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The General Automation Level Allocation (GALA) Framework, or: Why Do We Need Another Level of Automation Framework?

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ABSTRACT

This paper introduces the General Automation Level Allocation (GALA) framework as a response to recognized limitations in existing Level of Automation (LoA) frameworks commonly used in the development of sociotechnical systems. Existing frameworks, while contributing significantly to human-automation interaction design, face some challenges in dealing with new systems, including potential limited precision in categorizing LoA, limited support for identifying outcomes of human-automation-interactions, missing relevant function types automation, and inadequate means for addressing dynamic task allocation between human and automation. GALA addresses these issues proposing a classification of automation based upon types of automation according to the stages of a human information processing model and levels of automation at each of those stages. It provides the flexibility and precision needed in designing new systems, while staying compatible with previous frameworks and well-established methods for studying human-system collaboration (such as hierarchical tasks analysis). The paper concludes with plans for validating GALA framework to study its applicability across diverse sociotechnical systems.

Keywords: Automation levels, Task allocation, Human factors, Human-computer interaction

INTRODUCTION

Automation, as classically defined by Parasuraman and Riley (1997) as "the execution by a machine agent (usually a computer) of a function that was previously carried out by a human", has evolved into a fundamental element within contemporary sociotechnical systems due to its potential for enhancing efficiency, streamlining processes, and responding to the escalating complexity of tasks. Furthermore, the capacity of automation to influence and optimize the distribution of tasks in real-time within sociotechnical systems provides a foundation for adaptive task allocation based on changing conditions and priorities. Critical aspects for characterizing principles of dynamic task allocation involve grasping how to integrate automation into collaborative activities and determining the optimal extent to which it should share information and participate in decision-making with humans.

These objectives may be attained through a structured approach employing so called Levels of Automation (LoA) taxonomies. These are categorization systems designed to provide structured means to understand and classify the types and degrees of automation in a system or the tasks within. Such frameworks are either one or two-dimensional. Representatives of the former type just cover multiple levels of automation ranging from "manual performance" or "full automation" of the task under analysis to full automation". Frameworks of the later type are structured based upon the stages of a human information processing model (e.g. Parasuraman et al., 2000) or the OODA-Loop (see Proud et al., 2003). After selecting the stage applicable to the task under analysis, the degree of automation is determined in a second step. The variation in the number of automation levels across frameworks arises from distinct categorizations, different granularity perspectives, specific application domains or technological advancements (Vagia, Transeth, and Fjerdingen, 2016). Despite this diversity in taxonomies, shared themes persist. These include shift from lower human control to increased automation within the framework, gradual decrease in human involvement with heightened system automation, and human-machine-interaction concepts, e.g. the potential for human intervention at automatic task conduction.

STRENGTHS AND WEAKNESSES OF EXISTING LOA FRAMEWORKS

The benefits of utilizing LoA frameworks relate to the understanding, evaluation, classification, and selection of the degree of automation within a system or task, such as: (1) Aiding in the design of automation systems by identifying potential advantages and challenges associated with each level of collaboration; (2) Providing support in understanding the implications and challenges of task allocation between humans and systems, encompassing aspects relevant to human factors and safety analysis; (3) Standardizing concepts and language across the diverse professionals and stakeholders involved in the design and development of new technology, along with the associated procedures and policies.

However, despite the merits of existing LoA frameworks, certain limitations are present, including: (1) Insufficiency in representing levels for certain functions automation can be applied to. Certain LoA frameworks may struggle to capture relevant functions automation can be applied to, such as the analysis of data gathered by sensors to provide systems state assessments. One dimensional Frameworks can be criticized for not differentiating between the human information processing stages (i.e., information acquisition, information analysis, decision selection, and action implementation). Those taxonomies have problems when classifying, for instance, a technology with a high level of automation for decision selection but a low level of support for action implementation, resulting in a lack of a corresponding unambiguous "level of automation". (2) Challenges in assigning LoA levels to the functions given by the frameworks. The differentiation between certain LoA may necessitate extensive knowledge in a specific domain, such as psycho-physiological expertise for assessing the levels of automation in a "perception task," where distinctions between the concepts of "sensation" and "perception" may be intricate. Additionally, for some frameworks, these distinctions may not always be clearly defined for all cases, leading to difficulties in assigning and/or discerning between different levels or types of automation even among experts. (3) Difficulties in determining outcomes of human-automation interaction at different LoA across the types of automation. Various LoA may exhibit unforeseen behaviors not considered during task allocation. For instance, assigning a high level of automation to action implementation could introduce a supervision task, which may not arise when lower levels of automation are assigned. This challenge becomes more pronounced in the presence of novel or undefined tasks, particularly when Artificial Intelligence learning capabilities are involved in discussions concerning safety-related implications. (4) Insufficient characterization of complex and/or novel human-machine cooperation (Miller, 2005). Current frameworks may fall short in adequately characterizing human-machine cooperation, often adopting a *binary* (man OR machine) *view of automation* (Dekker and Woods, 2002) rather than focusing on the question of *"How do we make them effectively collaborate?"* (5) Lastly, existing frameworks may not fully account for the dynamic allocation (adaptive and/or adaptable) of tasks and responsibilities based upon changing conditions and real-time priorities in non-fixed automation. The capability to dynamically allocate tasks in complex environments necessitates a comprehensive and flexible framework.

