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Human Intelligence in the Age of Artificial Minds: A Conceptual Framework for Cognitive Co-Adaptation in Human–AI Interaction

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Abstract

Artificial intelligence (AI) has evolved from a specific computational resource into an ever-expanding mental companion that influences human memory functions, learning processes, reasoning abilities, and decision-making methods. AI system implementation for daily operations and business activities has reached a level that requires scientists to analyse how this technology will influence human thinking abilities in future periods. The paper presents the Human–AI Cognitive Co-Adaptation Framework (HACCAF), which describes how human mental abilities and artificial intelligence systems develop through multiple interactions. The framework integrates cognitive offloading theory, cognitive demand theory, neuroplasticity theory, Human–AI symbiosis, and extended mind theory, drawing on research from cognitive psychology, neuroscience, and human–AI interaction studies. The analysis presents the Augmentation–Dependency Paradox, which demonstrates that AI technology produces opposite effects on human cognitive abilities because it intensifies mental functions while it makes people more dependent on technology. Using AI as a cognitive partner enables students to reflect, learn, and solve problems, leading to better cognitive flexibility, improved decision quality, and enhanced neuroplastic adaptation. The use of AI for memory functions and reasoning processes and judgment decisions at high levels would create mental dependence which would damage critical thinking abilities and decrease people's ability to monitor their own thinking processes. The framework presents nine theoretical propositions that exist within three separate domains: cognitive offloading, cognitive adaptation, and cognitive dependency. The study reveals essential factors that determine system boundaries,

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as well as elements that affect system performance, including AI literacy, user engagement, trust in AI, task complexity, and frequency of use. The paper presents cognitive co-adaptation as a continuous two-way process which establishes a common theoretical base between neuroscience and human–AI interaction research. The research study contributes to the emerging field of cognitive AI and workplace psychology by providing actionable knowledge that assists educators, organizations, technology designers, and policymakers in utilizing AI for cognitive enhancement while avoiding dependence.

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

I. Introduction

1.1 Human Intelligence in the Age of Artificial Minds

Artificial intelligence (AI) now functions as a core element that drives human mental processes during information retrieval and learning, as well as problem resolution and decision-making. The current AI systems work differently from previous digital tools because they now perform reasoning and pattern recognition and content creation and decision-making assistance. The research indicates that people develop different ways to focus and think and handle information after spending long periods with digital devices (Ward et al., 2017; Wilmer et al., 2017). The distribution of intelligence now takes place through linked human–AI systems which operate together as a network (Carr, 2020).

1.2 From Cognitive Tools to Cognitive Partners

Artificial intelligence has developed into an active cognitive partner that works alongside humans to enhance their thinking and decision-making capabilities. Modern AI systems now perform reasoning, knowledge synthesis, planning, and creative problem-solving, which enables them to collaborate with humans more effectively. AI performs cognitive operations which help users through its adaptive system instead of focusing on task automation (Jarrahi, 2018). Human–AI collaboration has developed into a new system which produces hybrid intelligence through the combination of human abilities with intelligent system capabilities to create results that humans and machines cannot achieve independently (Rai et al., 2019; Dellermann et al., 2019).

1.3 Research Gap

Research demonstrates that digital technology usage triggers mental process changes which affect memory operations and attention focus and modify the way people acquire knowledge and make choices (Firth et al., 2019; Loh & Kanai, 2016). People now use external technology to perform mental operations which they previously conducted independently, according to cognitive offloading research by Risko & Gilbert (2016). The research field has primarily focused on technology adoption, productivity enhancement, algorithmic trust, and the results related to automation. A major theoretical gap exists between these concepts. The present academic literature does not contain a unified framework that shows how AI contact affects human mental processes over multiple years. The field lacks proper research to investigate AI-based cognitive operations, which impact brain plasticity and how AI systems affect human mental abilities and the adaptive process between human brains and artificial intelligence systems. The lack of a complete theoretical framework has created an essential gap which stops us from forecasting system changes after AI deployment and prevents us from creating systems that defend human-AI relationships and from developing methods which support positive mental processes yet reduce cognitive dependency risks.

1.4 Purpose of the Paper

The document argues that artificial intelligence has two distinct impacts: it modifies job execution methods and simultaneously reshapes human cognitive processes, learning abilities, memory functions, and adaptation mechanisms. The research introduces the Human–AI Cognitive Co-Adaptation Framework (HACCAF) to describe these emerging patterns. The framework unites research from cognitive psychology and neuroscience and human–AI interaction studies to show how AI operations produce both positive and negative mental effects in people. The research presents the Augmentation–Dependency Paradox, which demonstrates that AI systems produce two opposing outcomes which either enhance human cognitive functions or decrease them depending on their operational environment. The research presents nine established theoretical models which scientists can validate through their work by demonstrating these models' effects on educational institutions and technological development and public administration and business organizations.

1.5 Contribution - Conceptual Foundations

The Human–AI Cognitive Co-Adaptation Framework (HACCAF) analyses how human thinking processes develop alongside artificial intelligence systems by integrating Cognitive Offloading Theory, Cognitive Load Theory, Cognitive Demand Theory, Neuroplasticity Theory, Human–AI Symbiosis, and Extended Mind Theory. The framework presents three main contributions to the field. The research presents cognitive co-adaptation as a continuous process which allows humans to affect AI systems while AI systems also influence human behaviour. The framework combines knowledge from cognitive psychology and neuroscience and human–AI interaction studies to establish a single integrated conceptual structure. The framework presents nine research-based propositions that will serve as core principles for future studies on cognitive enhancement, system adaptation, user interface dependency, and human–AI teamwork.

II. Theoretical Foundations

The Human–AI Cognitive Co-Adaptation Framework (HACCAF) establishes its foundation through five theoretical perspectives which describe the impact of artificial intelligence on human mental processes and learning mechanisms and adaptation abilities. The established multidisciplinary base from these theories enables scientists to investigate the emerging relationship between human mental capabilities and artificial intelligence systems. The study demonstrates that people require AI-based cognitive support because it reduces their mental work while it helps them learn and their brains adjust through multiple encounters with AI systems which function as human mental process extensions rather than simple technological tools.

