first break from that perspective comes with Sheridan's "*Model for Supervisory Control*" in 1978 [71]. Here, static design choices started to be questioned. As more tasks and jobs became computerized, the potential to question decision-making processes and other cognitive functions emerged. That model proposed scenarios in which a human operator controlled a physical process through an intermediate computer, creating temporal, and dynamic moments where static choices could be doubted.

Human-based reactive adaptation

A decade later, researchers such as Hancock [72,73], Parasuraman

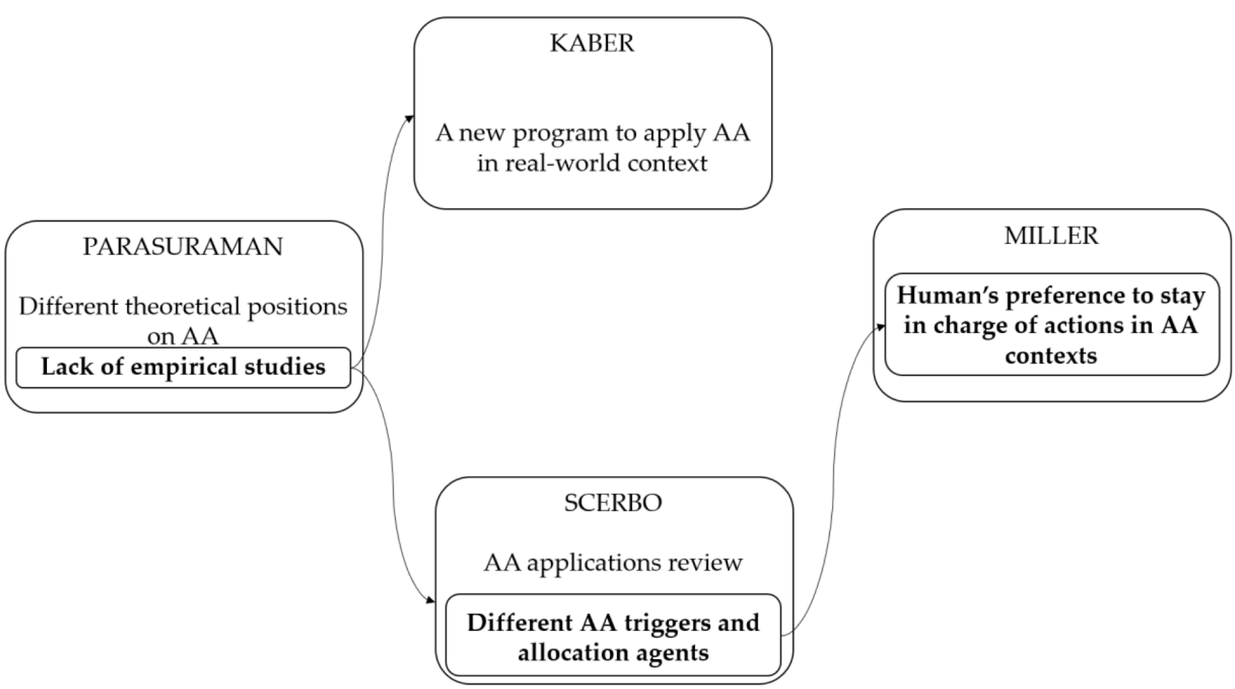

Fig. 4. The most influence authors' conceptual contribution on AA.

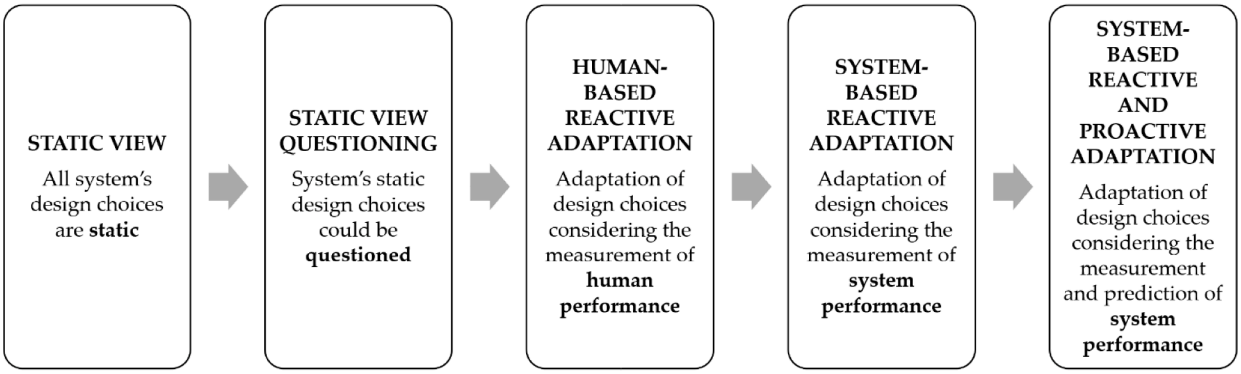

Fig. 5. Main conceptual phase of AA theories' evolution.

[63], and Rouse [74,75] suggested that design choices could be fitted to human performance. The design choices started to become adaptive considering the measurement of human performance. In 1980, Peter A. Hancock in *"The foundations of adaptive automation in physiological theories"* [76] argues that adaptation in human-machine systems is based on a redistribution of workload through the analysis of physiological and neurophysiological signals. This strand of research stated gaining ground when the U.S. Navy provided funding for empirical researches, namely by the "*Adaptive Function Allocation for Intelligent Cockpits (AFAIC) program*" in 1993 [77,78]. This program initiated a period of empirical research designed to examine the performance benefits and potential costs of AA. The results demonstrated the ability of AA systems to mitigate, at least in part, the costs associated with human-machine interaction, such as unbalanced mental workload [79], self-satisfaction [27] and reduction of situational awareness [80]. In the early 2000s, F. Wilson in "*On the use of physiological measures to determine the functional status of the operator in the implementation of adaptive aids*", states that AA can improve system performance by intervening when the operator needs it, providing the appropriate LOA [11]. This requires that the functional state of the operator is monitored continuously.

