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Impact of Automation on Neuroplasticity: A Systematic Literature Review and Conceptual Framework of Cognitive Adaptation in Human–AI Interaction

Anushka Batte[1] | Faiza Belal[2] | Dr. Debasis Dash[3]

Abstract

Automation systems that use artificial intelligence (AI), robotics, and algorithmic decision-making are now transforming human activities, impacting mental processes, learning methods, and decision-making abilities. Research studies have mainly studied productivity and efficiency, but scientists have not yet studied how automation reshapes human brain functions and neural plasticity. The research follows PRISMA guidelines to perform a systematic review of interdisciplinary studies which combine neuroscience with cognitive psychology and human–AI interaction research from 2010 to 2025. The review investigates how prolonged automation work affects human brain activity, which produces mental workload and changes how people focus their attention and make decisions that affect their brain adaptation process. The research shows two separate paths which automation follows to help people learn and solve problems and develop neuroplasticity through active mental involvement, but its excessive use results in mental delegation which causes decreased focus and wrong behavioral responses. The research presents a new conceptual framework which identifies automation as a cognitive environment instead of its traditional role as a productivity enhancement tool. The research connects automation with brain plasticity through cognitive adaptation, which produces theoretical advancements and practical recommendations for educational settings and cognitive rehabilitation programs and human-centered AI system development that support ongoing cognitive growth.

Keywords: Self-Concept | Consumer-Brand Relationships | Brand Perceptions | Brand Attributes | Media Managers

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1* SVKM's NMIMS Deemed to be University, Mumbai, India. (anushkabatte.college@gmail.com)

2 SVKM's NMIMS Deemed to be University, Mumbai, India. (faizaaa.belal@gmail.com)

3 SVKM's NMIMS Deemed to be University, Mumbai, India. (dashdebasis76@gmail.com)

Corresponding Author

I. Introduction

1.1 Background: Automation and Human Cognition

Research studies from recent years demonstrate that AI-based systems create two separate impacts which enhance productivity and modify how businesses choose their courses of action and their mental processes for processing data (Enholm et al., 2022; Gregory et al., 2021; Zirar et al., 2023). The present development of automation systems which include artificial intelligence (AI) and algorithmic systems has established a new approach which people use to handle information and acquire knowledge and select their choices. The existing body of research about automation systems examines how these systems affect both organizational performance and productivity results. However, there is increasing, interdisciplinary evidence suggesting that automation is changing human thinking and learning. Specifically, automation integration has resulted in new forms of human-machine input, stretching, distributing, and sometimes even replacing key cognitive tasks (Raisch & Krakowski, 2021; Rai et al., 2019). Digital technologies have also reshaped social interaction and cognition in online environments, influencing how individuals process information and engage with digital systems (Bargh & McKenna, 2004; Bavelier et al., 2010).

From a cognitive psychology perspective, one of the key ways in which automation can impact human cognition is as an opportunity for cognitive offloading, or information processing "less workfully" (Risko & Gilbert, 2016). Digital environments enable individuals to engage in cognitive offloading more than ever before, particularly with the rise of AI-assisted tools that externalise memory, reasoning, and decision-making processes (Risko & Gilbert, 2016; Gerlich, 2025). While cognitive offloading can help individuals complete tasks in the short-term, it shifts cognitive processing from internal to external sources. In fact, evidence shows that focus, reflection, and slow thinking are diminished at the expense of short-term task completion and that deep learning may also be negatively impacted (Sparrow et al., 2011; Ward et al., 2017).

This change can also be conceptualised from a *Cognitive Load Theory* (Sweller, 1988, 2011; Paas et al., 2003) perspective, which posits that learning is limited by the amount of information that can be processed in working memory at one time. From a CLT perspective, automation of a task can lighten the total cognitive load of a task and make learning more efficient by offloading extraneous load. However, it is important to keep in mind that too little load on the human learner can be detrimental to learning; in fact, learning is optimised under moderate cognitive load, displaying an inverted-U pattern as a function of cognitive load (Gkintoni et al., 2026). Therefore, total cognitive load (influenced by automation and workload) and human cognitive load (representing cognitive effort and engagement) may sometimes be in conflict.

Furthermore, recent findings in educational neuroscience and digital learning suggest that technology-rich learning environments are changing the way humans learn adaptively and not necessarily only supporting learning. For example, digital learning systems that exploit automation to manipulate task difficulty and cognitive load also drive changes in cognitive effort and learning profiles (Firth et al., 2019).

From a neuroscience perspective, all learning takes place via experience-dependent neuroplasticity or is resultant from changes in connectivity between neurones that are, in some cases, manifest as physiological changes in synaptic or dendritic structure and organisation but more often are measured as altered functional relationships between different brain regions (Kolb & Gibb, 2014; May, 2011). Importantly, many studies have shown that more neuroplastic changes occur under enriched and high-effort learning situations and that lack of effortful engagement in cognitive tasks can even result in negative brain changes (Kolb & Gibb, 2014).

