Journal of Digital Educational Technology
2026, 6(2), ep2625
e-ISSN: 2752-5503
https://www.jdet.net/

Review Article

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A systematic review of research issues with Levels of Automation (LOA)

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Citation: Memarian, B., & Doleck, T. (2026). A systematic review of research issues with Levels of Automation (LOA). *Journal of Digital Educational Technology, 6*(2), Article ep2625. https://doi.org/10.29333/jdet/19710

ARTICLE INFO

Received: 07 Apr. 2026

Accepted: 03 Sep. 2026

ABSTRACT

This systematic review critically analyzes the contexts and challenges of Levels of Automation (LOA), particularly in light of advancements by Artificial Intelligence (AI). Human–automation interaction (HAI) seeks to understand how humans interact with automated systems, particularly as increasing automation places operators increasingly out of the loop. A foundational framework within this field is the Levels of Automation (LOA) framework, which characterizes the respective roles and capabilities of human operators and automated systems. As AI becomes increasingly integrated into traditional HAI applications, a renewed examination of the current state of LOA is warranted. This systematic review examines the following research question: What research demographics, contexts, and challenges associated with LOA are reported in the literature? Data analysis, extraction, and open and axial coding were employed, and consensus was reached by iterative discussion between the authors. The review ultimately included 118 studies. The review identified six contextual categories and 26 challenge codes. The findings provide a comprehensive analysis of the evolving landscape of human–automation interaction. The contribution of this work is to outline weaknesses embedded in research with LOA and suggest a reform with prospects of enhanced HAI with AI.

Keywords: levels of automation, human–automation interaction, artificial intelligence, cognitive engineering, human factors engineering, automation, systematic review

INTRODUCTION

This study critically examines the seminal frameworks used in the human–automation interaction (HAI) literature (e.g., Vagia et al., 2016), with particular emphasis on the Levels of Automation (LOA) framework, and considers how these frameworks should evolve in response to advances in artificial intelligence (AI). Example foundational frameworks include:

- The early LOA and supervisory control concept by Sheridan and Verplank (1978), who proposed that automation is not binary but graded, advocating function allocation instead of a monolithic notion of automation.
- The influential multiple-function classes of LOA by Parasuraman et al. (2000), where automation can be exercised by multiple function *classes* (information acquisition, information analysis, decision selection, action implementation). For each function, automation can be present at various levels (from no automation to full automation).
- The six-level taxonomy of automation (Inagaki & Sheridan, 2019), which the vehicle industry uses to govern standard terminology for industry, regulators, and the public.
- The "out of the loop" problem and situation awareness demands by Endsley and Kaber (1999), where intermediate and adaptive automation is encouraged. This is because higher automation can often improve nominal performance but reduce situation awareness and recovery ability when failures occur.

Although the seminal studies provide different perspectives on LOA, they share several common findings, including the following:

- Automation is best understood as a multidimensional construct rather than a binary state.
- There is a tradeoff between performance and experience objectives as the level of automation approaches the extremes.
- The automation problem is intertwined with many constructs such as adaptivity, situation awareness, autonomy, etc.

Research on LOA often concerns expressions of seminal frameworks and lacks a more comprehensive review of their uses and outcomes, especially considering AI and emerging

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Table 1. LOA (adapted from Parasuraman et al., 2000)

Level	Description
1	The human operator does the task and turns it over to the computer for implementation.
2	The computer helps by determining the options.
3	The computer helps determine and suggest options. The human operator can choose to follow the recommendation.
4	The computer selects the action, and the human operator decides if it should or should not be done.
5	The computer selects and implements the action if the human operator approves it.
6	The computer selects the action and informs the human operator if the operator wants to cancel the action.
7	The computer does the action and tells the human operator what it did.
8	The computer does the action and only tells the human if the operator asks.
9	The computer does the action when told and tells the human operator only if the computer decides the operator should be told.
10	The computer does the action if it decides it should be done. The computer tells the human operator only if it decides that the operator should be told.

smart technologies. This gap motivates conducting a systematic literature review to understand the contexts and challenges of LOA applied in research.

Background

A dictionary definition of automation denotes (Merriam-Webster, 2023):

- "1. The technique of making an apparatus, a process, or a system operate automatically.
- 2. The state of being operated automatically.
- 3. Automatically controlled operation of an apparatus, process, or system by mechanical or electronic devices that replace human labor." (p. 1).

The above definitions often point to the mechanistic and routinized aspects of automated work, removing the need for human operators and instead putting them out of the loop. More technical automation definitions can be found in HAI and cognitive engineering literature. Examples include, but are not limited to:

- Automation is the replacement of human activity by machine activity (Satchell, 1998).
- Automation is the full or partial replacement of a function previously carried out by the human operator (Parasuraman, 2000).

The heightened role of machines as opposed to humans is highlighted in both layman's and technical definitions. HAI is undergoing substantial change as AI-enabled automation is increasingly integrated into human–automation systems (Oosthuizen, 2022). Ultimately, the considerations for using AI in HAI must be accounted for and may necessitate revising and updating the LOA frameworks.

Theoretical Underpinnings

With the increased use of automation in the industry, efforts were made to characterize the interactions between humans and automation, resulting in the development of the LOA framework. The levels of the automation framework (see example in **Table 1**) were developed to characterize the most probable types of human out-of-the-loop interaction with automated machines (Vagia et al., 2016). Among the frameworks proposed, the 10-level model of LOA (**Table 1**) is well-cited in the literature (Parasuraman et al., 2000). This model is considered educational regarding how human operators should go about discretizing interaction with automation. Yet, several issues are identified with human interactions and automation (Hancock et al., 2013; Kaber, 2018a, 2018b; Kaber & Endsley, 1997). Examples include, but are not limited to, decreased human interaction, limited detection during manual control, and task performance. As systems become more complex with the addition of automation, human operators may be challenged and require more time to reorient themselves to automated tasks or troubleshoot failures. The human operator may experience vigilance decrements, more bias and complacency towards automation performance, loss of situation awareness, taking more of a passive role, and having less knowledge of the quality or form of feedback received from the automation side ((Kaber, 2018a, 2018b). Research on the LOA framework has shown that increasing stages of automation progressively may improve performance and workload. Still, severe performance issues may be seen when the system fails (Li et al., 2013). As a result, humans are concerned about automated decision-making (Araujo et al., 2020) and the impact of automation on performance and workload (Li et al., 2014).

LITERATURE REVIEW

Work in automation and AI has been well established in the literature. Yet, less work has been done to review the integration of the two. In this section, we provide some context on views and work done surrounding the LOA alone and with AI.

LOA

Automation refers to the plan and execution of automating a task, such that the work of the human operator is outsourced to an automated agent. **Table 2** presents key work and perceptions on the LOA across the literature. As can be seen, much of the existing work relies on the established LOA framework presented in **Table 1**. Some authors point out challenges when using the LOA framework. Yet, due to its persistent use in academia and industry, researchers tend to use and modify rather than discard the LOA model.

Automation and AI

Table 3 presents key work and perceptions on the use of automation with AI across the literature. The topic has been recently discussed in the literature and is often intertwined with questions on how automation and AI may impact the workforce. Surprisingly, the literature on automation and AI minimally describes or explains findings concerning the levels of the automation framework. As such, there is a gap in examining the future of automation and AI based on existing challenges with LOA.