System-based reactive adaptation

Later, the adaptation was extended to the measurement of the performance related to the entire system. In 2007, Raja Parasuraman and Miller in *"Designing for Flexible Interaction Between Humans and Automation: Delegation Interfaces for Supervisory Control"* [81,82], focuses on resolving the debate between system-driven (adaptive) and user-driven (adaptable) automation, highlighting the combined benefits of both. Namely, both human and machine can initiate adaptive actions, shifting the operation between the two agents. In 2010, Richard Jagacinski in *"Comparison of decision-making and control task models"* states that a dynamic system or process is a sequence of dynamic decisions that must ensure the efficiency of the whole human-machine system over time [11]. The same year, Christopher D. Wickens in "*Stages and Levels of Automation: An Integrated Meta-analysis*" [29,83], considers that in some cases automation could fail and human must intervene, but also the contrary. So, both human and machine must be involved in generating alternative solutions to guarantee the proper functioning of the whole system cognition [80,84].

Human-based reactive and proactive adaptation

Human Factors and Ergonomics history was revolutionized in the 20th century when machines needed to adapt to users in a dynamic and continuous way [85–88]. The increasingly complex and close human-machine relationship begins to include subjective, human, and environmental aspects not entirely predictable and ever-changing, such as operators' physiological signals [89,90]. Furthermore, the literature stipulates machines should become context-aware, i.e., able to understand and learn from human behavior, adapting to human performance, emotions, and decision making [91]. Thus, besides reactive intervention, system performance analysis can also be performed to build predictive models, by estimating the state of both the operator and the machine.

6. Design elements

RQ4: What design elements are involved in an AA system?

By reviewing the documents, it emerges how, when designing an AA system, specific elements must be defined to be alterable over time. They effectively influence the configuration of the human-machine system and how it evolves. The authors refer to the Level Of Automation (LOA), Human Machine Interfaces (HMIs), and adaptive approaches to make adaptive shifts (Structural-, Functional- and Event-based approaches). The subsequent section provides a detailed explication of these elements of design. Each one answers a specific research sub-question, as reported.

6.1. Level Of Automation

RQ4.1 What LOA taxonomies emerged over time and how did the taxonomies integrate into AA contexts?

Within AA research, the topic of Level Of Automation (LOA) is pivotal, as it identifies functions involving humans and machines. This concept was pervasive in the automation literature since it was first introduced by Sheridan and Verplanck [92]. In the design of an AA system, the LOA needs definition, in terms of starting LOA and how it may change over time. These choices affect the whole system, ensuring the creation of effective human-machine interaction. Recently, a new branch of research investigates the impact of LOA on human performance, workload, and situational awareness [93–96]. Also, the importance of LOA definition lies in the practical ability to communicate to key stakeholders (e.g., system operators, designers, and managers) that there is not just one way to implement automation, but rather a range of options between fully manual and fully automated [96]. Although it may appear intuitive, such variety is often new to stakeholders, whose ideas about human-computer interaction are quite influenced by traditional systems implemented in the past. Table 1 summarizes the main LOA taxonomies arising in the literature, chronologically. For each LOA taxonomy collected, the table shows the author(s), the year, the context of application if available and the number of LOA proposed.

To understand how LOA taxonomies integrated into AA contexts over time, firstly the evolutionary time frames defined by the pioneers' theories presented were considered. When analyzing the temporal evolution, discontinuity elements that allowed the identification of different taxonomic approaches were investigated. The analysis revealed that the element of discontinuity consisted of activities initiated and managed by human and machine. Specifically, an increasing number of primary activities can be performed by human, machine, or shared: implement, control, select, communicate, and generate actions. A cross and in-depth interpretation of the content presented in the LOA

Table 1
LOA taxonomies over years.

Author(s)	Year	Context application	Number of LOA
Bright	1958	Manufacturing	17
Sheridan e Verplanck	1978	Avionics	10
Marsh and Mannari	1981	Manufacturing	6
Chiantella	1982	Manufacturing	6
Kern and Schumann	1985	Manufacturing	3
Endsley	1987	Avionics	4
Ntuen and Park	1988	Teleoperation	5
Riley	1989	No specific context	12
Kotha and Orne	1989	Manufacturing	4
Milgram	1994	Remote control operations	5
Endsley e Kiris	1995	No specific context	5
Draper	1995	Manufacturing	5
Anderson	1996	Telerobots	3
Schwartz	1996	Teleoperations of satellites	6
Billing	1997	Air traffic controller	6
Endsley e Kaber	1999	Air traffic, piloting, advanced manufacturing, teleoperations	10
Parasuraman, Sheridan, and Wickens	2000	Avionics	4
Wickens and Holland	2000	Manufacturing	Not defined
Groover	2001	Manufacturing	3
Lorenz	2001	Spacelift teleoperations	3
Duncheon	2002	Manufacturing	3
Clough	2002	Unmanned aircraft	4
Ruff	2002	Remotely operated and unmanned vehicles	3
Proud	2003	Spacelift vehicles	8
Fereidunian	2007	Electricity	11
Revisiting of LOA concept			

taxonomies resulted in the identification of disruptive and incremental taxonomies. Specifically, the disruptive taxonomies introduced new elements, logic, rules, or modes. In the incremental ones, the authors contributed to improving, augmenting, or consolidating the previous taxonomies. After all, the LOA taxonomies were grouped into time periods, as represented in Fig. 6 and detailed below. Still in Fig. 6 the authors who proposed disruptive taxonomies are given. Only from the second period onward, LOA characteristics account for AA features. The last period is still evolving.