So, interacting with automation over time may affect neuroplasticity, but not always the same way, as some forms of automation can enhance cognitive functions while others may lead to cognitive decline. Automation that enables higher-level thinking and cognition by supporting human-AI collaboration can have beneficial effects for neuroplasticity (Jarrahi, 2018). However, automation that supports cognitive offloading, or reduced cognitive effort, in the human user can lead to decreased brain changes and even cognitive decline (Risko & Gilbert, 2016). According to cognitive psychology, neuroscience, and digital learning approaches, automation offers immediate benefits for productivity and task execution; however, it also leads to lasting changes in how individuals process information and establish their routines.

1.2 Problem Statement

Research about automation primarily examines its impact on work efficiency, employee replacement, and required competencies, but scientists have not investigated how it influences fundamental mental operations, which include attention, working memory, and learning patterns. Over-reliance on automation versus cognitive augmentation and the resulting impact on neuroplasticity in the long run is still not well understood, as it seems more research has found positive effects of automation for decision-making and learning, while others have found negative effects due to a lack of critical thinking and cognitive effort (Carr, 2020).

1.3 Research Questions

This study addresses the following questions:

RQ1. How has the literature conceptualised the relationship between automation and human cognitive adaptations between 2010 and 2025?

RQ2. What mechanisms link automation exposure with attention, working memory, learning, and decision-making that influence neuroplastic outcomes?

RQ3. Under what conditions does automation support cognitive augmentation versus cognitive offloading?

RQ4. What conceptual framework can explain the psychological and neurocognitive consequences of sustained human–AI interaction?

1.4 Research Objectives

The study aims to:

(1) systematically review literature on automation and cognitive adaptation;

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(2) identify mechanisms linking automation, cognitive processes, and neuroplasticity; and

(3) produce a conceptual framework with theoretical propositions explaining adaptive and maladaptive outcomes.

1.5 Contribution of the Study

Integrating psychology, neuroscience, and human–AI interaction literature, this study explains how automation reshapes cognitive adaptation and behaviours through psychological, neural, and social mechanisms; advances toward a psychologically sustainable future by revealing tensions in cognitive offloading/augmentation; and provides insight on the psychology of sustainability in human–AI teaming and brain health. This framework can guide the design of learning environments, engineering systems and supervisors, and human–AI interaction that support healthy neural growth and plasticity for lifelong cognitive adaptation.

II. Literature Review & Prisma Method

2.1 Review Design

This study uses a systematic literature review (SLR) method to develop a systematic and transparent understanding of automation's relationship with neuroplasticity. An SLR is commonly used in multidisciplinary research to systematically identify, evaluate, and synthesise prior knowledge (Tranfield et al., 2003). To ensure quality and to provide replicable criteria for evaluation, this study follows the PRISMA guidelines for SLRs and meta-analyses (Page et al., 2021).

2.2 Search Strategy and Data Sources

In order to obtain sufficient results from the intersection of neuropsychology, psychology, and human–AI interaction research communities, a comprehensive set of keywords was developed as a search strategy, inspired by the research objectives. Databases searched to obtain high-quality sources included Scopus, Web of Science, Science Direct, Springer Link, IEEE Xplore, and PubMed. Peer-reviewed journals from every field were included since this is an interdisciplinary topic spanning technology, cognitive science, and neuroscience. Research published between the years 2010 and 2025 was the focus, since AI and automation technologies and research efforts have exploded in the past decade or so. The three main search strings used were (1) automation AND cognitive adaptation, (2) automation AND neuroplasticity, and (3) AI AND neuroplasticity.

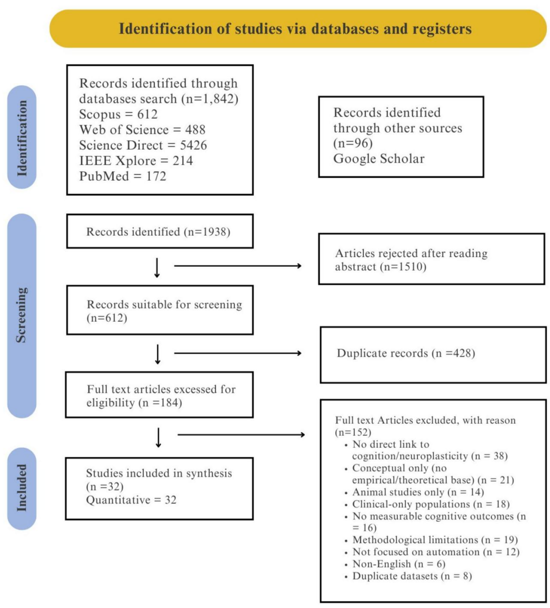
2.3 Inclusion and Exclusion Criteria

To ensure quality and appropriate focus in the search results, the following selection criteria were applied:
(1) Peer-reviewed journal articles,
(2) Studies considering automation, AI, or digital technologies, and
(3) Research on attention, memory, neuroplasticity, or learning.
Studies not published in peer-reviewed journals, conceptual and philosophical discussions without a theoretical or empirical research foundation, or studies not involving a cognitive or neurological outcome of interest were excluded.