2.1 Cognitive Offloading Theory

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Cognitive Offloading Theory explains how people use external resources to perform their mental work, which helps them conserve their mental resources (Risko & Gilbert, 2016). Artificial intelligence continues this pattern by enabling systems to perform tasks such as information retrieval, reasoning, prediction, content creation, and decision-making. People can achieve better operational results through AI systems which handle their cognitive tasks while they concentrate on their work. The dependency on outside mental assistance at high levels makes it difficult for people to develop their memory abilities and their capacity to think independently and assess information critically. The perspective establishes an essential basis, which demonstrates how AI systems boost their operational results through their need for outside mental resources (Risko & Gilbert 2016).

2.2 Cognitive Load Theory

According to Cognitive Load Theory, learning results from mental resource distribution, which determines how students process information (Sweller, 1988). The implementation of AI technology reduces unnecessary cognitive load by automating routine operations, data management, and providing instant help, which allows users to focus their attention on analytical work, comprehension, and problem resolution. The learning process would lose its necessary mental work when automation systems operate at maximum capacity. People who accept AI-generated results without questioning them will miss the chance to develop their critical thinking abilities and their ability to learn in depth. The value of AI emerges from its ability to maintain an appropriate balance between cognitive assistance and active mental involvement (Sweller, 1988).

2.3 Cognitive Demand Theory

Cognitive Demand Theory states that learning along with cognitive growth needs students to work hard while they stay focused and face suitable learning obstacles (Bjork & Bjork, 2011; Krämer, & Kahneman, 2011). The concept of desirable difficulty indicates that learning through reflection, retrieval, evaluation, and problem-solving activities leads to better long-lasting learning outcomes compared to tasks that prioritise ease. Krämer, & Kahneman, 2011) establishes that people need to execute planned analytical reasoning to develop correct judgment and acquire knowledge. AI systems in human–AI interaction environments handle routine cognitive tasks, which lets humans focus on critical thinking and reasoning activities. The maximum cognitive benefits emerge when AI technology operates as a supportive tool which enables users to handle essential mental operations instead of performing complete task automation (Bjork & Bjork, 2011; Krämer, & Kahneman, 2011; Sweller, 1988).

2.4 Human–AI Symbiosis

Human–AI symbiosis recognises that humans and intelligent systems function as equal partners who share common mental frameworks, according to the research of Rai et al. (2019), Gómez-Cruz et al. (2026) and Jiang et al. (2024). Humans provide their understanding of context together with their creative abilities and ethical decision-making and social skills, but AI systems deliver their processing speed and ability to recognize patterns and handle extensive data sets (Jarrahi, 2018; Seeber et al., 2020). AI systems work together with human beings to enhance their abilities instead of taking over their mental functions. The perspective establishes that human–AI partnerships need humans to preserve their decision-making power while using technology to its full potential, which guides the development of cognitive co-adaptation and collaborative intelligence systems.

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2.5 Extended Mind Theory

According to Extended Mind Theory, human cognitive processes reach past the biological brain to include outside objects and surroundings which assist with mental operations and memory storage (Clark & Chalmers, 1998). Clark's (2008) system shows that human cognition develops through continuous interactions between people and technological systems. AI functions as an active cognitive element which goes beyond tool usage to support reasoning processes and knowledge development and decision-making operations (Dellermann et al., 2019). This perspective establishes AI as a fundamental component that operates inside distributed cognitive systems to replace its current position as a separate technological tool.

2.6 Neuroplasticity Theory

Neuroplasticity Theory describes how the brain can transform its physical structure and operational mechanisms through repeated experiences and mental activities (Kolb & Gibb, 2014; May, 2011). Human–AI interaction involves the repeated use of AI patterns, which affects human cognitive processes such as attention, memory, learning, reasoning, and decision-making. AI systems which promote user reflection and learning through active participation help users develop adaptive cognitive abilities, but users who depend heavily on AI lose their ability to think independently and control their metacognitive processes. Neuroplasticity functions as a biological system, which explains how AI-based interactions lead to either cognitive development or cognitive dependence over time.

2.7 Synthesis of Theoretical Foundations

The Human–AI Cognitive Co-Adaptation Framework (HACCAF) integrates six complementary theoretical perspectives to explain how artificial intelligence influences human cognition, learning, decision-making, and adaptation. The table shows that people use AI systems for their cognitive work according to Cognitive Offloading Theory (Risko & Gilbert, 2016). The two theories, cognitive load theory and cognitive demand theory, show how AI systems decrease mental workload while students continue to spend their entire cognitive capacity on learning and development activities (Sweller, 1988; Bjork & Bjork, 2011; Krämer, & Kahneman, 2011). Neuroplasticity Theory demonstrates how biological elements of the brain develop their cognitive abilities through repetitive AI system interactions (Kolb & Gibb, 2014; May, 2011). Human–AI Symbiosis demonstrates how human intelligence works together with machine intelligence (Rai et al., 2019; Gómez-Cruz et al., 2026; Jiang et al., 2024). The Extended Mind Theory shows that AI functions as an active element in distributed cognition instead of being a simple external device (Clark & Chalmers, 1998; Clark, 2008). The various perspectives show that AI does not produce any natural advantages or disadvantages for human mental processes. AI systems generate cognitive results that depend on the methods of application, the level of human involvement, and the specific ways in which people interact with intelligent systems. The theoretical framework which combines multiple elements serves as the foundation for HACCAF while proving that human–AI interaction over time will produce either enhanced mental abilities or full mental reliance through continuous cognitive adaptation (Table 1).