Period I

In the early beginning, LOA taxonomies focused on statically defining "who", the human or the machine, implement actions and has the definitive decisional control, without explicitly describing how the operator and the machine share information in the control of the systems. Bright in 1958 proposed a LOA taxonomy to define who, i.e., human or automation, is initiating the control [97]. To this period belongs the pioneering work of Thomas Sheridan and William Verplanck (1978), who provided the starting point for many later-developed taxonomies [92]. Here, the LOAs range from a fully manual to a fully automated system. The authors stressed which activities were assigned to humans and to machines, for each LOA, and which of the two agents held ultimate decision-making control [26,81]. Later, Marsh and Mannari (1981) defined "automaticity" LOAs, that range from the possibility to conducts tasks manually, to fully automated [98]. In 1981 Chiantella referred to automation in manufacturing as a two-based class of automation: mechanization and computerization [99]. He stressed the topic of control actions by feedback, describing how information gathered from the process can be used to generate a control loop [44,99]. Kern and Schumann (1985) taxonomy described static LOAs in terms of implementor agents (human or machine) in manufacturing systems [100]. Similarly, Endsley (1987) identified which functions the human operator or machine is in charge of [101].

Period II

From Riley's (1989) taxonomy onward, new aspects emerge. More than implement and control actions, the agents can select actions between a wider range of alternatives. Namely, different decision-making elements can guide the choice of LOA. In this way, different moments of system control arose, up to now only intended as final decision-making control. Riley proposed a two-dimensional matrix whose rows correspond to LOA and columns to levels of intelligence. For each LOA, a different combination of actions and agents can be chosen. Each combination is called an "automation state". In this approach, the agent has multiple elements to consider in deciding what is the correct combination of actions to be performed [102]. Kotha and Orne (1989) introduced levels of mechanization [44,103], i.e., the possibility to select a different number of operations to be performed manually. Each combination defines the system LOA. Milgram (1994) introduced a multi-dimensional approach. It includes different criteria, such as the structure of the environment, and the different roles the human operator could play [104], providing a range for selecting different actions to be executed for a given LOA.

Period III

The elements introduced in the taxonomy of Endsley and Kiris (1995), start to address the static automation's concerns for human beings. Endsley and Kiris focused on the problem of out-of-loop performance, i.e., the inability to guarantee the manual control in the system in case of failure. This problem originates in the static allocation of functions between man and machine and in the ineffective communication between the two agents. Their specific goal was to identify how to sufficiently keep human operators in the control loop during the normal system operation. Also, Draper in 1995 recognized the need for communication between operators and machines. He entered in his LOA taxonomy the function of sharing critical information between agents [101,105]. One year later Anderson introduced a context-specific taxonomy [44], as well as the Schwartz's (1996), focused on a context-based communication. They specified which information is needed for the effectively operations among different LOAs. Billing (1997) proposed not a single progression from total manual control to fully automated, but a parallel control-management continuum, where the agents can exchange and share information and activities over time [44]. Endsley and Kaber (1999) provided a LOA taxonomy which included a broader range of cognitive and psychomotor tasks that require real-time control and communication. They referred to specific domains that have common characteristics, e.g., situation with high task demands and limited time resources [38]. Parasuraman, Sheridan and Wickens (2000) based on the earlier work of Sheridan and Verplank (1978) proposed that each LOA should be evaluated by examining the consequences on human performance. Furthermore, they highlight secondary evaluation criteria, including the reliability of automation and the costs of the consequences of decisions and actions [106]. Finally, Wickens and Holland (2000) proposed a LOA from a human information processing perspective [107,108].

Period IV

Lorenz (2001) stated that LOA should be regulated and changed over time to protect humans and system performance. Humans themselves can hold the authority to generate actions, and to decide which actions to perform, by producing different LOA's options. Lorenz presents a taxonomy that considers LOAs with a human-centric rationale. The operator can choose among alternatives when actions are proposed by the automation system. A rejection by the operator is equivalent to a switch of actions [26]. Duncheon (2002) proposed a similar approach focused on assembly activities [109], while Ruff et al. (2002) on the remote operations [44]. Clough (2002) presented a taxonomy focused on the amount of human-machine interaction in the system and on the point at which it occurs [26,110]. Clough's perspective was followed by Proud's (2003) multidimensional approach. Therein, LOAs are differentiated by considering who among the human and the machine is the primary agent, in terms of observing, directing, deciding, and acting