2.4 Screening Process

As recommended by the PRISMA organisation, four screening stages were implemented: identification, screening, eligibility, and inclusion (Moher et al., 2009). In the first stage, all records are identified using the selected databases. In stage 2, duplicate and irrelevant articles are removed, and the search is refined. In stage 3, articles are reviewed using the inclusion criteria to determine eligibility for the review. In stage 4, only studies that meet the inclusion criteria are included. As illustrated in *Figure 1*, a total of 1,842 articles were initially identified across all databases. After removing duplicates and irrelevant studies, 152 articles remained for screening. Following full-text assessment based on inclusion criteria, 32 studies were included in the final review.

Figure 1: PRISMA Flow Diagram



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Source: Author's synthesis adapted from Page et al. (2021)

The review maintained full transparency because the system operated with total clarity while delivering complete and unbiased evaluation results which followed standard academic requirements.

III. Conceptual Foundations

The study synthesises four conceptual findings from the data set that provides a foundational understanding of how automation impacts cognition and neuroplasticity. Together, these themes highlight how technology reshapes attention, memory, learning, and brain adaptability, leading to both positive and negative cognitive outcomes.

3.1 Automation, Cognitive Offloading, and Attentional Redistribution

Automation enables offloading of cognitive capacity, which has been heavily conceptualised as 'cognitive offloading', or the use of physical action to reduce the cognitive demands of a task (Risko & Gilbert, 2016). In the modern era, this process is most commonly envisioned as "outsourcing" information, navigation, or decision-making to a digital (potentially artificially intelligent) system.

Cognitively, offloading to automated systems redistributes rather than erases cognitive functionality. However, attention is assigned to system monitoring and verification, as well as the integration of multiple information streams, rather than encoding, retrieval, learning, and creative problem-solving. In single-task paradigms, intentional events that rely on working memory and attentional control decrease with increased automation, especially when automation is reliable (Risko & Gilbert, 2016; Sparrow, Liu, & Wegner, 2011).

However, research in digital cognition has demonstrated that over time, reliance on external systems in fact changes the way a user naturally allocates attention. Digital cognition research has indicated that people learn to remember how and where to access information instead of actually remembering it (Carr, 2020). This has important implications on supporting cognitive functioning at the neurocognitive level, since decreased effortful brain activity makes requirements for adaptive neuroplasticity less likely to be met. Automation adapts to and "supports" cognition by changing the way attention is allocated to a high-level task. Furthermore, this redistribution aspect of automation is not always negative; it can allow a manager or operator with many responsibilities to devote cognitive effort toward reasoning, judgement, or decision-making. When automation and human cognition are in a symbiotic relationship, the operator takes advantage of the offloading potential of automation in order to dedicate more effort to tasks requiring higher-order cognitive functions, rather than using automation as an excuse to pay minimal attention and cognitively "coast" through a task. Recent work further suggests that AI-driven tools are accelerating cognitive offloading behaviours by enabling real-time delegation of reasoning and memory tasks (Gerlich, 2025).

Table 1. Source-to-Theme Synthesis of Literature

Theme	Key Focus	Core Mechanisms	Representative Studies	Key Insights	Implications for Neuroplasticity
Theme 1: Automation, Cognitive Offloading, and Attentional Redistribution	Delegation of cognitive tasks to machines; redistribution of attention	Cognitive offloading; metacognitive evaluation; reduced working memory engagement; shift from active processing to monitoring	Risko & Gilbert (2016); Sparrow et al. (2011); Carr (2020)	Automation reduces cognitive effort but shifts attention from deep processing to supervision; individuals rely more on external systems than internal cognition	Reduced cognitive engagement may weaken neural stimulation required for plasticity; potential long-term decline in memory and attention-related neural pathways
Theme 2: Technology-Induced Changes in Memory, Attention, and Decision-Making	Transformation of cognitive processes through digital environments	Memory externalisation, attentional fragmentation, reliance on algorithmic	Loh & Kanai (2016); Wilmer et al. (2017); Firth et al. (2019)	Digital technologies reshape attention span, memory strategies, and decision-making	Continuous reliance on external systems may rewire neural pathways toward rapid information

		decision-making, digital dependency		patterns; increased reliance on external cognitive systems	access rather than deep processing and retention
Theme 3: Neuroplasticity, Learning Environments, and Adaptive Challenge	Brain adaptability in response to cognitive demand and learning conditions	Experience-dependent plasticity; cognitive load regulation; synaptic strengthening; neural efficiency	Kolb & Gibb (2014); Park & Bischof (2013); Gkintoni et al. (2026)	Neuroplasticity is optimised under moderate cognitive challenge; both underload and overload reduce learning effectiveness	Optimal cognitive engagement strengthens neural connectivity; insufficient stimulation or excessive automation may impair adaptive plasticity
Theme 4: Human–AI Collaboration, Cognitive Augmentation, and Rehabilitation	Interaction between humans and AI for enhanced cognition	Complementarity; augmentation vs substitution; decision support; adaptive learning systems	Jarrahi (2018); Raisch & Krakowski (2021); Reddy (2025)	AI can enhance cognition when used collaboratively rather than substitutively, supporting higher-order thinking and skill development	Active engagement with AI systems can promote adaptive neuroplasticity by stimulating complex cognitive processes and learning