Table 1. Key Theoretical Foundations of the Human–AI Cognitive Co-Adaptation Framework (HACCAF)

Theory	Core Proposition	Relevance to the Present Study
Cognitive Offloading Theory (Risko & Gilbert, 2016)	Individuals transfer cognitive tasks such as remembering, information retrieval, and problem-solving to external tools and environments to reduce mental effort.	Explain how AI facilitates memory externalisation, information delegation, and reliance on digital cognitive support systems, thereby influencing cognitive engagement and dependency.
Cognitive Load Theory (Sweller, 1988)	Learning and performance depend on how limited cognitive resources are allocated during information processing.	Explains how AI can reduce extraneous cognitive load and support learning efficiency, while excessive automation may diminish active cognitive participation and deeper processing.
Cognitive Demand Theory (Bjork & Bjork, 2011; Krämer, & Kahneman, 2011)	Meaningful learning, cognitive adaptation, and skill development require effortful processing, desirable difficulty, and sustained mental engagement.	The framework demonstrates that learning requires students to face appropriate challenges that simultaneously develop their critical thinking skills and their cognitive abilities. AI systems should not handle all tasks because this would restrict human mental development through essential cognitive work.
Neuroplasticity Theory (Kolb & Gibb, 2014; May, 2011)	The brain continuously rearranges neural pathways in response to repeated experiences, learning activities, and patterns of cognitive engagement.	Suggests that sustained interaction with AI may influence neural systems associated with attention, memory, learning, reasoning, and cognitive adaptation over time.
Human–AI Symbiosis (Rai et al., 2019; Gómez-Cruz et al., 2026; Jiang et al., 2024)	Humans and intelligent systems function as complementary partners within shared cognitive ecosystems.	It provides the foundation for understanding cognitive co-adaptation, emphasising collaborative intelligence and the mutually reinforcing relationship between humans and machines' capabilities.
Extended Mind Theory (Clark & Chalmers, 1998)	Cognitive processes extend beyond the biological brain, including external artefacts, technologies, and environments that support thought.	Positions AI as an active extension of cognition rather than merely a technological tool, supporting the concept of distributed cognition and cognitive co-adaptation.

Source: Authors' synthesis.

III. Literature Synthesis: Emerging Cognitive Consequences of AI

Artificial intelligence has established itself as a permanent factor, which now affects every human mental process. People nowadays rely on AI systems to retrieve information while they also use these systems for making choices and solving problems and learning new skills and creating innovative concepts. AI functions as an advanced productivity system because it enables users to develop new thinking methods which lead to improved memory functions and better concentration and decision-making abilities. Research from cognitive psychology and neuroscience and human–AI interaction studies have found that extended AI system usage produces substantial effects on human cognitive abilities. The research shows that AI affects human thinking in five interrelated areas: memory externalisation, attentional redistribution, decision delegation, metacognitive transformation, and cognitive dependency.

3.1 Memory Externalisation

Memory externalization refers to the trend of people using digital systems to store and retrieve their information instead of keeping it in their own memories. Research indicates that people who heavily rely on their smartphones and digital technology devices tend to perform independent analytical thinking less often (Barr et al., 2015). Sparrow et al. (2011) conducted a study that showed that people tend to remember the location of information instead of the actual content when they access information through technology-based systems, which they call the "Google Effect". AI systems build upon this method through their ability to deliver immediate information access while they also perform knowledge retrieval and generate automatic system responses. The assistance enables people to save their mental capacity for essential operations, but it influences their memory acquisition and knowledge retrieval and application processes (Sparrow et al., 2011).

3.2 Attentional Redistribution

Artificial intelligence systems now determine how people distribute their attention while they process information and perform mental operations. Research indicates that extended usage of digital technology leads users to perform multiple tasks simultaneously while breaking down information into segments and undergoing modifications in their attention systems (Firth et al., 2019). AI systems generate quick responses, which help people focus their attention while they organise information and give customised answers based on individual requirements. The process of shifting attention between different elements does not create any negative effects. AI technology reduces basic mental work so people can focus on their creative and strategic tasks, which require their full attention. The cognitive results will emerge from AI systems which either make users stay longer on content while they analyse it thoroughly or enable users to navigate information at a superficial level (Ward et al., 2017; Wilmer et al., 2017).

3.3 Decision Delegation

AI-based decision-support systems have become more popular, which drives organizations to depend on algorithmic suggestions for their recruitment operations and their healthcare services and financial activities and strategic planning decisions. Research on algorithmic reliance suggests that individuals may place greater trust in automated recommendations than in their own judgement, even when the technology is imperfect (Skitka et al., 1999; Dietvorst et al., 2015). Users develop automation complacency because they lose their ability to assess system operations and verify the findings, as they trust that AI outputs will always be correct (Lee & See, 2004; Parasuraman & Manzey, 2010). AI systems require human supervision to support decision-making yet organizations need to develop their oversight methods for algorithmic decision systems.

3.4 Metacognitive Transformation

Metacognition enables people to observe their mental activities while they assess their thought processes and direct their thinking operations (Schraw & Dennison, 1994). AI systems now offer recommendations and feedback and performance guidance which affect how people evaluate their knowledge and monitor their learning development and choose their educational path (Zimmerman & Moylan, 2009). AI systems provide students with instant support and error correction, which improves their learning efficiency, but students who depend on automated guidance lose their chance to think independently and monitor their own learning process. AI systems which promote student inquiry and reflection and active learning participation will help students develop their metacognitive abilities and become more independent learners (Maples et al., 2025). AI's effect on metacognitive abilities becomes more effective when users select appropriate AI systems and apply these systems correctly in their activities.

3.5 Cognitive Dependency Risks

The field of human–AI research has developed a new concern about cognitive dependence, which happens when people depend on AI systems to handle their memory and perform their reasoning, judgement and problem-solving tasks. Research shows that automated system dependence for extended periods reduces human ability to practice mental abilities which leads to declining professional abilities and decreased awareness of situations and reduced ability to make independent decisions (Parasuraman & Riley, 1997; Parasuraman & Manzey, 2010). Research shows that people who use technology too much lose their ability to think critically and their motivation to solve problems and their trust in their own decision-making abilities (Goddard et al., 2012). The increasing presence of AI in daily mental processes requires a solution to achieve AI advantages while safeguarding human abilities which enable self-directed learning and independent thinking and decision-making. The Human–AI Cognitive Co-Adaptation Framework built in the next section bases its development on this particular concern.