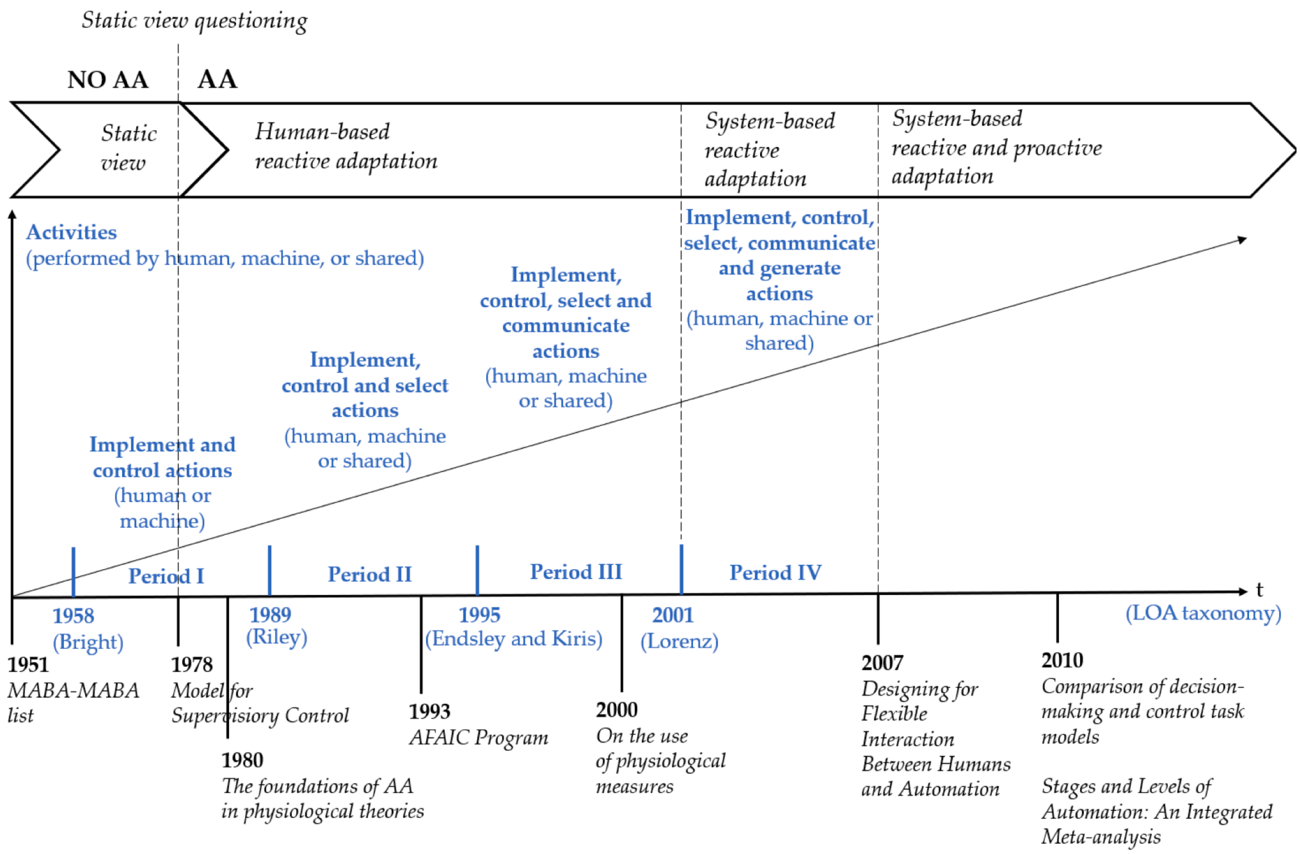

Fig. 6. Evolution of LOA taxonomies (marked in blue) and integration in AA context (top arrow), considering the element of discontinuity, i.e., the activities initiated and managed by human and machine, and the evolutionary time frames defined by the pioneers' theories.

[111]. Fereidunian's (2007) approach, extended Sheridan's methodology by introducing a lower staring LOA [26,112].

From 2007 on, the authors started to revisit the LOA concept. An evolution of the LOA taxonomy concept emerges in the work of Endsley [,[113] by the Human-Autonomy System Oversight (HASO) model. This model shows how LOA combines with other central design decisions, including dynamic principles, control granularity, and key characteristics of the automation interfaces. What emerges here, is how the concept of LOA is not the only important aspect of automation design but constitutes a central design decision that significantly influences the operator and how the operator interacts with the automation at the systemic level [114]. Moreover, the concept of working agreement is considered as an evolution of LOA topic. Working agreements define how and when human-automation teams divide tasks [115,116]. Also, in which situations the responsibilities over these tasks can change. Most of the effort in implementing such agreements is to reduce the discrepancy between different agents' expectations about the system and about how they interact with it, improving collaboration, transparency, and human-machine performance [117].

6.2. Human-machine-interfaces

RQ4.2 How should interfaces be designed for AA?

Even in highly automated systems, the human remains a central player in manufacturing operations [118]. Human operators interact with machines by means of user interfaces, i.e., the Human-Machine-Interfaces (HMIs), that constitute the modern cockpit of any manufacturing plant [14]. The HMIs become even more complex as new functions are implemented in systems [119]. Typically, automation requires a trade-off between performance and work sustainability [120]. New automation systems should incorporate HMIs that account for workers' skills and flexibility needs, compensating for their limitations and exploiting their expertise [121,122]. This must be ensured especially in AA contexts [123]. AA can introduce additional elements of complexity into system operation and control. As a result, operators require advanced HMIs that are useful to manage this complexity and improve system performance [123].

Typically, the HMIs design account for task and interaction interfaces, whose design input data and purposes are different [124]. These features lead to different possible levels of adaptation (Fig. 7). Considering the rationales on which AA system rely, the HMIs design cannot just consider task interfaces, but should also include interaction interfaces.

Designing the task HMIs implies considering human data to assigning functions to the operator and/or machine considering the ergonomic point of view. This results in tasks the operator can perform safely and efficiently, without damage to health or compromise of well-being. Here, the possible level of adaptation is the interaction-level, i.e., how to adapt the modality in which the interaction is enabled to generate optimized reciprocal influence by actions, communication, and contact.

For interaction HMIs, the proper design looks at human, machine, task, and environment data. Workers should be able to perform their assigned tasks without compromising their safety and efficiency, as well as the effectiveness and reliability of the machine operations. The reviewed documents show how interaction HMIs can play three roles: supportive, situation awareness, and training.

When it comes to a supportive role, HMIs should be designed to measure the user's capabilities, experience, and cognitive load [9]. The goal is to develop HMIs that fully fits the worker's physical and cognitive state, including impairments, and experience in the work scenario. Here, it is essential to build an accurate representation of the worker [125], accounting for static characteristics, e.g., cultural backgrounds, competencies, and ages, and dynamic states, e.g., fatigue.