Source: Authors

3.2 Technology-Induced Changes

Digital technologies are not passive tools but fundamentally change cognition and behavior in response to information and memory externalisation and distributed storage. People are less likely to remember information if they know they will have access to it later electronically, and they remember how to access information rather than the information itself (Sparrow, Liu, & Wegner, 2011). In effect, the memory adaptation to digital access is to use a transactive external memory store rather than encoding information internally. People who spend long periods with digital devices will develop broken attention patterns, which include regular task changes and a poor ability to maintain focus on complex tasks (Wilmer et al.). The effects stem from modifications in prefrontal and parietal network functions which now demonstrate stronger responses to external stimuli than to intentional goal-based actions. Media multitasking produces two negative results which damage memory capabilities and processing abilities to monitor attention, which blocks students from reaching the mental depth required for effective learning and cognitive growth (Lopez et al., 2018).
Decision-making is also mediated by information delivered by algorithms, be it irrelevant outputs from news feed sorting or the outcome of predictive graphs and automated trading systems. Notably, humans have a strong tendency to favour algorithms over their own decision when confronted with the two (Dietvorst et al., 2015), although contradictory evidence for algorithm aversion after seeing them make a mistake also exists (Dietvorst et al., 2015). In general, one can say that the emergence of human-algorithm decision teams results in a shift of cognitive power to the algorithm.

Trust in AI systems also plays a critical role in shaping decision reliance, as individuals may either over-rely on automated recommendations or resist them depending on perceived reliability (Einola & Khoreva, 2023; Gkinko & Elbanna, 2023). User interaction with AI systems is also shaped by trust and emotional responses, which influence how individuals rely on automated recommendations in workplace settings (Gkinko & Elbanna, 2022). Recent research also highlights the importance of user-centred design in shaping human–AI interaction and cognitive outcomes (Jiang et al., 2024).

Emotions are subject to content filtering: on social networks, news feeds are filtered and ordered through algorithms to regulate the percentage of positive and negative emotional content agreeable to the reader. This creates an atmosphere for online discourse and interaction, where enforced cheerfulness replaces uncontrolled hate speech and verbal violence. Importantly, these changes in memory, attention, and decision-making have additive, non-independent consequences (e.g., information retrieval via internet search can increase a tendency towards attentional fragmentation and algorithm-guided decision-making, and vice-versa). Ultimately, we hypothesise that they will result in brain network(s) being reshaped towards favouring fast access to information over deep elaboration abilities, as has already been evoked elsewhere (Loh & Kanai, 2016; Firth et al., 2019).

Overall, the literature reviewed here points toward a conception of digital technologies as reshaping cognitive

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habits and underlying brain networks. The scenario presents a double-edged sword: on the one hand, the brain may adapt to process information more efficiently and in larger quantities, but on the other hand, the opportunities for deep and creative thinking, which drive long-term brain development and enlightenment through the effort required, will likely be diminished.

3.3 Neuroplasticity and Learning

Neuroplasticity, generally defined as the ability for brain networks to adapt to stimulation, has been shown to be highly dependent on environmental challenge for efficient adaptation to take place (Kolb & Gibb, 2014; May, 2011). It is now understood that healthy cognitive ageing and development can only occur at both the behavioral and brain levels when humans are confronted with stimulation within an adaptive range of difficulty, individually calibrated to elicit optimal learning according to the highly cited Zone of Proximal Development model. When developing technologies, one should consider these factors to ensure they enhance rather than impede long-term cognitive functioning. A key takeaway from neuroplasticity research in both animals and humans is that enhancing brain networks is dependent on experience and necessitates effort. Importantly, when the challenge presented by a learning environment is too low, transiently activated brain networks will simply be inefficient and will not be strengthened or elaborated. Contrarily, when it is too high, limitations in working memory capacity and attention will prevent effective learning.

Many experiments on the impact of learning environment difficulty on cognition and brain networks resulting in these characteristics delineate an inverted-U relationship between level of difficulty and efficient learning and network adaptation in the brain (Gkintoni et al., 2026). Prefrontal and parietal brain networks in particular are recruited in response to challenge in the environment. When challenged on the low end, these networks are simply not activated, and when challenged on the high end, stress-related deleterious consequences can impede neuroplasticity. In this framework, automation can have a positive impact on neuroplasticity since difficulty, speed, and additional facilitator interventions can be regulated to ensure maximum adaptation. Real-time feedback to the learner also enhances efficient learning through reinforcement of the appropriate synaptic connections. However, when automation limits brain stimulation by reducing the level of difficulty or the necessity for cognitive effort, effective learning will be stunted by a lack of environmental challenge. Overall, the literature indicates that automation per se does not have a direct impact on neuroplasticity but that efficient, directed learning can only take place through the improvement of brain networks when the human involved is not underchallenged. In other words, automation is less likely to stunt brain plasticity when it limits only redundant cognitive effort rather than challenge and difficulty. Recent neuroscience research further highlights parallels between human neuroplasticity and machine learning optimisation, reinforcing that iterative, effortful engagement is essential for genuine neural adaptation (Sadegh-Zadeh et al., 2024). Similarly, hippocampus-inspired AI frameworks emphasise that the balance between stability and plasticity mirrors the brain's own mechanisms for consolidating learning under moderate cognitive challenges (Rudroff et al., 2024).