Table 2. Example views on LOA

Reference	Perspective on LOA
(Habib et al., 2017)	A methodological approach is presented based on a human-machine cooperation model to identify different interactions between humans and robots and then to define adequate LOA by accounting for the capacities and abilities of humans and robots according to the situation.
(Huiyang et al., 2014)	A meta-analysis of 18 studies examines how automation-induced human performance consequences depend on degrees of automation. Based on this model, it is seen that more routine operations can be highly automated.
(Jamieson & Skraaning, 2018)	Human automation interaction is becoming more complicated with technological developments. As a result, the LOA paradigm may become incompatible, as it was not first developed with recent technological enhancements in mind.
(Kaber, 2018a)	While there may be issues with the current LOA, it may be worthwhile to revise existing models that are extensively used in the industry and academia.
(Miller & Parasuraman, 2003)	Applying the LOA spectra across a detailed task model of tasks in a work domain leads to an LOA model of higher utility.
(Parasuraman, 2000)	Human performance consequences of particular types and LOA constitute primary and secondary evaluative criteria for automation design. Primary evaluative criteria include mental workload, situation awareness, complacency, and skill degradation. Secondary evaluative criteria include automation reliability, the risks of decision/action consequences, and the ease of systems integration. An important consideration is the integration of qualitative and quantitative approaches.
(Vagia et al., 2016)	A review of different taxonomies proposed on LOA is made. Findings show variable levels and notions of automation are employed across studies and research areas. Also, new terms like adaptive automation are emerging.
(Wickens et al., 2010)	A meta-analysis of 14 studies is conducted to examine the mediating effects of degrees of automation on routine system performance, performance when the automation fails, workload, and situation awareness.

Table 3. Work on automation and AI

Reference	Description
(Acemoglu & Restrepo, 2018)	There is a lack of a satisfactory conceptual framework and a dichotomy that automation will end work or increase demand for labor. The authors present a conceptual framework to help understand the implications of automation and bridge the dichotomy.
(Sarker, 2022)	A key component of the fourth industrial revolution is AI-based modeling. "A program, a script, or batch processing is commonly used in computing to automate tasks. AI-based automation takes the insights gained through computational analytics to the next level, allowing for automated decision-making" (p. 158)
(Tschang & Almirall, 2021)	A more critical conversation between society and business is needed on AI's augmentation of automation. Prior eras of automation witnessed the polarization of jobs into high and low-skilled ones. In AI-augmented automation, this imbalance may be further exacerbated.
(Nau, 2009)	Humans' understanding and task completion are different from those of AI. Consequently, automation may be different when humans versus AI is involved.
(Wang & Siau, 2019)	There are not only technological aspects, but also behavioral, societal, policy, and governance issues that need to be considered with the emergence of automation and AI.
(Johannessen, 2020)	The 4Cs of communication, creativity, collaboration, and change will be needed to put the AI and the autonomous robots of the Fourth Industrial Revolution to the best use for human workers.

METHODS

This section shares the underlying research goal and question, as well as the methodology employed for conducting a systematic review of the LOA literature.

Gap and Research Questions

Given the rapid use of automation and AI, we find the entanglement of the two inevitable (Janssen et al., 2019). Several commentaries on LOA exist (Kaber, 2018a, 2018b). Yet, little research has provided a holistic summary of contexts and challenges reported by the literature using the LOA. We see a review of current contexts and challenges with the LOA to be timely. Understanding the challenges of integral HAI frameworks may provide insight into what needs to be reconsidered, especially moving forward with integrating new technologies such as AI. This work reviews societal and ethical challenges and considerations for reconceptualizing HAI with AI. The contribution of this work is in outlining weaknesses embedded in research and suggesting directions for reform with prospects of AI in mind. Through a literature review, we examine the following overarching research question:

RQ: What research demographics, contexts, and challenges are reported with the LOA in the literature?

Search Protocol

A summary of the search process can be found in the PRISMA flow diagram in **Figure 1**, with criteria shown in **Table 4**. To examine the challenges of using LOA in research, we searched the following string in Web of Science: ("Levels of Automation" OR "LOA"). Web of Science was intentionally selected because it indexes high-quality peer-reviewed journals across engineering, computer science, human factors, psychology, transportation, and interdisciplinary research areas where LOA research is predominantly published. Its rigorous indexing standards and comprehensive citation coverage make it well-suited for systematic reviews emphasizing methodological consistency and reproducibility. Yet, the findings should be interpreted as representative of the Web of Science-indexed literature rather than an exhaustive review of every publication on LOA. We intentionally did not include AI in the search string to find a wide range of studies done on LOA. The terms challenge and context, and synonyms were used to find articles that explore these areas in the body of text. A total of 390 articles were retrieved from the Web of Science (WoS). A summary of the inclusion and exclusion criteria can be found in **Table 4**. The initial inclusion criteria contained review articles focusing on LOA or LOA and context or challenge that were disseminated in English in primary literature from Web of Science with an unlimited time frame. The initial exclusion criteria contained publications not focused on LOA or LOA and disseminated in non-English languages or from tertiary and grey literature or other databases. There were two duplicate studies and 11 studies

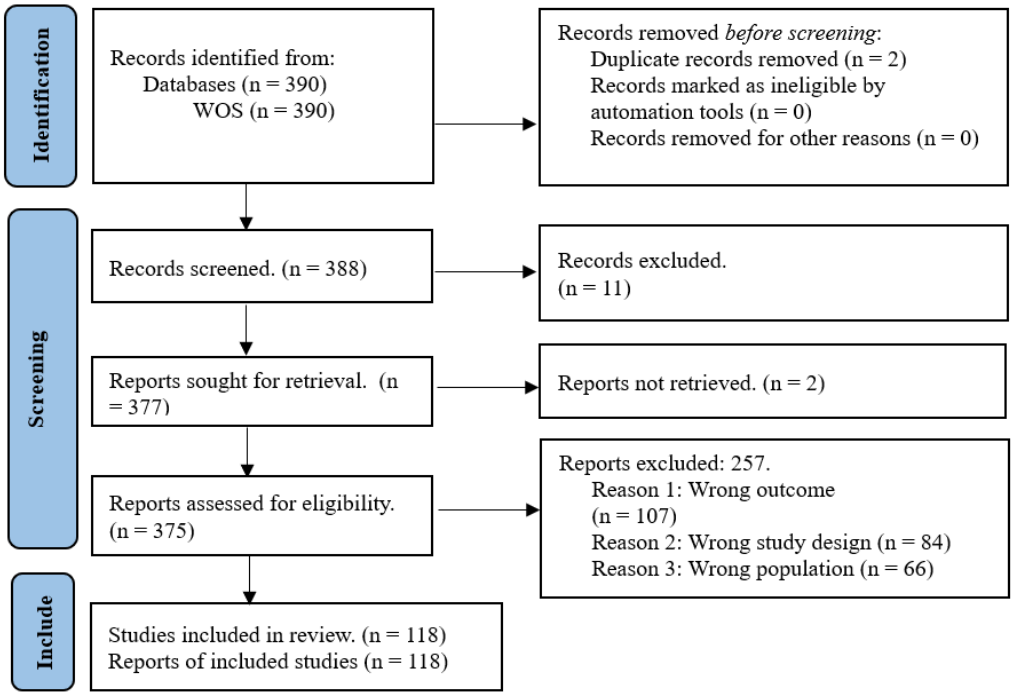


Figure 1. PRISMA flow diagram (Source: Authors' own elaboration)

Table 4. Inclusion and exclusion criteria

	Inclusion	Exclusion
Initial	Article and conference proceedings are disseminated in English with an unlimited timeframe in WoS.	Grey literature and studies that are not disseminated in English or in other databases.
	Review articles containing LOA or LOA and terms in context or challenge	Publications not containing LOA or LOA
Secondary	Studies specifically focused on LOA use, application, and challenges	Studies not focused on LOA or very briefly mentioning LOA

excluded, leading to 377 studies sought for retrieval. We were unable to retrieve two studies, leading to 375 studies for full screening. The secondary screening examined the full articles. Of the 375, 107 had the wrong outcome, 84 had the wrong study design, and 66 had the wrong population. This resulted in a total of 118 studies included in the review. This research contributes to the conceptualization and revision of LOA, considering emerging AI by analyzing the papers that share contexts/applications of LOA and challenges.