How to Address Open Issues

In light of these limitations, certain researchers argue that there is no imperative to delve further into LoA taxonomies as foundations for designing complex systems (Bradshaw et al., 2013; Jamieson and Skraaning, 2018). Despite these criticisms, LoA frameworks still continue to play a crucial role in systems engineering. This is because mapping functional capabilities and allocating tasks between human and automation provides a fundamental conceptual basis for designing system interfaces. Engineers must still consider the parallel interaction between humans and machines in order to outline and model teamwork approaches for effective interface design. Understanding what the human and computer / robot / virtual assistant are each doing and how they depend on each other, is still essential for effective system design (Ali et al., 2022). Once the range of functional distributions for a domain is identified, designers can discuss how various LoA can be presented to optimize system performance. In order to address the open issues and limitations of current LoA frameworks, it can be interesting to dive deep on the underlying concepts behind them (Bradshaw et al., 2013). For instance, some improvements can be done regarding the application of human information processing concepts used for types of automation in two-dimensional taxonomies (i.e., information acquisition, information analysis, decision selection, and action implementation) which may be too simplified when applied to new types of technologies (i.e. those stages were created having in mind the "human-computer" interaction and not with AI-based technologies for instance). The definitions put forth by Parasuraman et al. for the information processing stages used in some frameworks, consider cognitive nominal stages that might not comprehensively account for the influence of operator task experience, complacency, and heuristics on the delivery of system functions in complex systems. Moreover, the distinction between perception and action, in the context of embodied cognition, should be considered. Embodied cognition (e.g., Saphiro, 2019) emphasizes that human cognition is not limited to the brain but is interconnected with the body and its interactions with the environment, especially in skill-based behaviors. For instance, the differentiation of the skill-based stage (that involves automatic and intuitive actions rooted in learned motor patterns) vs the rule-based stage (that adheres to predefined rules to guide actions and decision-making) vs. the knowledge-based stage (that entails higher-level cognitive processes based on explicit knowledge and reasoning) could be beneficial to have a more precise model of "information processing" and "action implementation" stages. All these perspectives suggests that automation system design could consider to encompass not only cognitive aspects in nominal situations, but also the physical and sensory elements of human-system interaction beyond human information processing, not to mention other relevant factors such as teamwork, trust, and other factors.

The GALA Framework

Taking these factors into account, the human factors engineering team in Manching of AIRBUS Defence and Space GmbH has developed a framework called General Automation Level Allocation (GALA). This framework incorporates the strengths of previous frameworks while also addressing some of their limitations (as discussed above). The GALA framework strives to fill the gaps by assigning specific levels for each function type, acknowledging the dynamic nature of task allocation, and fostering understandability of human-automation collaboration when applying its types and levels of automation at describing modern human-machine systems.