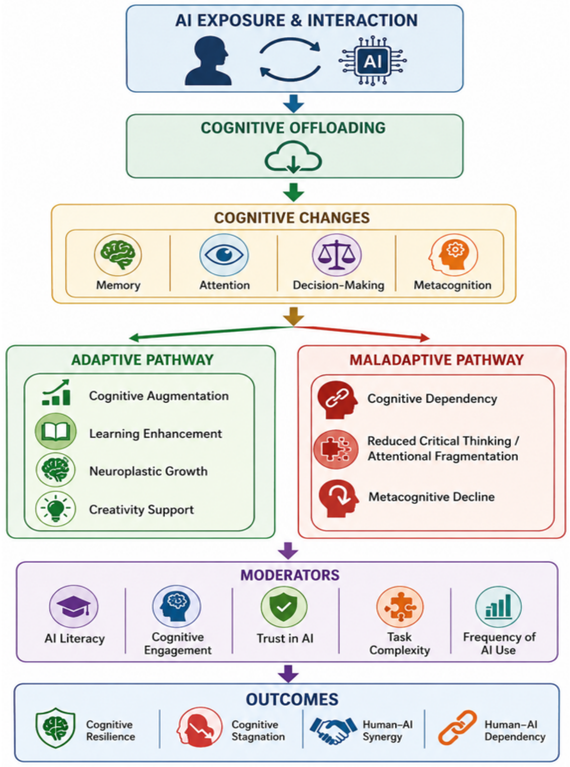
IV. Human–AI Cognitive Co-Adaptation Framework (HACCAF)

The Human–AI Cognitive Co-Adaptation Framework (HACCAF) represents the central theoretical contribution of this study. The framework shows that human cognitive abilities develop progressively when people maintain ongoing contact with artificial intelligence systems. The research shows that HACCAF identifies cognitive AI system results that emerge from human operator interactions with intelligent systems. The framework reveals that AI technology enables users to develop their cognitive abilities, yet users might develop technological dependence because of their interaction with these systems.

4.1 Framework Architecture

The Human–AI Cognitive Co-Adaptation Framework (HACCAF) explains how sustained interaction with artificial intelligence influences human cognition over time (Figure 1). The framework establishes AI as a cognitive partner that transcends its original role as a technological system, enabling it to perform tasks related to information processing, learning, problem-solving, and decision support. People use different amounts of cognitive offloading during their multiple interactions as they let AI systems handle their memory functions and their information retrieval and evaluation and analytical operations (Risko & Gilbert, 2016). HACCAF proposes that such interactions influence four key cognitive domains: memory, attention, decision-making, and metacognition. The research shows that AI-based assistance systems modify human methods for information storage, attention distribution, decision-making, and mental process control (Firth et al., 2019; Sparrow et al., 2011). The modifications do not ensure that they will produce good or bad results. The cognitive effects of human–AI interactions depend on the specific characteristics, strength, and quality of the interactions. The framework therefore advances a dual-pathway perspective. AI systems, which support reflection, learning, and decision-making processes, help users develop better cognitive skills, adapt, and become more creative while building their cognitive abilities. The excessive use of AI develops mental dependence, which weakens users' ability to think critically and make decisions independently. The repeated patterns that occur over time lead to different mental pathways, which influence how people acquire knowledge and interact with smart machines. HACCAF thus conceptualizes human–AI interaction as an ongoing process of cognitive co-adaptation in which the long-term effects of AI depend not simply on technological capability but on how humans engage with and govern their use of intelligent systems.

Figure 1. Human–AI Cognitive Co-Adaptation Framework (HACCAF)



Source: Authors

4.2 The Augmentation–Dependency Paradox

HACCAF presents the core theoretical concept which is known as the Augmentation–Dependency Paradox. The paradox demonstrates that AI systems will either enhance or diminish human thinking capabilities depending on user interactions with these systems (Raisch & Krakowski, 2021). The use of AI shapes cognitive outcomes, rather than the technology itself being inherently beneficial or detrimental. AI technology enables people to enhance their mental abilities through assistance with their standard duties, which lets them dedicate their complete attention to intricate work. Research on cognitive load and learning suggests that students achieve better learning results when they receive appropriate help along with challenging tasks, which leads to increased learning and adaptation (Sweller, 1988). AI functions as a cognitive enhancement tool which helps users achieve better results while they continue their professional development. People who depend on AI-generated outputs for consumption will lose their ability to think

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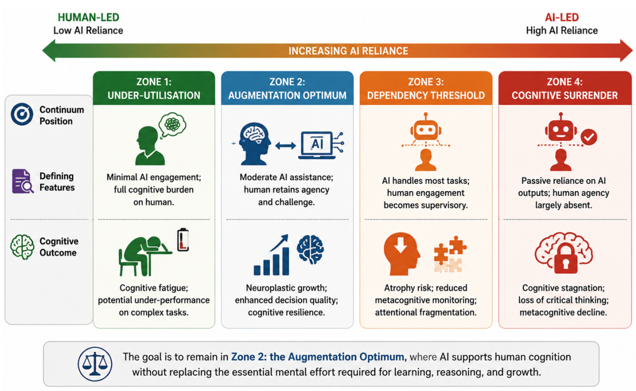
independently and solve problems and make their own decisions. The process will lead to skill deterioration while people become more reliant on automation and their thinking abilities will shrink (Parasuraman & Manzey, 2010).

Figure 2. Augmentation–Dependency Continuum



Source: Authors

AI systems generate different results through their operational methods, which either activate user participation or push users toward automated system operations. The process receives additional explanation through Figure 2, which shows an Augmentation–Dependency Continuum. The first stage of AI development produces intellectual overload for people who need to use it. The optimal middle zone functions as a system where AI technology enhances human abilities while humans maintain their decision-making power and their need to think critically. Dependence growth will lead to lower cognitive engagement after reaching a specific point, which will produce two negative effects, including mental immobility and dependency on others.

4.3 Boundary Conditions

The explanatory scope of HACCAF is subject to several boundary conditions. The framework establishes its main focus on ongoing human–AI partnerships which drive cognitive adaptation through multiple interactions instead of single interaction episodes. The second approach of HACCAF employs probabilistic evaluation to show that AI deployment does not create an automatic path to either improved human cognition or complete artificial mental control. The final results emerge from the combination of user actions, specific work requirements, system interface elements, and environmental factors. The framework targets multiple cognitive areas, which include memory and attention, as well as decision-making and metacognition, instead of focusing on particular job-related skills. The HACCAF system performs best when AI systems support educational processes and decision-based work and professional activities, but it fails to work in environments which need full automation and algorithmic monitoring and restricted user operations.