Moreover, the interaction HMIs aim to improve the worker's

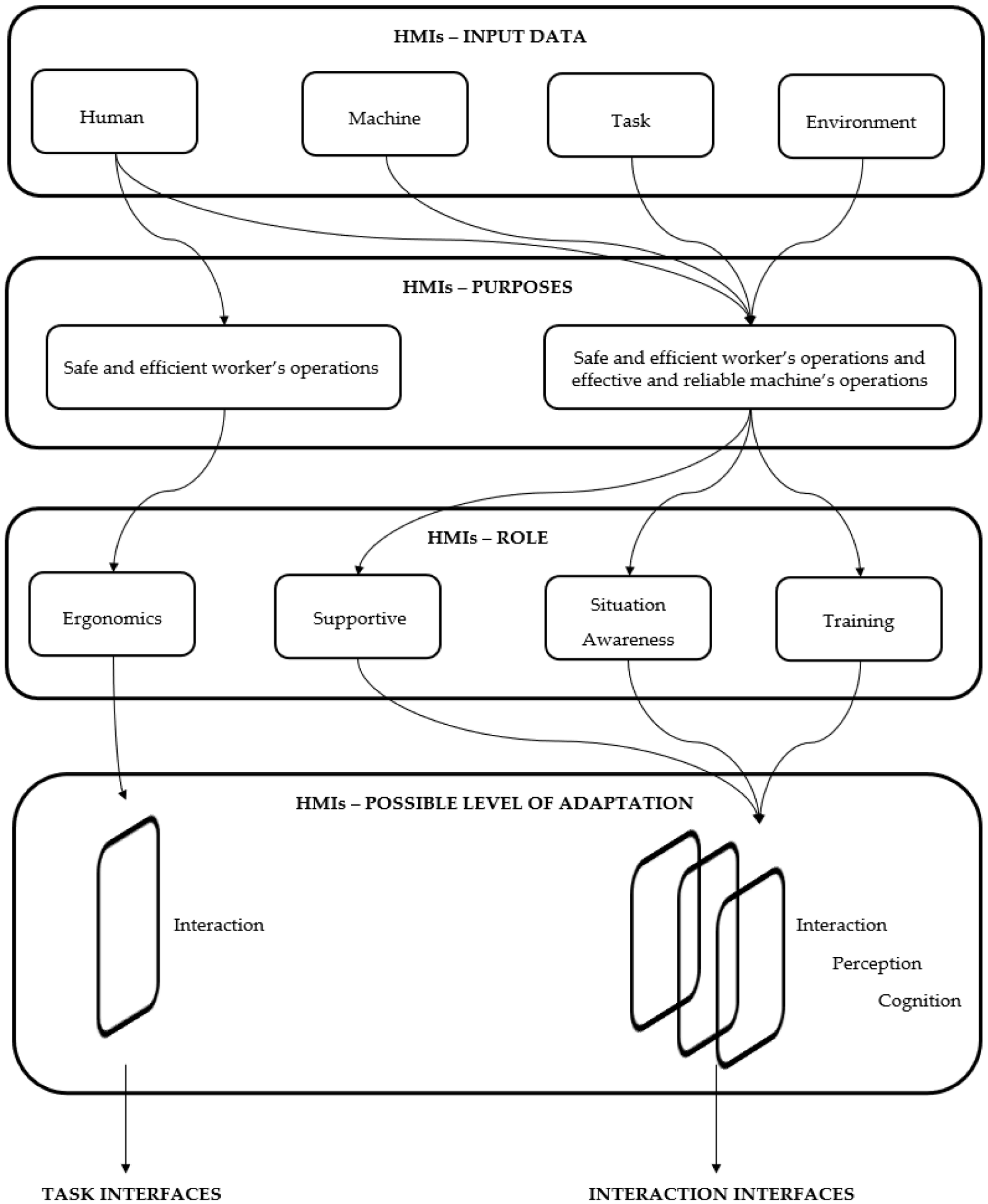

Fig. 7. Conceptualization of task and interaction interfaces.

situational awareness for timely interaction with the system, enabling a full understanding of system behavior and facilitating intervention in dynamic and unforeseen situations. So, the design of interaction HMIs must consider the dynamic contexts and environment in which the worker operates, including machine data, task progress, and environmental conditions. This supports the development of a complex and accurate situation model that is critical to the operator's situational awareness [121,126].

Finally, interaction HMIs can enhance worker capabilities, both in terms of on-the-job and long-term training. By providing offline, online, and real-time information, the HMIs increase performance and prevent failures [127].

Here, the possible levels of adaptation are three: the interaction-level, the perception-level, and the cognition-level. Thus, two more levels of adaptation than task interfaces. Namely, the perception-level considers how to adapt the way information is presented to produce positive observation and mental image directly and instinctively from the result of perceiving. This adaptation should generate awareness of the elements of environment, and of their relationships. The cognition-level considers how to adapt the typology of information presented to stimulate deep mental action and process of acquiring existing knowledge to discover new knowledge. This adaptation encompasses different intellectual processes and functions such as perception, memory, judgment, evaluation, reasoning, problem-solving and decision-making.

Within AA systems the HMIs design must consider all the aspects involving both humans and machines, conceived as a unified system [6, 124]. Also, the design needs to consider that the elements of the system may change dynamically. While in a static system the perception and cognition levels of adaptation could be minimal, in an adaptive system they gain prominence. Therefore, the HMIs design should follow both the principles of task and interaction interfaces.

6.3. Adaptive approaches

RQ4.3 How to make adaptive shifts?

To make adaptive shifts, three main approaches are proposed in literature. First, a structural-based approach. By mapping the process's nodes, connections, and relationships, some authors proposed a graph-based analysis to identify the adaptive elements of the process. Then, a functional-based approach, by defining the so-called invocation strategies. Those strategies can be reactive or proactive in nature. Finally, it's possible to implement an event-based approach, by timely defining triggers, i.e., alarm bells for the shift. Such approaches are not exclusive. For example, the choice of the trigger should be consistent with the invocation strategy.

6.3.1. Structural-based approach

When it comes to graph-based analysis, the main theoretical contribution is the Function To Task Design Process Model (FTTDPM) [2,128]. This approach helps the designer to evaluate how to allocate functions to human, machine, or dynamically among them. The illustration of the process highlights the complexity of AA systems from the earliest stages of design [128]. It is necessary to define both the general goal of the human-machine system and the specific goal of AA. The approach generates a graph of the system by decomposing the high-level functions into a network of nodes, which explore the relationships between each function. Mandatory or optional functions and relationships may emerge. Also, dependency relationships arise when the completion of one task directly affects another. Then, when functions are instantiated into tasks, the system designer assigns each function to an entity: human or machine. This assignment is a multi-objective optimization, shaped by system and human constraints. When mapping the process, the designer also formalizes if agents exchange tasks and information over time. By analyzing the structural properties of the graph, sets of nodes emerge that are the best candidates to become adaptive. To this end, several analysis tools can guide the choice of AA tasks, such as node clustering, branch counting, and comparison of intrinsic task load.