Codification and Analysis Process

Our protocol included the following steps:

- Entered the search string in WoS.
- Downloaded the full records of all the papers.
- Uploaded the full records to Covidence.
- Used Covidence to identify and remove duplicate studies.
- Reviewed the title and abstract of each article and decided whether it was relevant (following the initial inclusion and exclusion criteria).
- Downloaded and reviewed the full text of each article and decided whether it was relevant (following the secondary inclusion and exclusion criteria).
- Gathered the full demographic records of the studies selected for review.
- Extracted the data and applied open and axial coding, reaching consensus through iterative discussion among the authors; this identified and analyzed the word cloud summary of article title, year, and type of publication, the categories of contexts, and the codes of challenges.
- Presented the findings through tabular, word cloud, and column bar summaries.

RESULTS

Demographic Summary of Reviewed Studies

A word cloud summary of information extracted from the titles of the publications is presented in **Figure 2**. As expected, key themes were automation, level, system, etc., which matched the goal of the review search. A summary of the publication rate of the reviewed studies (per year) is illustrated in **Figure 3**. On average, an upward trend of publications can be seen post-2010, signifying the role such frameworks may still play in HAI.

Context and Challenge Summary of Reviewed Studies

We summarized and categorized the context of the reviewed studies. The categories and associated number of studies were:

(1) Air Traffic/Aircraft/Aviation/UAV/Space/Teleoperation (N = 16, 13%)

(2) Automated/Autonomous/Vehicle/Driving/Traffic (N = 39, 33%)



Figure 2. Word cloud summary of article titles (Source: Authors' own elaboration)

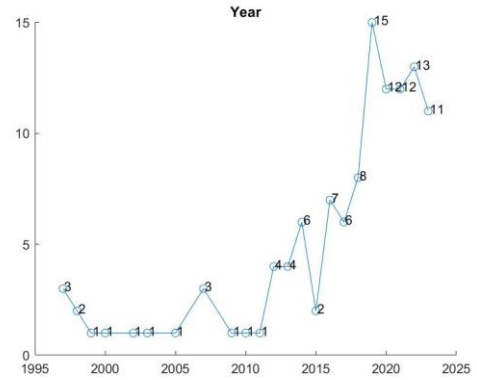


Figure 3. Number of publications per year (Source: Authors' own elaboration)

(3) Human Machine Systems/Interaction/Teaming/Interface (N = 41, 35%)

(4) Naval/Maritime/Water/Weather (N = 7, 6%)

(5) Other (N = 9, 8%)

(6) Process/Chemical/Nuclear/Modular Reactors/Safety Critical (N = 6, 5%)

We then charted and coded the challenges for each category. An overall summary of challenge codes and the number of studies per category can be found in **Table 5**.

Added layers of monitoring and integration: this may also increase LOA and necessitate monitoring for additional integrations of signals.

Automation does not aid or communicate with humans in decision-making: relates to insufficient knowledge sharing from the automation side to the humans, and taking feedback from the human side to the automation. This code suggests there needs to be mutuality, transparency, and homogeneity in communications between humans and AI, with the underlying goal of making it feel like humans are as aware and in the loop as possible.

Cloud computing errors in automation: denotes the challenges that may be introduced when adding cloud computing to the automation mix and Internet of Things (IoT) devices. Issues include security, compliance, and management of multiple clouds.

Complications of human behavior and needs with increased LOAs: points to how human actions may shift away from the norm with increased LOAs. This may be due to the need for different behaviors that are less understood or feasible for humans. This may also be due to the amplification

Table 5. Overall codes of challenge and their frequency count (green means the lowest and red means the highest number of studies with reported challenge)

Category	(1)*N=16* *13%*	(2)*N=39* 33%	(3)*N=41* 35%	(4)*N=7* 6%	(5)*N=9* 8%	(6)*N=6* 5%	*(Tot)N=118* *100%*
Added layers of monitoring, integration, and consolidation	2, 2%	0, 0%	0, 0%	1, 1%	0, 0%	0, 0%	3, 3%
Automation does not aid/in communicating with humans in deciding	2, 2%	1, 1%	2, 2%	0, 0%	0, 0%	0, 0%	5, 4%
Cloud computing errors in automation	0, 0%	1, 1%	0, 0%	0, 0%	0, 0%	0, 0%	1, 1%
Complications of human behavior and needs with increased LOAs	0, 0%	3, 3%	4, 3%	0, 0%	0, 0%	0, 0%	7, 6%
Missing critical design considerations beyond the LOA	0, 0%	0, 0%	3, 3%	0, 0%	0, 0%	0, 0%	3, 3%
Difficulty in differentiating LOAs from a human-centric perspective	0, 0%	1, 1%	1, 1%	0, 0%	0, 0%	0, 0%	2, 2%
Ethical, legal, and accessibility challenges introduced	0, 0%	2, 2%	1, 1%	0, 0%	0, 0%	0, 0%	3, 3%
Unsafe or inadequately designed fail-operational systems	0, 0%	1, 1%	0, 0%	0, 0%	0, 0%	0, 0%	1, 1%
Complexity of a heterogeneous user base	0, 0%	0, 0%	2, 2%	0, 0%	0, 0%	0, 0%	2, 2%
Uncertainty about how much automation is possible or allowed	0, 0%	1, 1%	3, 3%	0, 0%	0, 0%	0, 0%	4, 3%
Imprecision or ambiguity of the LOA makes the selection unknown or difficult	2, 2%	0, 0%	3, 3%	1, 1%	0, 0%	0, 0%	6, 5%
Difficulty in justifying increased incidents, failures, and errors	1, 1%	0, 0%	0, 0%	0, 0%	0, 0%	0, 0%	1, 1%
Increased LOA leading to degradation of objectives like situation awareness	2, 2%	5, 4%	8, 7%	0, 0%	4, 3%	1, 1%	20, 17%
LOAs each interact with objectives, such as situation awareness, differently	1, 1%	5, 4%	8, 7%	1, 1%	0, 0%	3, 3%	18, 15%
Lack of automation innovation	0, 0%	0, 0%	1, 1%	0, 0%	0, 0%	1, 1%	2, 2%
Lack of standardization, interoperability, or compatibility	1, 1%	0, 0%	2, 2%	1, 1%	0, 0%	0, 0%	4, 3%
Uncertainties with new or many levels or interactions of automation are introduced	1, 1%	1, 1%	0, 0%	1, 1%	1, 1%	0, 0%	5, 4%
Missing safety evaluation or guidelines	0, 0%	2, 2%	0, 0%	0, 0%	0, 0%	0, 0%	2, 2%
Not all LOA can be realized, or are missing	0, 0%	2, 2%	0, 0%	0, 0%	1, 1%	0, 0%	2, 2%
Not valid to predict emergent properties of a domain under LOAs	0, 0%	1, 1%	0, 0%	0, 0%	0, 0%	0, 0%	1, 1%
Perception of automation technologies is changing	0, 0%	1, 1%	0, 0%	0, 0%	0, 0%	0, 0%	1, 1%
Reliance and achievement of objectives at higher LOA are taxing	3, 3%	3, 3%	0, 0%	1, 1%	3, 3%	0, 0%	10, 8%
Difficulty in restricting or alerting to misuse or abuse	0, 0%	1, 1%	0, 0%	0, 0%	0, 0%	0, 0%	1, 1%
Complexity of role and authority allocation	1, 1%	1, 1%	2, 2%	0, 0%	0, 0%	0, 0%	4, 3%
Unsmooth transitions between levels of automation	0, 0%	1, 1%	0, 0%	0, 0%	0, 0%	0, 0%	1, 1%
Consequences of using select automation levels	0, 0%	6, 5%	1, 1%	1, 1%	0, 0%	1, 1%	9, 8%

of non-favorable human traits due to automation, such as sleepiness, lack of agency, self-confidence, and pro-social behaviors.