The GALA framework employs a two-dimensional approach, striving for compatibility with previous frameworks while being versatile in generating designs for future systems and facilitating dynamic task allocation in real-life scenarios. According to the framework, each task under analysis will first be classified based on the four stages of the human information processing model presented in Parasuraman et al. (2000). For each of those types of automation, the taxonomy provides six levels of automation, ranging from 0: no support to 5: fully automated. This amount of levels was chosen because it is still quite manageable for the analyst and at the same time offers sufficient granularity to distinguish all relevant aspects between the levels. By incorporating two pivotal dimensions (levels and types of automation), the structure is similar to other two-dimensional frameworks, e.g. the one of Save et al. or the one of Proud et al. (2003). However, in contrast to previous taxonomies, the levels are defined in a generalizable way so that they can be applied to tasks in systems of various domains. To promote the practicality and consistency of its usage, each level shares the same common meaning across all types. For example a LoA of 0 means always that the human operator performs the function without any automation support just relying on low-tech artefacts, such as binoculars for the stage "information acquisition" or pen & paper for the stages of "information analysis" and "decision making". To enhance its usability further, it offers tools to select appropriate levels, including a decision tree. While the stages of the framework are drawn from the information processing model proposed by Parasuraman, Sheridan, and Wickens (2000), similarly to the LOAT taxonomy (Save et al., 2012), GALA levels are primarily defined based upon thorough analysis of the following "one-dimensional" frameworks: the PACT framework (Tayorl, 2001), the "ten levels of automation for human–computer decision making" proposed by Sheridan, Verplanck and Brooks (1978) and the "levels of control and automation" by Endsley and Kiris (1995) and Endsley and Kaber, (1999). Next to considering existing frameworks, the LoA definition involved incorporating elements of adaptation compatible with coactive design methods (Johnson et al., 2014), simplification, combination, and integration in line with the state-of-the-art knowledge on the subject. The development also took into account the empirical experiences of the AIRBUS Human Factors Team, gained through the team's direct use of these frameworks in various projects over the years. Furthermore, efforts have been made to at least consider the applicability of GALA across domains (Barbieri et al., 2022), signified by the "General" reference in the acronym.

In the context of system design, the GALA framework provides means to assign automation levels for each pertinent task derived from a task analysis or for any function requiring design or assessment. Initially, the GALA framework mandates the identification of relevant information processing stages (A, B, C, D) associated with the task or function. Then, GALA requires the determination of appropriate levels or a range of levels of automation for each implicated stage (0, 1, 2, 3, 4, 5). To facilitate this process, GALA provides a decision tree complemented by triggering questions. These resources are designed to assist in allocating suitable automation levels for the respective information processing stages and enhance the understanding of implications on human-automation performance.

Table 1. Levels of automation according to the GALA framework.

Level Type	A Information Acquisition	B Information Analysis	C Decision Selection	D Action Implementation
0 No Support No or only low-tech artefact support	Operator acquires relevant information directly (not mediated via display), might include usage of low-tech artefacts (e.g. binoculars)	Operator compares, combines and analyses different information items, might include usage of low-tech artefacts (e.g. pen & paper)	Operator generates decision alternative(s) and selects (chooses and confirms) the appropriate one, might include usage of low-tech artefacts	Operator executes and controls all actions, might include usage of low-tech artefacts
1 Low Support Simple function under control of operator	Sys acquires & provides information to operator	Sys conducts "simple" analysis operations corresponding to lower level of cognitive skill (e.g. comparing information to detect differences, making linear predictions) Support is based on user's settings	Sys generates & provides feasible decision alternative(s) and/or assists operator by generating decision alternatives (e.g. by evaluating them) Operator can select one of those, modify it or can generate and select an alternative option	Operator initiates action implementation and is prime executor Sys executes part(s) of the action and/or provides execution support (e.g. by constraining action space) Operator is able to monitor, modify and/or interrupt at any time

(Continued)