3.4 Human–AI Collaboration

Although early writings about the possible impacts of automation on cognition focused mainly on substitution, several recent lines of research emphasise the leveraging of automation for cognitive augmentation rather than replacement, leading to the view of human–AI teams as new, hybrid cognitive systems. These teams consistently achieve better results than what humans or AI systems can generate independently, according to Jarrahi (2018) and Raisch and Krakowski (2021). Automated systems process high volumes of data through their superior calculation and optimisation abilities, which exceed human capabilities, but humans must manage unexpected uncertainties that develop during regular activities and new experiences and mistakes. This perspective aligns with broader research on human–AI augmentation, which emphasises the integration of human judgment with intelligent systems to enhance decision-making and performance (Makarius et al., 2020; Nguyen & Elbanna, 2025).

From a cognitive perspective, this collaboration does not necessarily reduce cognitive effort but can shift the resources that must be allocated in the brain during activity to higher-level analysis, judgement, and interpretation. It has been shown that AI can be used to assist rather than replace human decision-making (Rai et al., 2019). Neural reallocation under these circumstances should rather have a positive impact on decision-related, interpretive, and creative brain networks in humans. As opposed to deductive and algorithmic automation, inductive automation can give rise to cognitive insight in humans, since the AI's decision can serve as an additional input in an incompletely deterministic environment to aid human judgment. Importantly, these effects are dependent on humans staying "in the loop", since corresponding augmentation effects are not seen if the research subject is passive. Accordingly, a distinction is emerging between augmentation-orientated systems and automation-orientated systems, defined by the degree of necessary human interaction involved (Raisch & Krakowski, 2021). Inductive automation can be particularly beneficial for inductive reasoning (the ability to make analogies, discover relations, analyse, and systematise), which has been shown to improve with cognitive training and age and is supported by varying configurations of prefrontal and default mode brain networks.

Another important implication of collaborative human–AI systems concerns learning and neuroplasticity. Here, the benefits of automation and AI for individually adjusted speeds and levels of difficulty are already being leveraged by educational technologies, along with improved evaluation and error classification systems for personalised learning. These learning advancements are known to reinforce plasticity and favour efficient structural enhancement in the brain compared to traditional classroom environments due to the replacement of rote memorising and subject understanding expressed through written essays with puzzle-solving and problem analysis. Rehabilitation of brain impairments in both children and adults is increasingly ICT-enabled. Direct interaction with virtual avatars has been shown to boost mentalising abilities in autistic children. Interactions with artificial learning systems can be beneficial for neuroplasticity in adults, as they can repeatedly stimulate cognitive enhancement at the levels of working memory, mentalising, and executive control brain networks. Brain-computer interfaces, neurofeedback, and similar brain-machine-human interactive systems have proved successful at directly stimulating neuroplasticity and recovering functionality after damage, owing to the goal-directed activation of brain networks for stimulation-dependent reorganisation and stabilisation.

Real-time physiological and behavioral feedback, as facilitated by the integration of neurotechnologies and AI, has even been implemented in closed-loop systems functioning to maintain the learner within a healthy zone of cognitive, and therefore neural, challenge. The benefits of human–AI teaming and collaboration therefore reach beyond the immediate positive consequences of increased performance and capacity for handling large and complex objectives, with strong implications for learning, rehabilitation from brain injury, and neuroplasticity. However, cognitive augmentation does not always realise its benefits. A consistent finding throughout the literature is the dual path of automation when it comes to cognition: too much automation may generate an opposite effect, such as cognitive atrophy, where employees do not exercise thinking, are less engaged, and receive less stimulation; proper levels of augmentation can help promote thinking stimulation and learning. Hence, most work highlights the importance of human-centered design principles.
Human and AI collaboration is perhaps the best example of automation shifting from its traditional sense (work substitution) to work augmentation: when done well (i.e., to augment cognition rather than eliminate it), AI systems can help with thinking and learning, as well as brain plasticity; when done poorly (i.e., ATP and lower barriers to cognition and mental slack), it can result in less engagement and long-term cognitive atrophy. In other words, cognitive and neuroplasticity effects are not a direct result of automation itself but rather of the way the technology will be used for learning.