4.4 Mediating and Moderating Variables

HACCAF proposes that AI implementation creates cognitive effects through two separate systems which control the connection between AI deployment and cognitive results. People use cognitive offloading as their main method to transfer their memory and reasoning and problem-solving and decision-making tasks to AI systems, according to Risko and Gilbert (2016). People who perform cognitive offloading tasks achieve better efficiency, yet they minimise their mental work requirements. The results of cognitive offloading depend on various elements which affect both the environment and human behavior. Table 2 presents data which shows that AI literacy together with cognitive engagement and trust in AI and task complexity and AI usage frequency and user expertise and organisational or educational environment determine whether AI implementation leads to cognitive enhancement or dependence on AI systems (Lee & See, 2004; Long & Magerko, 2020; Ng et al., 2021; Einola &

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Khoreva, 2023; Afroogh et al., 2024; Montealegre-López, 2025).

Table 2. Mediating and Moderating Variables in the Human–AI Cognitive Co-Adaptation Framework

Variable Type	Variable	Description	Expected Influence on Cognitive Outcomes
Mediator	Cognitive Offloading	Extent to which individuals delegate memory, reasoning, problem-solving, and decision tasks to AI systems.	Greater offloading increases efficiency but may reduce cognitive engagement if excessive.
Moderator	AI Literacy	User understanding of AI capabilities, limitations, biases, and appropriate use.	Higher AI literacy promotes critical evaluation and reduces blind reliance on AI.
Moderator	Cognitive Engagement	Degree of active participation, reflection, and independent thinking during AI-assisted tasks.	Higher engagement strengthens learning, metacognition, and cognitive augmentation.
Moderator	Trust in AI	The level of confidence users place in AI-generated outputs and recommendations.	Moderate trust supports effective collaboration; excessive trust increases dependency risks.
Moderator	Task Complexity	Cognitive demands associated with the task being performed.	Complex tasks preserve human reasoning and reduce passive reliance on AI.
Moderator	Frequency of AI Use	Regularity and intensity of interaction with AI systems.	Repeated use amplifies either augmentation or dependency effects over time.
Moderator	User Expertise	Existing domain knowledge and experience of the user.	Greater expertise enables critical scrutiny of AI outputs and reduces automation bias.
Moderator	Organisational/ Educational Context	Norms, policies, and practices governing AI use.	Human-centred AI environments encourage augmentation; overautomated environments may foster dependency.

Together, these variables explain why similar AI systems may produce different cognitive outcomes across users and contexts. They also provide the conceptual foundation for the propositions that follow and reinforce HACCAF's central premise that cognitive outcomes emerge

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through an ongoing process of human–AI co-adaptation.

V. Conceptual Propositions

Drawing on the Human–AI Cognitive Co-Adaptation Framework (HACCAF), this section presents nine propositions that explain how sustained interaction with artificial intelligence may influence human cognition. The propositions are organised into three interrelated clusters: cognitive offloading, cognitive adaptation, and cognitive dependency. Together, they provide a theoretical basis for understanding the conditions under which AI contributes to cognitive enhancement or increases the risk of cognitive dependency.

Cluster A: Cognitive Offloading Mechanisms

P1: Greater reliance on AI for cognitive tasks is positively associated with cognitive offloading and negatively associated with direct cognitive engagement.

P2: Research indicates that AI-assisted information retrieval through cognitive offloading leads to poor memory retention because users experience reduced ability to encode information for long-term storage (Sparrow et al., 2011).

P3: AI literacy moderates cognitive offloading, such that individuals with higher AI literacy are more likely to strategically allocate cognitive effort by using AI for routine tasks while retaining responsibility for complex cognitive activities (Long & Magerko, 2020; Ng et al., 2021).

Cluster B: Cognitive Adaptation Mechanisms

P4: AI systems that keep their cognitive challenge at a moderate level show positive links to cognitive adaptation, which results in better learning and flexible thinking and enhanced problem-solving skills.

P5: Active involvement in tasks with AI assistance correlates with enhanced thinking skills and a heightened self-awareness of one's own learning.

P6: Users who need to understand AI-generated recommendations through evaluation and interpretation will develop better cognitive skills than users who use systems built for performance enhancement and automated work completion.

Cluster C: Cognitive Dependency Mechanisms

P7: The extended use of AI systems without human mental involvement results in negative effects on critical thinking abilities and attentional control skills and problem-solving autonomy.

P8: People who trust AI recommendations more than they should will delegate their decisions to others while they lose their ability to make independent choices and monitor their thinking process (Lee & See, 2004; Skitka et al., 1999).

P9: AI deployment produces cognitive effects which follow an inverted U-shaped curve because moderate AI support enables cognitive development through neuroplastic changes, yet excessive AI dependency results in mental decline and complete dependence (Raisch & Krakowski, 2021). The relationship between these two variables becomes stronger when tasks become more complex and people need to focus more cognitively on their work.

These research propositions build upon current human–AI interaction studies by demonstrating that AI system effects on human cognition depend on the way humans interact with intelligent systems. The research establishes a starting point which future studies can use to investigate AI system cognitive adaptation through their operating mechanisms and resulting system transformations.

VI. Framework Theoretical Contributions

The research develops the Human–AI Cognitive Co-Adaptation Framework (HACCAF), which serves as a theoretical model to study how people think when they interact with artificial intelligence systems throughout their lives. The framework studies the permanent mental impacts that result from using AI to perform tasks, acquire knowledge, and make choices. The HACCAF framework delivers three linked contributions, which consist of cognitive co-adaptation theory and human–AI system evaluation through neuroscience methods and the Augmentation–Dependency Paradox concept.

6.1 Cognitive Co-Adaptation as a Theoretical Construct

The research team presented cognitive co-adaptation as their initial finding, which describes an evolving system where humans and AI systems continuously affect each other. The HACCAF framework builds upon neuroplasticity theory to show how users develop cognitive skills through their repeated interactions with AI systems (Kolb & Gibb, 2014; May, 2011). AI systems now use their capabilities to learn from user actions and feedback and adapt their operations according to individual user requirements. The research adopts a different approach from standard technology-user models by studying human-AI interaction within a dynamic system where both human and artificial intelligence systems adapt to each other while gaining knowledge (Dellermann et al., 2019; Seeber et al., 2020).