Table 1. Continued

Level Type	A Information Acquisition	B Information Analysis	C Decision Selection	D Action Implementation
2 High Support Complex function under control of operator	Sys acquires & provides information to operator Sys supports by integrating data, filtering and/or highlighting information Support is based on user's settings	Sys conducts "complex" analysis operations corresponding to higher level of cognitive skill (e.g. interpretation, classification, complex predictions) Sys might trigger alerts Support is based on user's settings	Sys generates & presents one or more feasible decision alternative(s) Sys preselects (chooses but doesn't confirm) one decision alternative Operator can approve preselection or can generate and select a different decision alternative	Sys executes full action sequence Operator initiates action implementation or approves sys initiation proposal Operator is able to monitor, modify and/or interrupt at any time The operator must be ready to intervene (interrupt/adapt) immediately at any time
3 Supervised Automated function under supervision by operator	Sys acquires & provides information to operator Sys supports by integrating data, filtering and/or highlighting information Support is based on criteria set by sys or at design-time. Criteria are still modifiable by the operator	Sys conducts analysis operations corresponding to higher cognitive skill level (see above) Sys might trigger alerts Support is based on criteria set by sys or at design-time. Criteria are still modifiable by the operator	Sys generates & presents one or more feasible decision alternative(s) Sys preselects one decision alternative Operator has adequate time to veto before automatic decision implementation (in case of veto, the "fallback" should be specified)	Operator or Sys initiates action implementation Sys executes full action sequence The operator is able to monitor, modify and/or interrupt at any time The operator must intervene within a reasonable time, when prompted by the system
4 Monitorable by Operator Automated function sometimes checked by operator	Sys acquires & provides information to operator Sys supports by integrating data, filtering and/or highlighting information Support is based on criteria which are set by sys or at design-time Criteria are visible/accessible but not modifiable by the operator	Sys conducts analysis operations corresponding to higher cognitive skill level (see above) Sys might trigger alerts Support is based on criteria set by sys or at design-time Criteria are visible/accessible but not modifiable by the operator	Sys generates feasible decision alternative(s) Sys selects one of those autonomously (no further approval by operator needed) Operator is only informed about the decision	Operator or Sys initiates action implementation Sys executes full action sequence Operator can monitor and interrupt
5 Fully Automated Fully Automated function completely decoupled from human	Sys acquires information Sys integrates and filters data Support is based on criteria which are set by sys or at design-time Criteria are neither visible nor modifiable by the operator	Sys conducts analysis operations corresponding to higher cognitive skill level (see above) Sys might trigger alerts Support is based on criteria set by sys or at design-time. Criteria are not visible/accessible and not modifiable by the operator	Sys generates feasible decision alternative(s) Sys selects one of those autonomously (no further approval by operator needed) Operator is not informed about decision	Sys initiates action implementation Sys executes full action sequence Operator cannot monitor or interrupt action

Classifying Concrete Automation Example With the GALA Framework

Consider the AMAN (Arrival Manager) as an example for classifying different automation levels. AMAN is a tool designed to automate sequencing arriving traffic at an airport by providing advices for air traffic controllers (ATCOs). It continuously calculates arrival sequences and times for flights, utilizing a combination of flight-plan information, radar data, weather details, local airspace, route information, and an aircraft performance model in trajectory prediction. This results in a 'planned' time for each individual flight, provided to the ATCO and required time suggestions (e.g. Time to Lose/Gain information). The controller is then responsible for confirming and applying an appropriate method (vectoring, path stretching, speed changes, or holding) for the aircraft to meet its advised time or position in the sequence. According to GALA framework, in nominal situations, it would be possible to assign high-level of automation to the information analysis tasks (e.g. level A3: system acquires information according to criteria that, if/when needed are visible modifiable by the ATCO), and for the calculation analysis tasks (e.g. B5: the system conducts complex analysis and the operator is informed of the results). At the same time, it could be possible to assign low-level of automation to the decision tasks (e.g. **C2** for vectoring: system can preselect some advisory to be approved e.g. "L2 - lose 2 minutes to fit position in the sequence") and low levels to action implementation tasks (e.g. **D0** as the ATCO provides the actual vectoring instructions to the aircrew). In an increasingly complex traffic environment, to improve runway arrival throughput, while ensuring a safe separation of aircraft and avoid mental overload of the responsible ATCO, the relationship between human and automation may require a change, for instance by providing the controller with more tools for decision making and action implementation. Designing AMAN improvements and integrations could require to maintain the same automation levels for information acquisition (A3) and analysis (B5), but could dynamically increase (whether *adaptive* or *adaptable*) decision making levels (e.g. up to **C3** by pre-selected aircraft instructions for early delay absorption, vetoable by ATCO) and action implementation (e.g. **D4**: provide controlled time of arrival to the aircraft, monitorable by ATCO).

Future Directions

The GALA framework, briefly introduced in this paragraph, represents its initial version, and it is currently subject to ongoing validation and refinement process. This process aims to incorporate diverse perspectives and tools, resulting in more nuanced and comprehensive taxonomies that capture the intricacies of automation in human-machine systems. The validation will: (1) refine and finalize the framework, considering allocation to the so called "indivisible tasks" or novel tasks arriving at uncertain times (Tsarouchi et al., 2017); (2) seek improvements in performance outcome predictions through empirical data; (3) develop modeling templates for human-automation cooperation and emerging tasks, applicable for safety assessments and the integration of other frameworks used in designing human-autonomy joint teaming activities; (4) Enables dynamic task allocation at the operator level, incorporating a dedicated GALA-O taxonomy; (5) Produce empirical data by applying the framework to technologies with various automation modalities and from in-depth discussions with subject experts in different domains, in order to infer task performance in reasonably complex systems and construct knowledge and extract design principles for integration into models.