Missing critical design considerations beyond LOA: speaks to the implications of the LOA paradigm on the formulation of the system. This code describes the complexity of using the LOA in a problem's context. It aims to highlight that LOA cannot give a complete picture of design considerations and may introduce added complexities that need to be characterized.

Difficulty differentiating LOAs from a human-centric perspective relates to the importance of differentiating between and, at times, including diverse perspectives surrounding LOAs: acceptable definitions of LOA, such as the 10-level model, have been proposed in the literature. Yet, in practice, human perspectives and human-centered practices may be adopted with LOAs. This may, in turn, lead to diversities in understanding and representation of LOAs, which may introduce both benefits and disadvantages in controlling a system of interest with an LOA framework.

Ethical, legal, and accessibility challenges introduced: relate to the effect of automation on regulations and standards. LOA has ethical and moral implications on the safety and well-being of humans and the ecosystem. Making humans less involved or aware by introducing higher LOAs may threaten governance and the dissemination of ethical, fair, accountable, responsible, and transparent practices.

Unsafe or inadequately designed fail-operational systems: relate to systems that recover and adapt to failure appropriately. With failure in LOA, the immediate repercussions need to be well understood and accounted for. Fail-operational systems facilitate functioning even in system failure, reducing the likelihood of costs and casualties.

The complexity of a heterogeneous user base: reflects the diversity of types of operators or users working with or benefiting from automation. It emphasizes that users may have differing abilities and motivations for LOA, so it should be conceived and operationalized with a heterogeneous user base.

Uncertainty about how much automation is possible or allowed: shares the restrictions on execution and use of LOA. LOA may lack proper functioning in critical situations. Types and LOA in a context may further dictate how much consequent automation is possible or allowed, suggesting challenges with automation. Yet, abandoning the LOA framework that has been implemented and tested for years with a new framework may not be immediately achievable or safe.

Imprecision or ambiguity of LOA, making selection unknown or difficult: relates to the ongoing challenge of humans and systems to make exact inferences with existing LOA frameworks. Complex issues may arise when trying to find and choose the appropriate level of automation, so much so that the level of automation framework may not offer useful insight into the design and operation of highly automated systems.

Difficulty in justifying increased incidents, failures, and errors: this may be brought up with careless or uneducated use of automation. Technical advances combined with increased use of LOA, specifically at higher levels, may lead to more incidents.

Higher levels of automation may degrade objectives such as situation awareness, particularly under certain conditions: the studies show that when LOAs are increased to higher levels, humans' understanding of the inner workings and state of the system decreases, which can have serious complications in times of failure. This is particularly seen and is problematic in automated driving and safety-critical scenarios.

LOAs each, interacting with objectives such as situation awareness, differently: highlights that automation, no matter the level selected and whether it is at lower or higher levels, influences performance outcomes specifically of human user groups, hindering overall system performance. Maintaining ability, authority, control, situation awareness, trust, and responsibility, among other things, may become difficult.

Lack of automation innovation: points to the lack of research done to innovate in the LOA framework and take systematic and universal efforts to create a "2.0 version" that is more inclusive, functional, less hazardous, and modular in the sense of having the same efficiency regardless of whether the entire or select LOA framework is used.

Lack of standardization, interoperability, or compatibility: relates to the little work done to make the LOA framework standardized and compatible in diverse domains, contexts, problems, and technologies. For example, interoperability and information management issues, issues with migrating systems at different hierarchy LOA control, and integration of mutually incompatible technologies make the standardization of LOA difficult.

Uncertainties with new or many levels or interactions of automation are introduced: highlights that once automation is used in a situation, there may be no turning back, and complications may arise due to the need to increase levels and interactions in automation. Unprecedented LOAs and decision-support tools will be needed, and new types of interactions will emerge, so old kinds will likely become more complicated.

Missing safety evaluation or guidelines: touches upon the lack of safety protocols and standards with existing LOAs. Safety assessment is a crucial aspect of system development. Yet using frameworks long established in the literature, such as LOAs, may give the false hope that safety assessment is redundant and unnecessary.

Not all LOAs can be realized, and some points are missing from the pragmatics of making LOAs realized and implemented: there are scenarios, such as automated or conditional driving, where not all LOAs are present. This may pose complications for the user groups who are used to more comprehensive LOAs and may make errors.

Not valid to predict emergent properties of a domain under LOAs: explains how models used to simulate and predict a domain, such as vehicular traffic, are not valid to predict emergent properties of that domain under LOAs.

Perceptions of automation technologies changing relate to how humans perceive and form opinions about

automation and LOAs: specific demographic groups, such as older adults, are especially in danger of having more negative experiences with automation and, hence, withdrawing from LOAs more quickly and unsafely.

Reliance and achievement of objectives at higher LOA are taxing: it explores the added costs and liabilities introduced in the presence of higher LOA. While such an increase may present opportunities, it also presents new considerations, accountability of new or more intricate parameters, and its impact on other technologies, such as AI.

Difficulty restricting or alerting to misuse or abuse: touches upon the fallacy of use. Both humans and automation are prone to misuse or abuse in situations to maximize their benefit. The transfer of control and autonomy becomes more problematic if allocated to an entity with more potential for misuse or abuse.

The complexity of role and authority allocation: pertains to appropriately recognizing and distributing authority between humans and automation. Authorities often assume one party is taking responsibility and control over a set of decisions or actions. Yet, dependencies and dynamics exist between humans and automation, making complete authoritative allocation to one party almost impossible.

Unsmooth transitions between levels of automation: relate to the challenges faced by human user groups or systems when transitioning between LOA. Depending on the situation, the transition may require a salient and seamless transition at different times. As such, the identification of the type of transition becomes tricky.