6.2 Integration of Neuroscience and Human–AI Interaction

The research combines neuroscience with human–AI interaction studies to produce its second major contribution. The field of human–AI studies has concentrated on trust and adoption and performance results, but neuroscience reveals how people learn and focus and store information and how their brain structure changes. The HACCAF framework connects different fields through its demonstration that AI implementation creates effects which extend past behavioral results to affect the brain processes which help people learn and adapt. The framework establishes a complete model which demonstrates how AI-based cognitive assistance affects neuroplasticity to show the long-term effects of AI user interaction on human brain development (Kolb & Gibb, 2014; May, 2011).

6.3 The Augmentation–Dependency Paradox

The third contribution is the Augmentation–Dependency Paradox. The ongoing discussion about AI presents two conflicting views which describe it as either a tool for mental enhancement or a system that causes skills to deteriorate (Raisch & Krakowski, 2021). The HACCAF framework shows that AI implementation leads to two possible outcomes, which depend on how humans interact with artificial intelligence systems. The controlled use of technology helps students learn better and develop their thinking abilities, but heavy dependence on technology will reduce their ability to think independently and solve problems without assistance (Parasuraman & Manzey, 2010; Sweller, 1988). The paradox creates a theoretical framework which explains why people develop different cognitive abilities while emphasising the need to preserve mental abilities when developing artificial intelligence systems that focus on human interaction and their control systems.

VII. Discussion – The Augmentation–Dependency Paradox in Practice

The Human–AI Cognitive Co-Adaptation Framework (HACCAF) proposes that AI systems generate cognitive effects which depend on human interaction methods instead of the technological components. The Augmentation–Dependency Paradox shows that an AI system can create either cognitive growth or cognitive dependence through its operational deployment. AI systems become useful for learning and adaptation and cognitive flexibility when users actively assess and interpret and challenge the automated results that AI systems produce. The extended use of AI systems without active human mental participation will lead to a decline in people's ability to think critically and make independent decisions and maintain focus (Parasuraman & Manzey, 2010). Research on cognitive load and neuroplasticity indicates that AI systems generate the best cognitive advantages when they decrease unnecessary mental work but keep users engaged in thinking and problem-solving activities (Kolb & Gibb, 2014; Sweller, 1988). The approach demands artificial intelligence systems to achieve cognitive sustainability through suitable design and oversight systems which support human agency (Shneiderman, 2020).

VIII. Implications for Human-Centered AI Design

HACCAF states that AI systems need to show their value through operational efficiency and performance metrics and their influence on human thinking processes. The framework establishes that AI system development needs to focus on creating systems which help users learn and think critically and make their own decisions without needing too much mental support. The Augmentation–Dependency Paradox reveals that AI systems either enhance human cognitive abilities or reduce them based on their design and operational methods. Human-centred AI requires development to improve human cognitive abilities while people maintain their decision-making skills and their mental abilities remain stable through the years.

8.1 Implications for Education

HACCAF proposes that AI should operate as an educational companion which supports learning instead of taking over human cognitive functions for problem-solving and thinking (Azevedo & Aleven, 2013). Educational systems must create learning environments that encourage students to critically evaluate AI-generated answers using evaluation methods and response justification, rather than blindly accepting them. AI literacy needs to become a fundamental educational requirement that teaches students about the functions of intelligent systems, their operational boundaries, and the built-in prejudices they may have (Long & Magerko, 2020; Ng et al., 2021). The assessment methods need to sustain their focus on individual thinking skills and analytical abilities and problem-solving competencies because AI-based learning approaches should help students develop their mental abilities instead of taking over their thinking processes.

8.2 Implications for Organizations

Organizations now implement AI systems to help their decision processes and their knowledge management operations and their operational systems. HACCAF emphasises that people need to stay actively involved in these operations. Human-in-the-loop methods allow individuals to retain their decision-making abilities, responsibility for their choices, and essential evaluation skills by utilising the output of AI systems (Parasuraman & Manzey, 2010; Seeber et al., 2020). Organizations need to provide their staff with AI literacy education and responsible-use training programs which teach them to assess AI system output properly while learning to detect system errors and optimise their system trust levels.

8.3 Implications for Technology Designers

Technology designers now use HACCAF to study how AI systems impact human mental operations instead of concentrating on system efficiency alone. Designers must evaluate AI system effects on human thinking and learning processes and metacognitive abilities together with their impact on system performance (Shneiderman, 2020). The system enables users to interact with explainable outputs by utilising reflective prompts, adjustable automation, and guided problem-solving, all of which enhance cognitive engagement and improve decision-making processes (Amershi et al., 2019). AI systems which support interpretation and reflection will build up human abilities better than systems which only focus on ease of use and automated operations.

8.4 Implications for Policymakers

HACCAF identifies the requirement for AI governance systems which assess both mental effects and economic impacts and social outcomes. The protection of critical thinking and independent judgment and lifelong learning abilities requires policymakers to support cognitive impact assessments together with ethical review systems and human-centered AI standards (Endsley, 2016; Shneiderman, 2020). AI systems require human cognitive abilities to operate, which makes cognitive sustainability a vital principle. The main objective of environmental sustainability involves defending natural resources while cognitive sustainability works to protect essential thinking abilities together with metacognitive knowledge and learning abilities and flexible problem-solving abilities throughout the years. AI governance systems which function properly will enable technological advancement to occur while they defend the mental abilities which support human independence and strength and sustainable growth through time.

IX. Limitations and Future Research

9.1 Limitations

HACCAF has produced various achievements, yet the system includes multiple operational restrictions. The framework exists as a conceptual model which requires experimental validation to become an established framework. The proposed relationships, together with the augmentation-dependency paradox, need to be verified through studies that will involve various population groups, different environmental settings, and AI system implementations. Second, HACCAF primarily focuses on voluntary AI use in learning, decision-making, and professional settings; its applicability to environments characterised by mandatory automation, algorithmic surveillance, or limited user autonomy remains uncertain. The framework focuses on cognitive results through memory and attention and decision-making and metacognition, but it does not adequately address the emotional and motivational and social and identity-related effects which AI implementation produces. Neuroplasticity Theory serves as a fundamental base for the framework, but the evidence supporting neuroplasticity in this framework remains primarily based on logical deduction. Research must conduct longitudinal studies which combine behavioral analysis with cognitive assessment and neuroscientific techniques to verify and enhance the established connections (Kolb & Gibb, 2014; May, 2011).