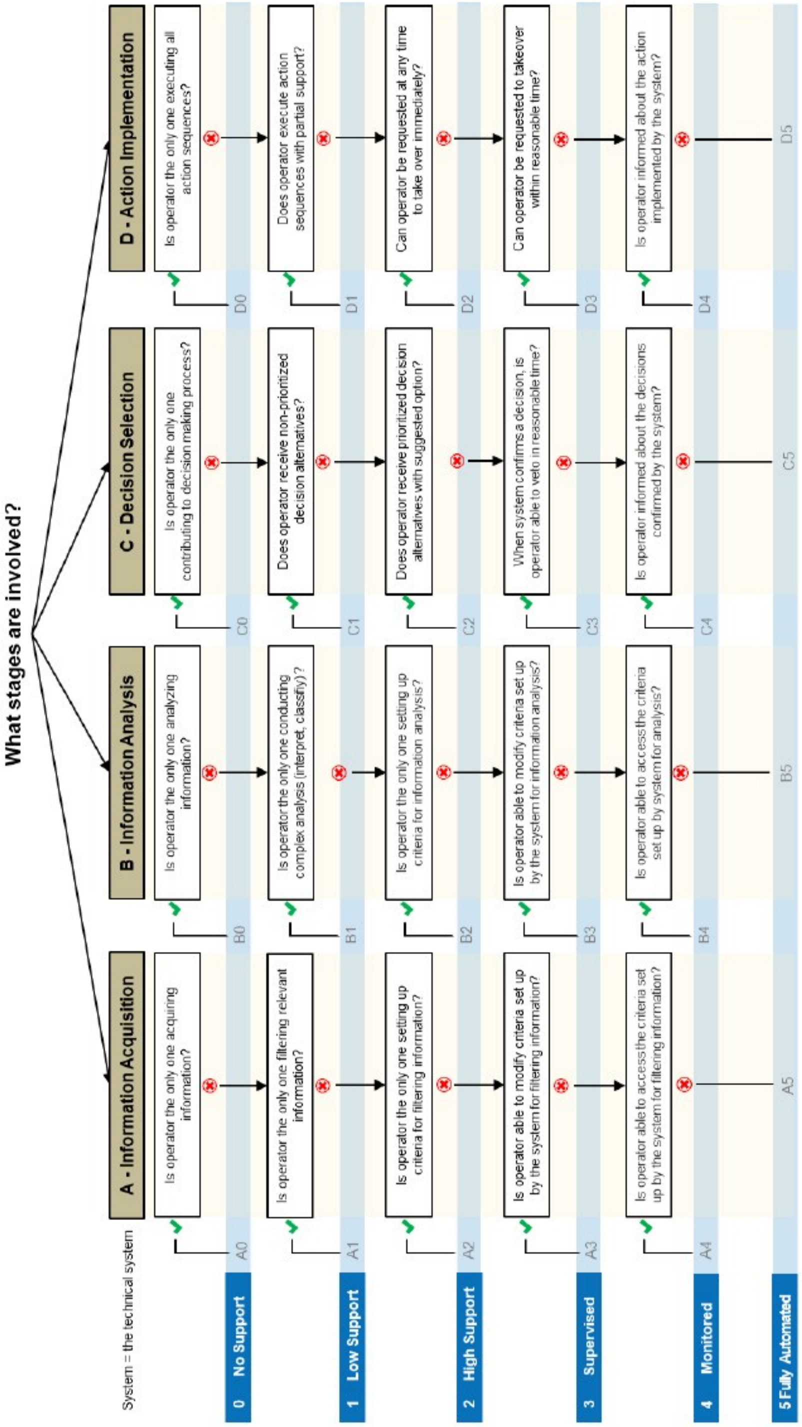

Figure 1: Decision tree to determine the LoA of a system or function according to GALA.