Consequences of using select automation levels: happens when only a portion of the LOA is implemented or emphasized. This may be particularly seen in driving and autonomous vehicles, where levels 2, 3, or 4 are more heavily relied on. The degree to which select automation levels can adapt to the environment and user groups and respond to hazards is still unknown and needs further examination. The most frequent challenge was increased LOA and decreased objectives, such as situation awareness (*N*=20, 17%). The most frequent challenge per category was:

(1) Air Traffic/Aircraft/Aviation/UAV/Space/Teleoperation (*N* = 16, 13%):
- Reliance and achievement of objectives at higher LOA is taxing (*N* = 3, 3%)

(2) Automated/Autonomous/Vehicle/Driving/Traffic (*N* = 39, 33%):
- Using select automation levels and their consequences (*N* = 6, 5%)

(3) Human Machine Systems/Interaction/Teaming/Interface (*N* = 41, 35%):
- Increased LOA and decrease of objectives like situation awareness (*N* = 8, 7%)
- Interaction of LOA with objectives such as situation awareness (*N* = 8, 7%)

(4) Naval/Maritime/Water/Weather (*N* = 7, 6%):
- Added monitoring and integration, consolidation (*N* = 1, 1%)
- LOA have imprecision or ambiguity; selection is unknown or difficult (*N* = 1, 1%)
- Interaction of LOA with objectives such as situation awareness (*N* = 1, 1%)
- Lack of standardization, interoperability, or compatibility (*N* = 1, 1%)
- New or many levels or interactions of automation are introduced (*N* = 1, 1%)
- Not all LOA can be realized or are missing (*N* = 1, 1%)
- Reliance and achievement of objectives at higher LOA is taxing (*N* = 1, 1%)

(5) Other (*N* = 9, 8%), which encompassed studies in hardware, software, cybersecurity, etc.:
- Increased LOA and decrease of objectives like situation awareness (*N* = 4, 3%)

(6) Process/Chemical/Nuclear/Modular Reactors/Safety Critical (*N*= 6, 5%):
- Interaction of LOA with objectives such as situation awareness (*N*=3, 3%)

A detailed summary of categories and context, codes, and challenges can be found in **Appendix**.

DISCUSSION

This work presents a systematic review of the literature in the WoS to mine and summarize challenges reported with the concept of LOA. The discussion shares a summary of findings and implications for future work.

Summary of Findings

A review of 118 articles informed six categories of context and 26 codes of challenges. Despite the longstanding research in HAI, there are criticisms about the frameworks and models used in the field. The systematic review showed that areas of research seem fragmented. Given that most applied fields are witnessing a renovation considering AI, existing research may likely fall short when addressing the needs and challenges of AI automation interaction (i.e., including AI with human automation interaction). Here, we discuss potential challenges and insights regarding the LOA or LOA framework. We should note that we understand that AI may be placed into the human-automation interaction in different ways, and AI may help the human side, the automation side, or both. There are diverse views regarding the use of a LOA framework (Jamieson & Skraaning, 2018; Kaber et al., 2006). While recognizing the limitations of LOA, authors such as Kaber et al. (2006) suggest not discarding these frameworks until a better one is tested. Authors such as Jamieson and Skraaning (2018) suggest that reliance on a faulty model may only hold back human automation interaction research. For example, Miller warns that the discretization of an inherently continuous space offered by the LOA framework may be overly simplistic and dysfunctional (Miller, 2018).

A reformulation of the LOA framework is presented in **Table 6**. The reformulation proposed in **Table 6** emerged directly from the synthesis of the qualitative findings rather

Table 6. LOAs are reformulated into their constituent components

Level	Options by	Decision made by	Implemented by	Feedback to humans?
1	-	Human	Technology	-
2	Technology	Human	Technology	-
3	Technology	Human	Technology	-
4	Technology	Human	Technology	-
5	Technology	Human(approve)	Technology	-
6	Technology	Human(cancel)	Technology	-
7	Technology	Technology	Technology	Yes, always
8	Technology	Technology	Technology	Yes, if a human asks
9	Human	Technology	Technology	Yes, if tech decides to do so
10	Technology	Technology	Technology	Yes, if tech decides to do so

than from a priori redesign of the framework. Across the 118 reviewed studies, the dominant challenge codes consistently concerned uncertainty in authority allocation, communication between humans and automation, degradation of situation awareness, ambiguity in selecting appropriate levels of automation, and limitations in feedback mechanisms. Rather than representing isolated problems, these recurring challenges clustered around four frequent functional dimensions of human–automation interaction: who generates options, who makes decisions, who implements actions, and how feedback is communicated to human operators.

This synthesis provides the theoretical rationale for decomposing the traditional LOA framework into its constituent functional components. Instead of treating automation as a single ordinal progression of ten levels, the reviewed evidence suggests that these four dimensions vary semi-independently across contexts. The proposed reformulation, therefore, reflects the underlying structure repeatedly observed throughout literature while preserving the intent of existing LOA frameworks.

Here, we have broken down the 10 levels into their constituting components: whether the decision-making options, decisions made, and implementations are done by technology or humans. We further add whether the technology presented feedback to the humans. We find a reconceptualization of the LOA framework, in the sense that modifying the 10 levels may not be plausible. The 10 levels do not follow a level (incremental increase) logic. As shown in **Table 6** and the original definition presented in **Table 1**, levels 1 to 8 have decision-making options presented by technology. Then level 9 has a human to present options, and level 10 reverts to technology. Similar non-linear increments can be seen in the feedback to humans presented by technology. Such discrepancies may take away the essence of levels in the LOA framework.

In summary, the goal of this work is not to insist on a proposed new pedagogical framework, but rather to acknowledge that theories and methods used in human automation interaction research may come to be perturbed considering technological (e.g., AI) integrations. Prior work has shown that in the event of failures, a lack of human understanding can have fatal drawbacks for the systems, humans, and the environment (Schmitt, 2012). Yet, we also contend that access to comprehensive system information can support error detection and vigilance. Knowledge is "power," but biased, poorly constructed, collected, or presented information may be even more detrimental to survival than remaining uneducated.

Implications

We find several areas of work on human-automation interaction with AI worth exploring in the future. Examples are examining and understanding:

- HAI from a data analytics perspective: Whether more personalized interaction is useful or detrimental to work outcomes. Here, personalization can be conceived in two ways: personalization of the process control (plant) or personalization of the capabilities of the human out of the loop. In either case, explainable AI may become useful.
- LOA that have not been perceived before: Whether there are unwritten levels that can be acknowledged by AI and safely tested. For example, in medical decision support, an AI-enabled level could continuously generate multiple treatment pathways while dynamically explaining the confidence, uncertainty, and evidence supporting each recommendation before any action is implemented. Likewise, in nuclear power operations, AI could temporarily assume diagnostic responsibilities during abnormal operating conditions while simultaneously maintaining continuous human situational awareness through transparent explanations and adaptive feedback. Such levels would move beyond traditional function allocation toward adaptive collaboration in which automation dynamically adjusts authority according to context, uncertainty, and operator state.
- The nature of the LOA: Should LOA be discretized and broken down into infinitely smaller compounds, or should LOA be composed of principal levels that cannot be broken down or regrouped?
- Feedback on automation bias due to complacency: Does more input from humans, AI, or both lead to less bias?
- LOA as a blank canvas: Can LOA be newly constructed each time based on the goals of the system and AI?
- AI types: Is AI better for helping humans become superhumans or helping automation become precise, narrow, or general AI?
- AI complexity: Can AI be used as narrow or general AI for logistical automation tasks, but become super AI to diagnose faults and explain them to humans?