3.5 Cross-Theme Synthesis

As shown in Table 1, there is a distinct conceptual progression in research: the nature of automation and cognitive adaptation is first considered as cognitive offloading and/or attentional redistribution (Theme 1), with automation affecting allocation of cognitive effort, followed by changes in memory, attention, and decision-making in general as a function of technology (Theme 2). These cognitive changes are closely tied to neuroplasticity in learning environments (Theme 3), and evidence suggests that neuroplasticity is a function not of automation itself, but of cognitive effort as a function of automation. The newest research points to the future of human–AI collaboration as cognitive augmentation, rather than automation replacing human cognition (Theme 4; Jarrahi, 2018; Raisch & Krakowski, 2021). Thus, the literature as a whole on automation, cognitive adaptation, and neuroplasticity can best be conceptualised as existing on a spectrum from cognitive atrophy to cognitive augmentation, as a function of attention and context.

IV. Thematic Synthesis of Literature

4.1 Automation as a Cognitive Environment and Its Neurocognitive Outcomes

The research indicates that automation functions as more than a productivity enhancer because it establishes a cognitive environment, which affects human thinking processes and focus and decision-making abilities. A structured pathway explains this process: automation exposure influences cognitive load, attentional allocation, and decision reliance, which then drive cognitive change and ultimately affect neuroplastic outcomes (Risko & Gilbert, 2016). Two opposing results emerge from this process. The implementation of automation systems enables cognitive support through enhanced decision processing and decreased mental work requirements. The excessive use of automated systems creates problems for human attention systems which results in decreased working memory performance and produces suboptimal thinking strategies, according to Carr (2020). Research findings demonstrate that these results emerge through non-linear patterns. The effects of automation systems depend on users' interactions with them, which are influenced by their task familiarity, professional skills, emotional state, automation usage patterns, and differences in brain development. Research indicates that moderate cognitive challenge is most effective in supporting learning and adaptive neuroplasticity (Gkintoni et al., 2026).

4.2 Research Gaps in Automation, Cognition, and Neuroplasticity

Current research has not yet provided a clear and integrated model that explains the connection between automation, cognition, and neuroplasticity. Most research studies concentrate on immediate cognitive effects and technological results, yet they do not investigate how the brain changes across extended time periods (Firth et al., 2019). Research needs to focus more on interdisciplinary studies which should combine neuroscience with psychological science and human-AI interaction research (Raisch & Krakowski, 2021). In addition, longitudinal studies are essential to understand how continuous exposure to automation influences cognitive processes and long-term neural development (Gkintoni et al., 2026).

V. Cross-Theme Synthesis and Unresolved Tensions

5.1 Integrating Themes Across Automation, Cognition, and Neuroplasticity

The research shows that automation functions as an evolving mental system which goes beyond its role as a basic efficiency mechanism. The studies about cognitive offloading and neuroplasticity and human–AI teamwork show that automation changes how people distribute their attention while they handle data and perform their decision-making processes (Risko & Gilbert, 2016; Kolb & Gibb, 2014). The process requires multiple operational levels to understand its structure because automation exposure demands workers to manage cognitive load and their attention while they decide which tasks to prioritise for decision-making. The conceptual framework (*Table 2*) presents core elements which include automation exposure and cognitive engagement and learning stimulation and neuroplasticity. The research shows that these concepts link together through complex relationships which go beyond their individual characteristics. Automation does not always decrease cognitive engagement because it makes people focus on monitoring tasks and evaluation activities and interpretation work. The system uses automation to redirect mental work instead of making it disappear completely.

5.2 Key Tensions in the Literature

The literature shows a major conflict between cognitive offloading and cognitive augmentation. Automation systems minimise the need for mental labour, which leads to decreased working memory activation and reduced attentional control systems (Carr, 2020). Human–AI collaboration enables users to develop advanced thinking abilities because it assists them in making complicated choices and solving difficult problems (Jarrahi, 2018). The process of learning stimulation continues to face an unresolved conflict. Automation systems allow students to receive customised education and assessment results, but they need to avoid removing the essential mental work which students require for successful learning. Research on neuroplasticity reveals that the brain performs best when people work with moderate mental challenges instead of working with too little or too much mental load (Kolb & Gibb, 2014).

Table 2. Key Constructs in the Conceptual Framework

Construct	Description
Automation exposure	Degree to which tasks are performed or supported by AI and automated systems
Cognitive engagement	Level of mental effort, attention, and problem-solving required
Learning stimulation	Opportunities for skill development and knowledge acquisition
Neuroplasticity	Adaptation and reorganisation of neural pathways

Source: Authors

5.3 Non-Linear Effects and Moderating Conditions

The research reveals that automation produces complex effects on brain function and neural adaptability which depend on specific environmental factors and display non-linear patterns. The diagram in Figure 2 illustrates how task complexity, human oversight, learning environments, and the frequency of automation use act as moderators that determine the final results. The research identifies additional elements that influence system responses to automation, including task novelty, user expertise, emotional stress, and factors related to neurodiversity or clinical status. The moderators reveal that similar technologies will produce different results when used by various users in different situations. The system provides automation support to beginner users, but it makes experienced users lose interest because they become too dependent on its functionality.