CONCLUSION

Levels of Automation frameworks are important and useful tools. The mapping and classification of tasks based on info processing stages and the allocation of LoA are required for the design of human-machine-interaction concepts. Once the range of functional distributions has been identified it could be possible to proceed to discuss how to optimize the joint human-machine performance, or assess trade-offs and risk of interactions with automation. Although this mapping may be complex, it does not necessary mean that using structured Levels of Automation frameworks is preventing "teamwork analysis". On the contrary, it may be difficult to understand how to begin to identify the "*things the human depends on the computer for*" or "*things the computer depends on the human for*" if we do not consider before what things the human and computer (each) may be doing (Kaber, 2018). These insights collectively underline the necessity of considering a more dynamic, adaptable, and context-aware approach when applying LoA frameworks, recognizing the intricate interplay of psychological factors and the dynamic nature of real-world operational environments. Better taxonomies may be required, but still taxonomies are required for system design. Overall, the resulting GALA table and decision trees, provide an overview of automation levels associated with the respective information processing stages. This overview can be useful for matter and non-matter experts for: assigning and discussing appropriate/required LoA, as it supports shared understanding of automation; during the design and evaluation of tasks and its implications (e.g. emerging tasks, workload and SA assessments, etc.); for the application of additional frameworks (e.g. in case of joint/shared human and high levels of automation activities); in ethical considerations; and for analyzing *observability*, *directability* and *predictability* of automation.

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REFERENCES

Ali, A., Azevedo-Sa, H., Tilbury, D. M. and Robert Jr, L. P., (2022). Heterogeneous human–robot task allocation based on artificial trust. Scientific Reports, 12(1), p. 15304.

Barbieri, G., España, A. and Sanchez-Londoño, D., (2022). A Taxonomy for Levels of Automation based on the Industrial Revolutions. IFAC-Papers OnLine, 55(17), pp. 368–373.

Bradshaw, J. M., Hoffman, R. R., Woods, D. D. and Johnson, M., (2013). The seven deadly myths of "autonomous systems". IEEE Intelligent Systems, 28(3), pp. 54–61.

Endsley, M. R. and Kiris, E. O., 1995. The out-of-the-loop performance problem and level of control in automation. Human factors, 37(2), pp. 381–394.

Endsley, M. R. and Kaber, D. B., (1999). Level of automation effects on performance, situation awareness and workload in a dynamic control task. Ergonomics, 42(3), pp. 462–492.

Dekker, S. W. and Woods, D. D., (2002). MABA-MABA or abracadabra? Progress on human–automation co-ordination. Cognition, Technology & Work, 4, pp. 240–244.

Jamieson, G. A. and Skraaning Jr, G., (2018). Levels of automation in human factors models for automation design: Why we might consider throwing the baby out with the bathwater. Journal of Cognitive Engineering and Decision Making, 12(1), pp. 42–49.

Johnson, M., Bradshaw, J. M., Feltovich, P. J., Jonker, C. M., Van Riemsdijk, M. B. and Sierhuis, M., (2014). Coactive design: Designing support for interdependence in joint activity. Journal of Human-Robot Interaction, 3(1), pp. 43–69.

Kaber, D. B., (2018). Issues in human–automation interaction modeling: Presumptive aspects of frameworks of types and levels of automation. Journal of Cognitive Engineering and Decision Making, 12(1), pp. 7–24.

Miller, C. A., (2005). Levels of Automation in the Brave New World: Adaptive Autonomy, Virtual Presence and Swarms-Oh My!. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 49, No. 10, pp. 901–905). Sage CA: Los Angeles, CA: SAGE Publications.

Parasuraman, R. and Riley, V., (1997). Humans and automation: Use, misuse, disuse, abuse. Human factors, 39(2), pp. 230–253.

Parasuraman, R., Sheridan, T. B. and Wickens, C. D., (2000). A model for types and levels of human interaction with automation. IEEE Transactions on systems, man, and cybernetics-Part A: Systems and Humans, 30(3), pp. 286–297.

Proud, R. W., Hart, J. J. and Mrozinski, R. B., (2003). Methods for determining the level of autonomy to design into a human spaceflight vehicle: A function specific approach (No. JSC-CN-8129).

Save, L., Feuerberg, B. and Avia, E., (2012). Designing human-automation interaction: A new level of automation taxonomy. Proc. Human Factors of Systems and Technology, 2012.

Shapiro, L., (2019). Embodied cognition. Routledge.

Sheridan, T. B., Verplank, W. L. and Brooks, T. L., (1978). Human/computer control of undersea teleoperators. In NASA. Ames Res. Center The 14th Ann. Conf. on Manual Control.

Taylor, R. M., (2002). Capability, cognition and autonomy. In Proceedings of RTO Human Factors and Medicine Panel (HFM) Symposium.

Tsarouchi, P., Matthaiakis, A. S., Makris, S. and Chryssolouris, G., (2017). On a human-robot collaboration in an assembly cell. International Journal of Computer Integrated Manufacturing, 30(6), pp. 580–589.

Vagia, M., Transeth, A. A. and Fjerdingen, S. A., (2016). A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed?. Applied ergonomics, 53, pp. 190–202.