Future Work

Future work should move beyond treating the 26 challenge codes as isolated findings and instead synthesize them into a smaller set of higher-order dimensions (e.g., **Table 7**). These dimensions, such as cognition, decision authority, system design, adaptability, human diversity, and governance, would

Table 7. LOAs are reformulated into their constituent components

Higher-order theme	Example challenge codes
Cognitive limitations	Situation awareness, workload, complacency, trust, monitoring
Decision authority	Role allocation, responsibility, autonomy, misuse
System design	Ambiguity, interoperability, missing safety evaluation
Dynamic adaptation	Transitions, adaptive automation, AI integration
Human diversity	User heterogeneity, accessibility, expertise
Governance	Ethics, regulation, accountability

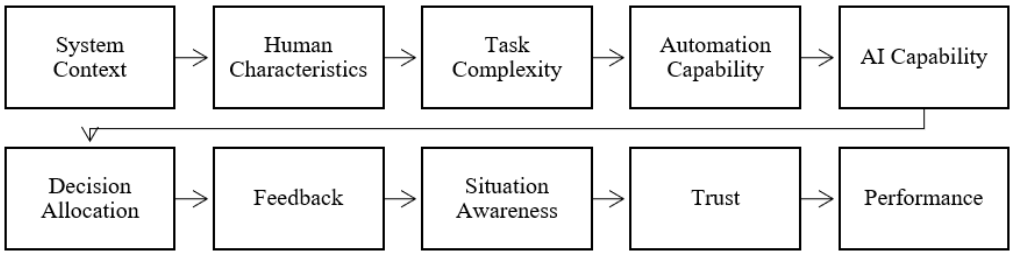


Figure 4. LOAs are reformulated into their constituent components (Source: Authors' own elaboration)

reveal the underlying structural causes of LOA limitations and provide a more theoretically coherent interpretation of the literature.

A unified conceptual framework may also be needed (e.g., **Figure 4**) to connect system context, human factors, task demands, automation, and AI capabilities, and downstream outcomes such as decision allocation, trust, and situation awareness. Such a model would help position LOA as a dynamic interaction system rather than a static taxonomy and would strengthen the theoretical contribution of the review.

Future research could explicitly model AI as a distinct actor in human–automation systems rather than embedding it within traditional automation. There is also a need to more fully theorize adaptive LOA systems in which levels of automation are not fixed but continuously adjusted based on context, workload, and system state. Explainable AI should be integrated as a core requirement of future LOA systems, particularly because many identified challenges—such as trust, awareness, and communication—depend on system transparency. Future LOA frameworks should thus prioritize trust calibration rather than static trust levels. Overall, LOA should evolve toward a human–AI teaming paradigm in which humans and intelligent systems share initiative, planning, and decision-making. Instead of discrete ordinal levels, future LOA models should account for real-world AI behavior, which rarely operates in fixed categorical states. Moreover, future LOA research should account for emerging technologies such as foundation models, multi-agent systems, digital twins, and embodied AI. A key future direction is the concept of cognitive authority, where AI systems influence idea generation, reasoning, and uncertainty interpretation. This extends LOA beyond physical or decision authority into epistemic domains, raising new questions about control and responsibility. Future LOA frameworks should explicitly incorporate uncertainty as a central organizing principle. Authority allocation should depend not only on task structure but also on uncertainty in humans, AI systems, and environments, enabling more adaptive and resilient decision-making systems.

The proposed LOA reformulation should be treated as a conceptual synthesis rather than a validated replacement model. Future empirical studies are needed to test whether its functional dimensions better predict outcomes such as performance, workload, trust, and resilience across domains.

Limitations

We recognize that this review comes with limitations. We focused on English-language publications indexed in Web of Science. Although Web of Science provides extensive multidisciplinary coverage, relevant studies indexed exclusively in databases such as Scopus, IEEE Xplore, ACM Digital Library, or PubMed may not have been captured. Consequently, our findings should be interpreted within the scope of the reviewed literature while recognizing that future reviews employing multiple databases may provide even broader coverage. We should acknowledge that several LOA frameworks exist. Here, we assumed the underlying (i.e., level-like) concepts of such frameworks are the same and, as such, examined the idea of LOA holistically and did not delve into the similarities or differences between specific names and types of LOAs. Understandably, technology has been in a race for advancement. Yet, some frameworks and perceptions towards human automation interaction have remained the same. Arguments regarding whether to renovate or dismiss frameworks such as LOA (see **Table 1**) are worthwhile (Jamieson & Skraaning, 2018; Kaber et al., 2006). While frameworks such as LOA seem "fitting" to function allocation as Fitts first introduced (pun intended!), we find AI will likely impact human-automation interaction. The goal in this work has thus been to present a comprehensive set of existing challenges with LOA and new perspectives on human-automation interaction considering AI.

CONCLUDING REMARKS

This work presents a review of the literature in the WoS to mine and summarize challenges reported with the concept of LOA. A review of 118 articles informed six categories of context and 26 codes of challenges. The most frequent challenge was increased LOA and decreased objectives, like situation awareness (N = 20, 17%). The most frequent difficulties per category were further discussed. Collectively, these findings suggest that future LOA research should shift

from viewing automation as a fixed hierarchy toward understanding it as a multidimensional interaction between humans, automation, and AI. Such a perspective better accommodates adaptive automation, explainable AI, and evolving human supervisory roles across increasingly intelligent systems. We find research and pedagogy in nearly any field are not immune to changes proposed by AI, and the field of human automation interaction is no exception. AI may strengthen the human and automation sides of the interaction. With an added agent such as AI, the system is prone to drastic cognitive changes; hence, frameworks, established or not, may witness modifications. Here, we presented a framework used in cognitive engineering and human-automation interaction, namely the LOA framework, and offered a summary of challenges reported by 118 studies from the literature and suggestions on areas of improvement.

Author contributions: BM: conceptualization, methodology, validation, formal analysis, investigation, data curation, visualization, writing – original draft, writing – review & editing; **TD:** conceptualization, software, validation, writing – review & editing, funding acquisition, project administration. All authors approved the final version of the article.

Funding: This work was supported by the Canada Research Chair Program and the Canada Foundation for Innovation.

Ethics declaration: The authors stated that the study did not involve human participants, human subjects, or the collection of personally identifiable or sensitive personal data requiring ethics committee approval. Therefore, formal ethics approval and informed consent were not applicable to this study. No sensitive or confidential personal data were collected or analyzed.

AI statement: The authors stated that generative AI and AI-based tools were used for language editing and proofreading of the manuscript. The authors reviewed and verified the resulting text and remain fully responsible for the accuracy, originality, and integrity of the article.

Declaration of interest: The authors declared no competing interest.

Availability of data and materials: All data generated or analyzed during this study are available for sharing when appropriate request is directed to corresponding author.

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Table A1. Studies included in this review

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Table A2. Summary of category number and context, challenge code and description, and reference for each reviewed study