Figure 2. Conceptual Model: Automation–Neuroplasticity Cognitive Adaptation Model

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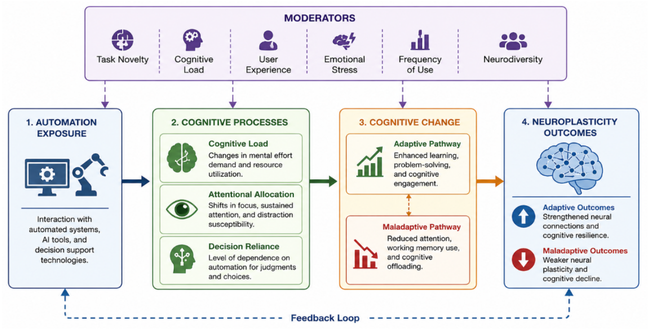

Source: Authors

5.4 Unresolved Research Gaps

The area shows rising popularity, but numerous essential gaps need to be resolved. Real-world studies that demonstrate how automation creates permanent neuroplastic changes in brain structure remain very limited. The majority of research focuses on immediate mental impacts instead of studying how the brain adapts permanently. The current field of research lacks complete models which combine neuroscience with psychology and human–AI interaction studies. The research shows that automation creates effects which stem from both technological development and its ability to modify human mental work and educational environments and personal characteristics across different periods.

VI. Human-Automation Neuroplasticity Framwork

The Human–Automation Neuroplasticity Framework, which this study presents, explains how automation systems transform human mental functions and brain plasticity through psychological and neuroscientific methods. The framework presents automation as a cognitive system which produces ongoing effects on human mental processes and learning development and attention distribution throughout time. The framework follows a structured pathway that includes the following steps: Automation Exposure, Cognitive Load, Attentional Allocation, Decision Reliance, Cognitive Change, and Neuroplasticity Outcomes. Users experience all automation systems and AI-based tools through a complete range of operational contacts, which they must handle at all times. After experiencing this event, people distribute their mental capacity differently because they need to manage their mental work requirements, maintain focus, and seek assistance from automated systems. People start to use cognitive offloading when automation reaches high levels because they allow external systems to perform memory functions and analytical operations and judgment tasks (Risko & Gilbert, 2016).

The human brain uses different mental processing approaches, which leads to two distinct results. The human brain develops its adaptive cognitive abilities through automation, which enables people to perform complex thinking tasks and solve problems and acquire new knowledge. The development of maladaptive cognitive changes occurs when people depend on things too much, which leads to decreased mental processing abilities and reduced focus and participation (Carr, 2020). The way people use their brains determines how their brain reshapes its neural connections through the process of neuroplasticity, which enables the brain to form new neural pathways from learning and life experiences (Kolb & Gibb, 2014). The continuous practice of mental tasks leads to stronger neural connections, but discontinuing these activities will result in neural connections that become weaker over time. The framework presents these connections as non-linear relationships which develop differently depending on the particular situation in question. *Figure 2 demonstrates that multiple factors, which serve as moderators, affect the results by influencing task novelty, cognitive load level, user expertise, emotional stress, frequency of automation reliance, and neurodiversity or clinical status.* The moderators function as decision-making elements which establish if automation systems will produce beneficial or harmful results for cognitive development and neural growth. The framework establishes a solid base which helps people understand automation effects on two separate systems while showing them how to develop human–AI systems and learning environments and rehabilitation tools for extended cognitive and neuroplastic advancement.

6.1 Theoretical Propositions

Building on the Human–Automation Neuroplasticity Framework (see Figure 2), this section develops theoretical propositions that explain how automation influences neuroplasticity through key cognitive processes. The framework shows that automation creates three main effects on human cognition which modify how people handle their mental resources and how they distribute their focus and their dependence on decisions. The research shows that automation systems which have been implemented through strategic methods will either decrease or increase the mental effort people must expend when operating these systems (Risko & Gilbert, 2016; Jarrahi, 2018). The following five propositions have been developed based on the information presented in *Figure 2*.

Proposition 1 (P1): The more automation people encounter during their routine work activities, the more they transfer tasks to machines, which results in decreased mental effort but potentially reduces brain development from neuroplasticity.

Proposition 2 (P2): The connection between automation exposure and neuroplasticity results depends on three cognitive processes, which include cognitive load and attentional allocation and decision reliance.

Proposition 3 (P3): Learning spaces which offer the right amount of mental difficulty will create positive neuroplasticity changes, but too little or too much mental effort leads to harmful brain development, according to Kolb and Gibb (2014).

Proposition 4 (P4): The process of automation leading to either positive or negative cognitive adaptations depends on five key elements, which include task novelty and user expertise and emotional stress and automation use frequency and neurodiversity.

Proposition 5 (P5): Human–AI systems which combine automated processes with human decision-making methods produce better cognitive involvement, which leads to improved cognitive engagement and support adaptive neuroplastic outcomes (Jarrahi, 2018).

These propositions demonstrate that automation systems do not have an immediate impact on neuroplasticity development. The system produces effects which depend on how people think and the situations they encounter to produce either improved mental function or deteriorated mental function.