6.3.2. Functional-based approach

Other authors proposed a functional-based approach based on the definition of the so-called invocation strategies [20,21],[48,129]. Those strategies can be reactive or proactive in nature, i.e., they can guide the allocation shift after or before the event of interest. Before implementing the strategies, three aspects must be defined. What is of interest for the strategy, e.g., which event or indicator; when is critical, i.e., the threshold definition; and how to monitor it, i.e., the detection systems statement, which can be intrusive or not. Functional-based approaches are based on three main invocation strategies: critical event-, psycho-physiological-, and performance-based. Critical events strategies shift the allocation when a critical event arises. Such an event determines the performance degradation of the system or introduces risk within it. Specifically, three rationales are possible when critical event strategies are implemented, reflecting different LOA [80,130]: emergency, executive, and automated visualization. Emergency rationale, if the shift does not require any human intervention; executive rationale, if the shift requires both human and machine intervention, and the machine generates the options, while the man selects, and implements the modification. Finally, the automated visualization when the shift requires both human and machine intervention. The psycho-physiological measures require the measurement of human parameters [131–133], due to the strong correlation between these parameters and workers' cognitive, emotional, and operational states. The Electroencephalogram (EEG) is a non-invasive recording of electrical activity in the brain using external electrodes [133]; the functional Near-Infrared Spectroscopy (fNIRS) measures the hemodynamic activity rather than electrical activity of the brain [132]. Electrocardiogram (ECG) monitors heart rhythm and electrical activity, through sensors fixed to the skin used to detect electrical signals produced by the heart. Eye-tracking (ET) exploits cameras to track eye and eyelid movements and is based on assessment metrics such as the PERCLOS method (PERcentage of eye CLOSure), the Fixation Rate (FR), the Transition Rate (TR), the Glance Ratio (GR), the Blink Rate (BR), and the Pupil Size (PS). Eye-tracking measures are also used to indicate changes in confidence [131]. Measurements can also consider the Heart Rate (HR) [131]. The review of the possible measurements reveals the cost of psycho-physiological measures. Measuring such parameters requires effort in the selection, implementation and tuning of instrumentation, which furthermore can be invasive for humans and expensive for organizations. Also, the analysis of detected parameters must be customized to each person, as the critical thresholds for measured parameters are highly subjective and cannot be defined beforehand. Critical issues also stem from the privacy of the sensed data. Appropriate policies and regulations must ensure the privacy and security of human data collected. An additional element of sophistication stems from the consideration that before defining such measures, the MWL (Mental-WorkLoad) must be defined, subjectively. It results in three classes of indicators [37]: physiologies (e.g., strain, fatigue, stress, physiological activation, etc.); behavioral (i.e., linked to performances: accuracy, reaction time, etc.); and subjective (i.e., linked to the perception of time pressure, mental fatigue, etc.). In AA contexts, the NASA-Task Load Index is exploited, which measures the mental, physical, and temporary effort required, such and performance, effective effort, and frustration [23].

Other invocation strategies are based on performance measures. They refer to the whole factory system and are external (e.g., flexibility, quality, service), or internal (e.g., productivity, efficacy, logistics, maintenance, reliability, security). Like psycho-physiological measures, performance measurement requires high efforts in the detection, setting, customization and analysis stages.

The above-mentioned aspects can also be modeled to prevent future events and behavior and act proactively. Consequently, the following models emerge [134]: of critical events; of psycho-physiological measures; of performance measures. The described strategies are not mutually exclusive and can be implemented in a hybrid way.

6.3.3. Event-based approach

The event-based approach is based on the definition of specific triggers that guide the adaptive shift. There are several triggers to initiate the changes behind adaptations [135–138], characterized by a different level of onerousness for their definition, implementation and monitoring. Operator-based trigger generates adaptations triggered directly by the operator or by a systematic evaluation of the operator's status. Here, like the functional approaches based on psycho-physiological measures, measures of the operator's status need to be detectable and appropriately evaluated. The cost-effectiveness depends on the detection instruments and the customization of the analyses. The instruments may be expensive and intrusive to human beings, and the critical thresholds of the detected measures need to be tailored to individual operators. For these reasons, applying these logics extensively can be onerous. It appears simplest to confine them to a small number of operators and activities. Further event-based approaches are less onerous in terms of customization of analysis. Although they require the definitions of measurement and monitoring plans and the availability of detection tools, these can be defined beforehand and implemented on larger portions of the system. In detail, these are system-based triggers, task and mission-based triggers, environmental-based triggers, and spatiotemporal-based triggers. A system-based trigger states that the current or predicted states of the system can be used to trigger adaptations, such as the different operating modes. Then, the task and mission-based trigger defines a mission as the composition of a coherent set of objectives and sub-objectives, realized by a set of tasks. Triggers may be based on task or mission status. Here, a dynamic representation of the tasks performed by the human-machine joint system is needed. Therefore, it is essential to know how to represent the system and how to monitor it in real time. The measurements need to be compared with the expected states of the tasks or missions, to understand where to intervene. However, the discretion and customization level of measurements is lower compared to operator-based triggers. The environmental-based trigger is an estimation and a representation of the events and considers the environment apart from the machines and the operator. For a given scenario, it is required to detect and know how to analyze significant environmental parameters and compare them with pre-defined thresholds. Finally, a spatiotemporal-based trigger is an estimation of spatio-temporal criteria including time and position. There is a need for plans and tools to detect spatial and temporal measures and evaluate where these deviate from the expected thresholds.

7. Practical applications

RQ5. Which applications of AA emerged in manufacturing?