Detailed context (1)	Key challenge	Reference
(1) Aircraft cockpit	(b) The inability of the interface to communicate the status and behavior of the various modes of the machine at increased LOA	(Andre & Degani, 1997)
(1) Cargo Handling Unmanned Aerial Vehicles	(m) Enable increased level of automation	(Brenner & Stutz, 2022)
(1) Unmanned aircraft systems	(p) Absence of software standardization	(Cuadrado et al., 2013)
(1) Virtual sensing of longitudinal parameters	(a) Increasing LOA requires monitoring and consolidation of signals about some key flight parameters	(Hardier et al., 2015)
(1) Virtual Sensing of Longitudinal Flight Parameters	(a) Increasing LOA requires monitoring and consolidation of signals about some key flight parameters	(Hardier et al., 2013)
(1) Aviation operators' efficacy in highly automated systems	(l) Technical advances and the adaptation of higher LOA serve as incidents	(Jazzar et al., 2023)
(1) Teleoperated multi-robot human-agent search and rescue teams	(b) Adding features to the automation that will allow the operator to use common strategies and provide necessary information using multiple sensory channels	(Khasawneh et al., 2019)
(1) Unmanned Aerial Vehicles	(q) To meet guidelines, new LOA must be reached	(Kikutis et al., 2017)
(1) Unmanned Aerial Vehicles	(m) Increased LOA reduces objectives such as safety	(Kingston et al., 2016)
(1) Space Teleoperations	(k) Stage of automation on the performance and perceived workload during simulated robotic arm control tasks in routine and off-nominal scenarios	(Li et al., 2014)
(1) Pilot-automation coordination	(v) Reliance on higher LOAs to manage the consequences of an error	(Nikolic & Sarter, 2007)
(1) Automated Air Traffic Control-Investigating	(k) Proper LOA for given capacity targets is unknown	(Prevot et al., 2012)
(1) Multiple simulated unmanned air vehicles	(n) Automation level interacted with the other factors for subjective measures of workload, situation awareness, and trust	(Ruff et al., 2002)
(1) Air Traffic Control	(v) Achieve Automatic Speech Recognition at higher LOAs	(Srinivasamurthy et al., 2017)
(1) Urban Air Mobility	(x) Assess Human-Automation Role Challenges	(Vempati et al., 2021)
(1) Feature tracking	(v) Temporal scale space modeling can help reach higher LOA	(Zafiropoulos & Schenk, 1998)
(2) Railway	(n) Resilience engineering in railway transportation	(Arenius & Strater, 2014)
(2) Automated driving systems	(r) Lack of safety assessment	(Böddeker et al., 2021)
(2) Partially automated vehicles	(r) Safety development	(Boelhouwer et al., 2019)
(2) Autonomous vehicles	(z) Five sub-levels for level 4 automated driving.	(Chen et al., 2023)
(2) Driver's functional state	(n) Situation awareness	(Collet & Musicant, 2019)
(2) Design of Level 2 and Level 3 Automated Vehicles	(w) Transfer of control between LOA and back to normal driving, and the misuse and abuse of automated vehicles	(Creaser & Fitch, 2015)
(2) Motion sickness in automated vehicles	(m) Motion sickness due to the increased level of automation	(Dam & Jeon, 2021)
(2) Keynote speech on modern vehicles	(m) Gaining the trust of the users with increasing LOA	(Dianati, 2022)
(2) ADHD and autonomous driving	(z) Level 2 automation on response to roadway hazards	(Ebadi et al., 2021)
(2) Guest editorial on Connected and Automated Vehicles	(q) New types of interactions will emerge (and old types of interactions are likely to become more complicated) between vehicles at different LOAs and other road users	(Farah et al., 2023)
(2) Intelligent vehicles	(z) Issues of Level 2 automation on vigilance tasks and interaction	(Fisher et al., 2016)
(2) Advanced Vehicle Technologies	(z) Levels 0 to 3 of automation that require human driver oversight, congruency with driver needs	(Furlan et al., 2020)
(2) Older adults' willingness to use vehicles with different LOAs	(u) How older adults perceive advanced vehicle technologies	(Hassan et al., 2021)
(2) Automated driving	(d) The development of higher LOA currently requires different human behavior than feasible	(Heikoop et al., 2019)
(2) Partial and fully automated truck platooning simulation	(d) LOA led to a higher degree of sleepiness	(Hjalmdahl et al., 2017)
(2) Automated driving user experience	(s) Not all LOA can be realized	(Hock et al., 2018)
(2) Critique of SAE conditional driving	(s) Not complete, and at least one level is missing	(Inagaki & Sheridan, 2019)
(2) In-vehicle assistance systems	(x) Recognize authority about LOA	(Jansson et al., 2014)
(2) Connected vehicles	(c) Malicious fog node management framework	(Kalsoom et al., 2023)
(2) Automated vehicles	(y) All LOAs will be granted on the road, but challenging situations may arise when transitioning between LOAs	(Khan et al., 2019)
(2) Automated driving	(m) Increased LOA reduces objectives such as situation awareness	(Kohn et al., 2019)
(2) Self-driving vehicles	(g) Ethical and legal challenges	(Kuru, 2022)
(2) Autonomous vehicle	(g) Equity and accessibility issues for users with disabilities	(Kuzio, 2021)
(2) Automated driving	(z) SAE level 4 to inform the driver more	(Kyriakidis et al., 2019)
(2) Automated driving systems	(b) Supporting mutual communication, enhancing observability and detectability	(Lee et al., 2023)
(2) Connected and automated vehicles	(z) Fail-operational with higher LOA (level 4 and above)	(Li et al., 2023)
(2) Adaptive cruise control	(v) Adaptive Cruise Control may facilitate increased LOA	(Makridis et al., 2020)
(2) Autonomous vehicles	(m) Significant decrease in well-being responses as LOA increases	(Naiseh & Shukla, 2022)
(2) Driving automation system	(f) Differentiate LOAs from a human-centric perspective	(Novakazi et al., 2021)
(2) The NATO Generic Vehicle Architecture	(j) Types and LOA are a big challenge as to how much automation is possible and should be allowed	(Pradhan & Ota, 2016)
(2) Accurate Friction Estimation	(n) Adapt intervention thresholds and vehicle velocity	(Prokes et al., 2016)
(2) Mixed Traffic	(d) Acting prosocial will become increasingly important	(Şahin et al., 2021)
(2) Advanced Driver Assistance Systems	(m) Increasing LOA leads to functionality that either assists or takes over in both normal and emergency scenarios	(Segler et al., 2019)
(2) Automated Driving	(n) LOAs dependent on traffic situations	(van den Beukel & van der Voort, 2011)
(2) Traffic Operations	(t) Models used today to simulate and predict vehicular traffic are not valid to predict emergent properties of traffic flows under LOAs	(van Lint et al., 2016)

Table A2 (Continued). Summary of category number and context, challenge code and description, and reference for each reviewed study