VII. Discussion in Relation to Neuroscience and Human Psychology

7.1 Theoretical Interpretation of Automation as a Cognitive System

Neuroscience and psychology provide essential theories, which enable a deeper understanding of the results obtained from this research. *Cognitive Load Theory* explains that learning depends on how mental effort is managed. Automation systems decrease human work requirements, but they can prevent people from learning essential knowledge when they handle basic tasks. The *Extended Mind Theory* demonstrates that AI technology functions as an external system that supports human thought operations, memory storage, and decision-making processes. The concept connects directly to cognitive offloading because people use digital tools to handle their mental work according to Risko & Gilbert (2016). The human–AI complementarity concept shows that human-machine collaboration produces better results than using machines to substitute human workers (Jarrahi, 2018).

7.2 Dual Pathways and Contribution to Knowledge

Two distinct cognitive pathways emerge from neuropsychological analysis of automated systems. The *cognitive atrophy pathway* develops because people rely excessively on automated systems which causes their attention to deteriorate and their working memory capacity to decrease and their overall cognitive activity to drop. The process will eventually reduce neural activation, which leads to a decrease in brain plasticity (Carr, 2020). The *cognitive augmentation pathway* emerges when automation systems enable users to perform active thinking and problem-solving and learning activities. The brain stays active during these circumstances, which leads to stronger neural links and improved brain ability to adapt through neuroplasticity (Kolb & Gibb, 2014).

The research establishes a connection between neuroscience and cognitive psychology and human–AI interaction to develop its research findings. The research demonstrates that automation systems generate outcomes through their influence on human attention and memory functions and learning processes.

VIII. Implications for Education, Rehabilitation, Human-AI Interaction, and Ethical Design

8.1 Educational Implications for Cognitive Development

Research findings indicate that educational spaces need to establish academic environments which maintain an equal distribution between student mental demands and their active involvement in learning activities. The implementation of automation and AI systems enables adaptive learning because they modify task complexity to create suitable learning challenges for students. The method allows students to develop their focus, enhance their ability to work with information in their working memory, and improve their capacity to learn for extended periods through brain plasticity (Kolb & Gibb, 2014). Users should not depend on automated systems because this practice will prevent them from developing their critical thinking abilities and their ability to learn at an advanced level. Research conducted in the present time demonstrates that digital cognitive training programs help students build new neural connections which lead to better educational results when learning through technology (Park & Ha, 2024).

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8.2 Implications for Rehabilitation, Human–AI Interaction, and Ethical Design

The rehabilitation process benefits from automation because it provides customised treatment plans, which deliver immediate responses to help patients recover their brain functions and enhance their cognitive abilities. AI-based tools help individuals with cognitive impairments or neurodiverse conditions through their ability to activate brain functions. Human–AI systems need to function as human judgment assistants because they should enable users to think actively while preventing them from relying too much on automated support (Jarrahi, 2018; Risko & Gilbert, 2016). The ethical framework of automation needs to include systems which provide open information while delivering fair treatment and supporting the mental health of users. Designers need to establish augmentation as their main objective because digital technology adoption will create lasting effects on human cognitive abilities according to de Barros (2024).

8.3. Limitations and future research directions

This research utilises a qualitative, systematic literature review approach, which excludes actual data collection and time-based studies to prevent researchers from making inaccurate cause-and-effect links. Most existing studies focus on short-term cognitive effects, with limited evidence on long-term neuroplastic changes due to automation. The research field needs to conduct extended studies which will track human reactions to automation systems and their effects on brain operations. Neuroimaging-based research which uses fMRI and EEG methods reveals how the brain adapts through its operational systems. The developed framework requires validation through human–AI interaction experiments and specific industry studies which will test its performance in various operational settings.

IX. Conclusion

Research findings demonstrate that automated systems enhance operational efficiency while they influence human brain processes which control learning mechanisms and brain adaptation and structural changes. The research paper shows that automation creates an indirect effect on neuroplasticity through its combination of neuroscience with cognitive psychology and human–AI interaction studies. The process depends on mental functions, which include how people focus their attention and their mental capacity and their need for guidance when making choices. The learning environment quality also plays a role in this process. The conceptual framework (*Figure 2*) demonstrates how automation creates a cognitive environment which produces both beneficial and detrimental results according to the thematic synthesis (*Table 1*) and theoretical propositions. The research results prove that people need to maintain their mental abilities because modern automation systems require this skill. Systems that prioritise speed and efficiency create conditions that drive users to perform cognitive offloading, which leads to reduced critical thinking abilities, according to Risko & Gilbert (2016). Human-centered automation systems, which assist users in problem-solving, learning, and decision-making processes, enable the development of adaptive neuroplasticity and permanent cognitive growth, according to Kolb & Gibb (2014). The research demonstrates that results depend on how tasks are structured, how users participate, and the context in which AI systems operate, thereby supporting the need for equal human-AI teamwork (Jarrahi, 2018). Organisations, together with educators and policymakers, need to develop technologies which enhance human intellectual abilities instead of creating systems that would eliminate human involvement. The method achieves its goal by using automation to enhance system performance while it simultaneously supports ongoing mental development and personal growth in digital spaces.

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