The major AA applications exist in aviation, aeronautics, and automotive [10,11,139–145], mainly concerning safety issues. Also if the literature shows that several manufacturing processes are a suitable environment for AA [146,147], practical applications are still scarce. Applications mainly have been tested in the assembly stages. That's because the assembly stages are largely based on manual labor [148]. Some human skills, such as cognitive and problem-solving abilities, are not yet effectively replaceable [149]. Nevertheless, Manual Assembly Systems (MAS) present important limitations [150,151]. MAS lack productivity, which is low compared to automated systems, and accuracy of tasks performed, due to the variability of human nature [152]. Issues in terms of ergonomics are also experienced [153]. Workstations, if not carefully designed, can further reduce productivity, and cause musculoskeletal disorders, leading to disease, absenteeism, and stress [154]. To improve such limitations, higher levels of automation and human-machine collaboration are expected [146,155,156] by the design of reconfigurable, adaptive, and collaborative assembly systems, even leveraging digital technologies [157].

Some practical applications of AA represent the attempt to test theoretical models in real-world scenarios. That is, in [146,158] where the authors present the design, engineer and test of a prototype, i.e., the Intelligent Self-Adaptive Assembly System. The analysis between different assembly configurations confirms improvements in flexibility and productivity, making the proposed system of potential interest and immediate applicability in the industry. Moreover, in [14], different models are compared to determine the applicability of AA in assembly systems. Three additional case studies emerged in [9], focused on human-machine interaction in robotic assembly and manufacturing solutions. In [159], the authors tested an adaptive robotic prefabrication process, while in [147], an adaptive human-machine collaboration paradigm based on machine learning is presented and tested. In [35] an adaptive robotic system architecture is conceptualized, and an application example is provided. It is based on a combination of adjustable and modular approaches to achieving static and dynamic balancing of robotic systems. In [160] a framework for manufacturing system configuration and optimization is designed and validate to determine the optimum locations for robots, and to reconfigure the layout basing on dynamic situations. In [1], AA solutions are tested in several manufacturing sectors to integrate the operator into the technology loop. The findings show improvements in production performance, worker safety and well-being. In [2] a new Adaptive Task Sharing model in the human-robot assembly is presented to guide its implementation; the authors outline the design principles and show the increased flexibility in assembly operations.

8. State of the art

The current research on AA relies on the basis that Industry 4.0 enables new types of interaction between operators and machines, promoting a transformation that emphasizes the centrality of humans, in line with the principles of Industry 5.0 [161–163]. The system moves from the independence of automated and human activities to a human-automation symbiosis [146]. Even if for different purposes, AA approaches need the formalization of workers' and work environments' characteristics, as well as the consolidation of new ways of communication and interaction [164]. AA represents a further possibility to enhance human physical, and cognitive capabilities thanks to a synergic relationship within all the cyber-physical system [158,165].

Compared with static automation, AA modifies different design aspects. Static automation needs to define two agents within the system, the ones who collaborate in the process, i.e., the human and the machine. Between them, the tasks are allocated in a time-fixed way. In AA, the tasks can be dynamically exchanged between these two agents, and so it's also necessary to define the AAA, i.e., the party authorizing the task shift. In AA the LOA changes over time to ensure enhanced system performance by dynamically analyzing human and machine activities. This possibility requires the two agents to be properly informed about the system's states and events, communicating reciprocally. Moreover, when needed, they could also decide to deviate from the expected standard operation, proposing new actions themselves. Thus, from an adaptive perspective, the agents must communicate actions and should generate actions, more than only implement, control, and select actions. Therefore, in AA it's imperative the role of interactive HMIs, since interfaces design must jointly improve the performance of human and machine, looking at the whole system. In this sense, users should be able to perform their assigned tasks without compromising their comfort and safety, as well as the effectiveness, efficiency, and reliability of the system. HMIs should not only be designed to adapt at interaction-level, i.e., modifying the interaction's modality to optimize the reciprocal influence by actions, communication, and contact. HMIs should adapt the way information is presented and the typology of information presented. This, to generate awareness of the elements of environment, and of their relationships, and to stimulate the mental process of acquiring existing knowledge to discover new knowledge, respectively. This means adaptation at perception and cognition level. Moreover, while in static automation the functions are allocated following compared-, leftover- and economic-based principles, the adaptive approaches introduce structural-, functional- and event-based principles. These main differences are summarized in Table 2.

Analyzing these results from a systems design perspective, AA requires a shift from a technocentric to an anthropocentric approach [166,167]. AA principles are anthropocentric as they resort to user-centered design and adapt system behavior by considering the user's capabilities and comfort during interaction [168]. Anthropocentric design

Table 2
Main distinguishing features between static and adaptive automation.

Feature	Declination Static automation	Adaptive Automation	Difference
Agent design	Human, and machine	Human, Machine, and Allocation Autority Agent	Type of activity demanded to human and machine
Task allocation design	Human, or machine	Human, machine or shared	Existence of shared activities among human and machine
LOA design	Implement, control, and select actions	Implement, control, select, communicate, and generate actions	Activities initiated and managed by human and machine
HMI design	Interaction adaptation	Interaction, perception and cognition adaptation	Possible level of adaptation of the human-machine system
Approaches design	Comparison-, leftover-, and economic-based	Structural-, fuctional-, and event-based	Strategies for system's analysis and activities' allocation between human and machine

methodologies reintroduce users into decision-making and feedback loops [1,33],[101,169]. Human decisions must merge seamlessly with those made by intelligent decision-makers, i.e., the machines, to adapt to exogenous and endogenous factors [41]. All the processes, as well as the underlying technologies, should be understandable and transparent to humans. In turn, new system goals, aimed at improving both worker well-being and overall performance must be established and shared among all agents in the process. The effectiveness of the solutions adopted needs periodic evaluation to identify and fix any misalignment or side effects [170]. As such, the AA approach is based on continuous and incremental improvement to promote worker-centered purposes [171]. However, is quite important that both parties, human and machine, provide information that enables the other to adapt, guaranteeing a mutual adaptation between technology and user over time [15,172]. The applications in manufacturing show how the research is still embryonic, with testing cases mainly in assembly activities. However, a strong potential for the development of AA emerges [147]. Flexible machines can adapt to cope with the physical and mental conditions of workers. Information about the system, collected and transmitted to all the actors within the system, allows for effective instrumentation of workplaces. The continuous collection and updating of static and dynamic data allow for the implementation of customized interventions and for the creation of a complete and informed digital representation of the production system. In this way, short-term and long-term reconfigurations are possible. Short-term reconfigurations can support the human-machine system when their performance deviate from optimal ones. Long-term reconfigurations solve intrinsic and systemic problems, such as the design-, working method-, and work environment-related.