Detailed context (1)	Key challenge	Reference
(2) Automated Driving	(h) Need for fail-operational systems with increasing LOAs	(vom Dorff et al., 2020)
(2) Train Driving Performance	(n) The impact of different automation levels at different cognitive stages on high-speed train driving performance is still unclear	(Wang et al., 2022)
(2) AI for Automated Driving	(v) Achieving higher LOAS fundamentally hinges on the capabilities of AI to perform driving tasks	(Wilsch et al., 2019)
(2) Transitional Drift Control	(v) Increased LOA use	(Zhao et al., 2021)
(3) human-system interface between operators and automatic systems	(b) Avoiding breakdowns in communication between the human operator and the system	(Anuar & Kim, 2014)
(3) Critical Infrastructures	(p) Integration of mutually incompatible technologies	(Badri et al., 2016)
(3) Human-Robot Interaction in Agriculture	(n) Establishing viable, functional, and safe human-robot interactive systems	(Benos et al., 2023)
(3) Migration of industrial legacy automation systems in the cloud computing and Internet-of-things context	(p) Migrate legacy industrial functions and systems at different hierarchy LOA control	(Breivold, 2020)
(3) Commentary on Kaber's review of human-automation	(i) Challenges designers of automated systems face as a result of a heterogeneous user base	(Byrne, 2018)
(3) Automatic Critical Infrastructure Protection	(e) Critical scenarios with preventive automation	(Cazorla et al., 2013)
(3) Trends in work conditions and associations with workers' health	(i) Psychosocial hazards	(Cheng et al., 2020)
(3) Panel session: Object technology and systematic reuse	(m) Application of component ware to address increasing LOA	(Cohen, 1999)
(3) Product handling	(m) Increasing LOA	(Cornford et al., 2022)
(3) Brain-Computer Interface-Based Adaptive Automation	(m) Increasing LOA and lack of attention, loss of situational awareness, and de-skilling	(Di Flumeri et al., 2019)
(3) LOA for visual analytics	(b) The need for assisting tools that can automate the analysis process while keeping the human analyst in the loop is imperative	(Domova & Vrotsou, 2023)
(3) Commentary on Human-Automation Research	(m) Increasing LOA leads to lower situation awareness of human operators and less likelihood that they will be able to take over manual control when needed	(Endsley, 2017)
(3) Monitoring imperfect automated systems	(m) Operator attention and workload	(Ferraro & Mouloua, 2021)
(3) Cooperative human and machine systems	(n) Maintaining ability, authority, control, and responsibility.	(Flemisch et al., 2012)
(3) Evaluation of LOA in human-robot collaboration at different workload levels	(m) Quality of task execution and usability was better at high LOA for low workloads	(Gutman et al., 2021)
(3) Evaluation of LOA with different feedback modes for the elderly	(m) LOA identification for older adults while avoiding passiveness and sedentariness, appropriate coupling of LOA and feedback	(Gutman et al., 2023)
(3) cyber-physical systems in a multi-layered representation for safety and security analysis	(x) dependencies between LOA and human roles	(Guzman et al., 2020)
(3) Interface redesign for Nuclear power plant	(o) Use EID to analyze different LOA	(Hsieh et al., 2014)
(3) Critique of LOA for automation design	(k) LOA may not offer useful input to the design and operation of highly automated systems	(Jamieson & Skraaning, 2018)
(3) Analysis of the lumberjack model	(n) Situation awareness increased with increasing DOA, which contradicts the lumberjack model	(Jamieson & Skraaning, 2020)
(3) Commentary on human-automation interaction (HAI) in complex systems	(j) Abandoning an existing framework with some utility for design makes little sense	(Kaber, 2018a)
(3) Reflections on human-automation interaction (HAI) in complex systems	(f) Different perspectives can lead to richer human-automation interaction (HAI) model development	(Kaber, 2018b)
(3) Out-of-the-loop performance problems	(n) LOA has been put forth as an approach to ameliorating OOTL performance problems	(Kaber & Endsley, 1999)
(3) Domestic control systems	(n) Improving the level of trust	(Karjalainen, 2013)
(3) Automotive Automation and Autonomy	(e) Automation elements as part of a network address the issue of what's connected	(Lee, 2018)
(3) Advanced Control Room	(j) Considering which functions should be automated and to what extent	(Lin et al., 2009)
(3) Advanced Control Room	(n) examining and validating the influences of LOA on instrumentation and control systems	(Lin et al., 2010)
(3) Emergency Quick Disconnect	(j) There is an appropriate LOA in critical situations	(Marius et al., 2018)
(3) Simulated failure detection task	(k) Complex issues need to be considered when choosing the appropriate LOA	(Meyer et al., 2003)
(3) Hybrid human-AI learning technologies	(z) Six LOAs are introduced	(Molenaar, 2022)
(3) Robots that can be remotely controlled	(d) Suppress the decline in SoA by presenting auditory feedback that aims to blur the distinction between self and others	(Morita et al., 2022)
(3) Editorial for Special Issue: Human-Machine Interfaces of Automated Vehicles	(d) The interaction between automated and non-automated road users using exterior HMIs	(Naujoks et al., 2020)
(3) Cyber-physical system	(n) Enabling and controlling safe human-robot collaborative assembly operations	(Nikolakis et al., 2019)
(3) Condition-based monitoring	(x) Operators' control over the system is diminished or removed altogether	(Oldfield et al., 2022)
(3) Autonomous Systems	(g) Challenge pillars of society and the law	(Pagallo, 2017)
(3) Automation of manufacturing tasks	(d) skill, age, work experience, self-confidence, and trust in preferred LOA	(Rani et al., 2000)
(3) Human Autonomy Teaming	(e) Range of critical design considerations beyond LOA	(Roth et al., 2019)
(3) Comments on Issues in Human-Automation Interaction Modeling by Kaber	(k) Use of the LOA framework is difficult	(Sheridan, 2018)
(3) Taxonomy of human-machine collaboration	(n) Both automation and autonomy are needed, and gradual	(Simmler & Frischknecht, 2021)
(3) Cyber-physical systems	(m) Increasing LOA poses challenges in terms of safety and reliability	(Tao et al., 2020)
(3) Influence of LOA on the sense of agency	(d) Operators lose their sense of agency over the automated equipment	(Ueda et al., 2021)
(4) Production of portable water	(p) Interoperability and information management issues	(Afsarmanesh et al., 1998)

Table A2 (Continued). Summary of category number and context, challenge code and description, and reference for each reviewed study

Detailed context (1)	Key challenge	Reference
(4) Warning for severe convective weather	(z) Forecasters conditionally used automated object-based guidance within four LOA	(Karstens et al., 2018)
(4) Naval platform control	(v) Increased level of automation by increased systems integration	(Kasturi & Famme, 1997)
(4) Seawater desalination	(a) Integrated membrane processes may enable advanced LOA and remote control	(Macedonio et al., 2007)
(4) Operational river forecasting	(n) Challenges for hydrology on automation	(Pagano et al., 2016)
(4) Maritime autonomous surface ships	(k) Shortcomings in existing LOAs (e.g., imprecision and ambiguity)	(Poornikoo & Overgard, 2022)
(4) Irrigation networks	(q) Unprecedented LOAs and decision-support tools are needed	(Tariq et al., 2012)
(5) Hardware verification	(v) Opportunities for increased LOA	(Ayewah et al., 2005)
(5) Component-based development of software systems	(v) Increased LOA responsibilities	(Bate et al., 2012)
(5) Natural ventilation in green buildings	(v) Increasing LOA	(Chen et al., 2019)
(5) Automate the creation of NC programs by using the NC strategies in the CAD/CAM system Edgecam 2017 R2	(s) The gap between LOA in the fields of machining and pre-production	(Dodok et al., 2019)
(5) 4D trajectory-based enablers	(m) Subliminal control, ATC autopilot, and enhanced MTCD	(Gawinowski et al., 2007)
(5) Modern Automatic Test Equipment (ATE)	(q) Many LOAs needed for automating the system installation	(Headrick & Garcia, 2017)
(5) Cybersecurity	(m) Increased LOA may threaten cybersecurity	(Lee & Madnick, 2021)
(5) Judicial Use of AI	(m) LOA causing judges, and others, to not only rethink theoretical and practical approaches to law but also to reconsider the judicial role in the technological age	(Sourdin et al., 2023)
(5) Software Defined Networks	analyze the LOAs and complexity of security solutions in SDN environments	(Yungaicela-Naula et al., 2022)
(6) Nuclear reactor operations	(o) Limited automation innovation	(Alberti et al., 2023)
(6) Automation in process and energy industries	(n) safety, sustainability, and resilience	(Borghesan et al., 2022)
(6) Optimal LOA considering sustainability factors in the chemical industry	(n) Increasing LOA considering sustainability factors	(Hajghasem et al., 2022)
(6) Advanced Small Modular Reactors	(m) Adaptive automation for high LOA and low human performance costs	(Le Blanc & Oxstrand, 2014)
(6) Operator Training in process industry	(n) Increased LOA has necessitated new and emerging methods and technologies to perform tasks safely and effectively	(Tusher et al., 2020)
(6) Production Cost Function of Assembly Lines	(z) The issue of Industry 4.0 is associated with the topic of automation. Afterward, three LOAs are described	(Zenisek & Broum, 2020)