9.2 Future Research Agenda

The HACCAF system establishes a research base which enables scientists to examine human interactions with AI technology for their future effects on human mental functions. Table 3 presents an overview indicating that AI systems produce two types of results that impact memory, attention, decision-making, metacognition, and critical thinking abilities. The different results indicate that AI produces various effects based on how smart systems are implemented in cognitive operations and the level of human involvement in

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the process. Research needs to determine which situations enable AI to improve human cognition while it creates potential dangers for human dependence. Particular attention should be directed toward understanding long-term changes in learning, judgement, attention, and cognitive adaptation, as well as the mechanisms through which AI influences these outcomes.

Table 3. Adaptive and Maladaptive Cognitive Outcomes Across Four Domains

Cognitive Domain	Adaptive Outcome	Maladaptive Outcome
Memory	Enhanced working memory via AI scaffolding; better retention of higher-order knowledge.	Erosion of long-term retention; over-reliance on AI as an external memory store.
Attention	Redistributed focus toward complex, high-value tasks; reduced low-level cognitive noise.	Attentional fragmentation; reduced sustained focus; digital distraction dependency.
Decision-Making	More informed decisions through AI-generated insights; improved strategic judgement.	The delegation of moral and complex decisions to algorithms has led to a reduction in autonomous judgement.
Metacognition	Heightened self-awareness through AI-generated feedback; improved learning regulation.	Decline in self-monitoring; reduced awareness of cognitive processes and limitations.
Critical Thinking	AI-augmented analysis leads to deeper synthesis and broader reasoning.	Passive reliance on AI outputs reduces questioning, evaluation, and independent reasoning.

Source: Authors’ synthesis

Table 4 outlines the research priorities that require further development to build upon the existing domains. The main focus needs to be on Proposition 9 because it suggests that AI assistance produces a U-shaped effect on cognitive results. The research needs to test this proposition because it will show how different AI support levels affect performance results and human cognitive engagement. Researchers need to use experimental methods together with longitudinal studies and behavioural testing and neuroscientific research to establish a scientific basis for understanding human–AI cognitive co-adaptation (Kim-Spoon et al., 2021).

Table 4. Future Research Agenda

Research Theme	Key Research Question	Suggested Method

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AI and Memory Retention	Does prolonged AI use measurably alter declarative and procedural memory retention?	Longitudinal neuroimaging + cognitive battery
AI and Attentional Systems	How does habitual AI interaction reshape sustained and selective attention?	EEG / fMRI attention paradigms
AI and Neuroplasticity	What structural neural changes emerge from sustained AI-mediated cognition?	Voxel-based morphometry (VBM)
AI Trust & Dependency Threshold	At what level of AI trust does augmentation transition into cognitive dependency?	Experimental trust-manipulation designs
Workplace AI & Judgement	How does AI decision-support affect managerial judgement quality over time?	Field studies + cognitive assessment
Inverted-U AI Effect	Does moderate AI assistance produce superior cognitive outcomes relative to high or low assistance?	Controlled laboratory experiments
Human Cognitive Agency	At what point does AI support become cognitive substitution?	Controlled Experimental Design (Between-Subjects or Mixed Design)

Source: Authors' synthesis

X. Limitations and Future Research

The Human–AI Cognitive Co-Adaptation Framework (HACCAF) was established through research which shows how human mental processes evolve because of ongoing artificial intelligence system interactions. The framework incorporates five theoretical models that demonstrate how AI technology affects human memory systems, attention mechanisms, decision-making abilities, and metacognitive skills, as outlined by Clark & Chalmers (1998), Kolb & Gibb (2014), and Risko & Gilbert (2016). The research establishes the Augmentation–Dependency Paradox, which demonstrates that AI systems either enhance or reduce human mental abilities based on how people use them. The research reveals cognitive co-adaptation as an ongoing process, which demonstrates how humans and AI technology systems develop shared effects through their evolving connection patterns. Future research will build upon these nine theoretical propositions that examine cognitive AI, neuroplasticity, learning, and workplace decision-making. Intelligent systems will receive their future development through the ongoing partnership between human beings and intelligent technological systems. The main difficulty arises from determining the proper design of AI systems and the control mechanisms that should support human learning, decision-making, flexibility, and mental strength, while also protecting against system dependence and mental deterioration. Developers should base their AI system advancement on performance targets, operational efficiency, and cognitive sustainability principles to build intelligent systems that improve users' abilities.

References

1. Afroogh, S., Akbari, A., Malone, E. *et al.* (2024). Trust in AI: progress, challenges, and future directions. *Humanities and social sciences*