9. Open challenges and future development

To date, many experiments on AA are conducted by simulations, needing further demonstration and validation. Still referring to experimental tests, they lack generalization of results. Tests are often case-specific and fail in providing a basis for conclusions in other contexts. Also, difficulties emerge in determining the frequency at which it is feasible to alter function allocation, i.e., in defining the sensitivity of algorithms. Too rapid an alteration may cause performance degeneration, while a too slow may not be timely. The concept of working agreement previously introduced, may provide support in this sense, since it defines how and when human-automation teams divide tasks, considering different aspects such as responsibilities and agents' expectations about the system [115–117]. Even related to function allocation, more research is needed on invocation strategies, to understand what mechanisms are most appropriate in specific contexts and how they should be activated to minimize interruptions in operations and to ensure the best performance, even during change. Challenges emerge in the real understanding of intentions between man and machine. The so-called automation surprises, i.e., unexpected behaviors by the machine that destabilize the human being, can be mitigated by a careful HMIs design. Continuous improvement-based approaches to measuring and interpreting an AA system and understanding whether it is adapting at the right time and in the right direction, have not yet been developed. Additional work is needed to ensure that AA systems are not invasive or intrusive to humans. This, also to understanding the long-term implications of AA changes, in terms of human and system performance. Furthermore, the situational awareness of the operator in AA manufacturing contexts, as well as the level of real human trust in automation, has not been evaluated. In the current scenario, the complexity of systems and human-machine interactions is increasing, and the methodologies focused on human factors and cognitive engineering may no longer be sufficient [173]. The relationship between human and technology should be examined according to different features: technical, philosophical, organizational, and psychological. So, psychological, and physiological principles must be considered in the design of adaptive industrial plants, with a specific focus on the interaction between the human and the automation system [174].

The review shows how the characteristics and criteria behind AA are applicable to some new digitized manufacturing contexts, even if further steps are needed for pushing AA from test cases and lab to practice. Practically, a complete transition from static to adaptive automation is not hoped for in all the manufacturing settings. Instead, in some circumstances a coexistence among different automation rationales might occur. In others, the static automation is defeasible. Namely, in production processes with certain properties, e.g., high relevant accident risk. Here, a LOA as high as possible, tending to the fully automation and to the avoidance of the human-machine interaction is desirable. Settings characterized by a positive or required human-machine interaction and collaboration may consider the adaptive transformation. The closeness of intents and goals, as well as the degree of affinity of the activities performed, are also factors to assess for the applicability of AA. Where AA appears practicable, the degree of feasibility for applying these logics to manufacturing contexts requires analyses to scientifically confirm the expected benefits. Benefits in terms of human, machine, and economic performance. Out of the reviewed methodologies, the ones basing the shift of activities between man and machine on critical external events, such as environmental contingencies, show a higher degree of applicability. This is because when the shift involves direct measurement of human performance, or psychological or physiological parameters, the level of subjectivity is so high as to generate criticality in defining thresholds of acceptability and reliability. Although it is feasible to analyze system performance and define zones of optimality for both human and machine, the intermediate zones, where potentially both human and machine can operate positively, and the levels of performance that determine the shift, are still critical issues. Research conducted in other contexts where AA has reached a higher degree of maturity, such as aviation and automotive, can provide guidelines for the manufacturing sector. With the right abstraction effort, it is possible to understand the types of activities and tasks where AA logics are most likely to succeed. Then, given the cross-cutting nature of the expertise required to understand and implement AA, scientific effort and collaboration must come from a mixed and cohesive background, considering, for example, experts in technology, legislature, psychology, and ergonomics. This is to ensure the best connection between man and machine. Human well-being factors should be integrated into the conceptualization, design, and implementation of AA systems. Ensuring the best performance and conditions within a complex human-machine system are both perception-related factors and design choices. This affects the architecture of workplaces, the customization of tools and interfaces, and the approaches that drive AA allocation, requiring in-depth and multifaceted studies. These studies also should differentiate when an existing setting is transformed into an adaptive one and when it is designed from the outset. If carefully pursued, the AA design enables the system to respond positively to unexpected events, providing operators with the desired benefits. Also, to positively embrace this change, the role of training, both short-term and long-term, is crucial. Notably, the role of motivation, intended as work engagement and commitment, significantly influences job performance [175]. As shown by researchers [1] to fully enhance industrial productivity and human workers safety and well-being at the same time, the human should fully integrate into the whole process, considering his two dimensions as active operator and decision maker. Through AA, a successful balance between the Human-in-The-Loop (HiTL) and Human-in-The-Mesh (HiTM) condition can be wished for. HiTL and HitM are two important concepts for human involvement in automation [176]. Namely, HiTL refers to situations in which the worker is directly participating in the production process and its loop of control, enacted by the role of the operator. HiTM refers to situations in which the worker is participating in the process of production planning and its loop of control, at management level. Both loops should be ensured in AA systems, to address the features and the needs of organizations called to operate in complex, dynamic, and ever-changing environments [160]. Here, organizations should became a resilient ecosystem, which is able not only to adapt to perturbations, but to take advantage of variability and to turn it into innovation [177]. This transformation, addressed in literature as "transfactory" [174], can reinforce the co-evolution between humans and machines, enabling the immediate adaptation of technology to human needs and performance, and the long-term co-evolution, where changes concern aspects like knowledge, culture, identities, approaches, and job frameworks.

CRediT authorship contribution statement

Margherita Bernabei: Conceptualization, Methodology, Writing – original draft. **Francesco Costantino:** Writing – review & editing, Validation, Supervision.

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