CORTEXPLORE Journal of CORTEXPLORE

communications, 11, 1568. https://doi.org/10.1057/s41599-024-04044-8

2. Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., Inkpen, K., Teevan, J., Kikin-Gil, R., & Horvitz, E. (2019). Guidelines for human–AI interaction. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–13. https://doi.org/10.1145/3290605.3300233
3. Azevedo, R., & Aleven, V. (Eds.). (2013). *International handbook of metacognition and learning technologies*. Springer. https://doi.org/10.1007/978-1-4419-5546-3
4. Barr, N., Pennycook, G., Stolz, J. A., & Fugelsang, J. A. (2015). The brain in your pocket: Evidence that smartphones are used to supplant thinking. *Computers in Human Behavior, 48*, 473–480. https://doi.org/10.1016/j.chb.2015.02.029
5. Bjork, E. L., & Bjork, R. A. (2011). Making things hard on yourself, but in a good way: Creating desirable difficulties to enhance learning. In M. A. Gernsbacher, R. W. Pew, L. M. Hough, & J. R. Pomerantz (Eds.), *Psychology and the real world: Essays illustrating fundamental contributions to society* (pp. 56–64). Worth Publishers. https://www.scirp.org/reference/referencespapers?referenceid=3200676 (Accessed on 05 June 2026).
6. Carr, N. (2020). *The shallows: What the Internet is doing to our brains* (2nd ed.). W. W. Norton & Company.
7. Clark, A., & Chalmers, D. J. (1998). The extended mind. *Analysis, 58*(1), 7–19. https://doi.org/10.1093/analys/58.1.7
8. Clark, A. (2008). *Supersizing the mind: Embodiment, action, and cognitive extension*. Philosophy of Mind Series (New York, 2008; online education, Oxford Academic, 1 Jan. 2009), https://doi.org/10.1093/acprof:oso/9780195333213.001.0001, accessed 2 June 2026.
9. Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering, 61*(5), 637–643. https://doi.org/10.1007/s12599-019-00595-2
10. Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1), 114–126. https://doi.org/10.1037/xge0000033
11. Endsley, M. R. (2016). From here to autonomy: Lessons learned from human–automation research. *Human Factors; The Journal of the Human Factors and Ergonomics Society, 59*(1), 5–27. https://doi.org/10.1177/0018720816681350
12. Einola, K., & Khoreva, V. (2023). Best friend or broken tool? Exploring the co-existence of humans and artificial intelligence in the workplace ecosystem. *Human Resource Management, 62*(1), 117–135. https://doi.org/10.1002/hrm.22147
13. Firth, J., Torous, J., Stubbs, B., Firth, J. A., Steiner, G. Z., Smith, L., Alvarez-Jimenez, M., Gleeson, J., Vancampfort, D., Armitage, C. J., & Sarris, J. (2019). The online brain: How the Internet may be changing our cognition. *World Psychiatry, 18*(2), 119–129. https://doi.org/10.1002/wps.20617
14. Goddard, K., Roudsari, A., & Wyatt, J. C. (2012). Automation bias: A systematic review of frequency, effect mediators, and mitigators. *Journal of the American Medical Informatics Association, 19*(1), 121–127. https://doi.org/10.1136/amiajnl-2011-000089
15. Gómez-Cruz, N. A., Rodríguez Castro, D. Y., Rey-Sarmiento, F., Zarate-Torres, R., & Moncada Niño, A. (2026). Mapping Human–AI Relationships: Intellectual Structure and Conceptual Insights. *Technologies*, *14*(2), 83. https://doi.org/10.3390/technologies14020083
16. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007
17. Jiang, T., Sun, Z., Fu, S., & Lv, Y. (2024). Human-AI interaction research agenda: A user-centered perspective. *Data and Information Management*, 8(4), 100078. https://doi.org/10.1016/j.dim.2024.100078.
18. Krämer, W. Kahneman, D. (2011): Thinking, Fast and Slow. *Stat Papers* 55, 915 (2014). https://doi.org/10.1007/s00362-013-0533-y
19. Kim-Spoon, J., Deater-Deckard, K., Lauharatanahirun, N., Farley, J.P., Chiu, P.H., Bickel, W.K. and King-Casas, B. (2017), Neural Interaction Between Risk Sensitivity and Cognitive Control Predicting Health Risk Behaviors Among Late Adolescents. J Res Adolesc, 27: 674-682. https://doi.org/10.1111/jora.12295
20. Kolb, B., & Gibb, R. (2014). Searching for the principles of brain plasticity and behavior. *Cortex, 58*, 251–260. https://doi.org/10.1016/j.cortex.2013.11.012

21. Lee, J. D., & See, K. A. (2004). Trust in Automation: Designing for Appropriate Reliance. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *46*(1), 50-80. https://doi.org/10.1518/hfes.46.1.50_30392 (accessed on 05 June 2026). Available at - https://journals.sagepub.com/doi/10.1518/hfes.46.1.50_30392
22. Loh, K. K., & Kanai, R. (2016). How has the Internet reshaped human cognition? *The Neuroscientist, 22*(5), 506–520. https://doi.org/10.1177/1073858415595005
23. Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. https://doi.org/10.1145/3313831.3376727
24. Maples, B., Cerit, M., Vishwanath, A. & Peck, K. M. (2025). How AI Companions shape learner's socio-emotional learning and metacognitive development. *AI & Society*. https://doi.org/10.1007/s00146-025-02737-5
25. May, A. (2011). Experience-dependent structural plasticity in the adult human brain. *Trends in Cognitive Sciences, 15*(10), 475–482. https://doi.org/10.1016/j.tics.2011.08.002
26. Montealegre-López, N. (2025). Exploring the role of trust in AI-driven decision-making: a systematic literature review. *Management Review Quarterly*. https://doi.org/10.1007/s11301-025-00526-4
27. Ng, D. T. K., Leung, J. K. L., Chu, K. W. S., & Qiao, M. S. (2021). AI literacy: Definition, teaching, evaluation and ethical issues. *Proceedings of the Association for Information Science and Technology, 58*(1), 504–509. https://doi.org/10.1002/pra2.487
28. Parasuraman, R., & Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. *Human Factors, 52*(3), 381–410. https://doi.org/10.1177/0018720810376055
29. Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors; The Journal of the Human Factors and Ergonomics Society, 39*(2), 230–253. https://doi.org/10.1518/001872097778543886
30. Rai, A., Constantinides, P., & Sarker, S. (2019). Editor's Comments: Next-Generation Digital Platforms: Toward Human–AI Hybrids. *MIS Quarterly*, *43*(1), iii–x. https://doi.org/10.25300/MISQ/2019/431E0
31. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072
32. Risko, E. F., & Gilbert, S. J. (2016). Cognitive offloading. *Trends in Cognitive Sciences, 20*(9), 676–688. https://doi.org/10.1016/j.tics.2016.07.002
33. Schraw, G., & Dennison, R. S. (1994). Assessing metacognitive awareness. *Contemporary Educational Psychology, 19*(4), 460–475. https://doi.org/10.1006/ceps.1994.1033
34. Seeber, I., Bittner, E., Briggs, R. O., De Vreede, T., De Vreede, G.-J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., & Söllner, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information & Management, 57*(2), 103174. https://doi.org/10.1016/j.im.2019.103174
35. Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe and trustworthy. *International Journal of Human–Computer Interaction, 36*(6), 495–504. https://doi.org/10.1080/10447318.2020.1741118
36. Skitka, L. J., Mosier, K. L., & Burdick, M. D. (1999). Does automation bias decision-making? *International Journal of Human–Computer Studies, 51*(5), 991–1006. https://doi.org/10.1006/ijhc.1999.0252
37. Sparrow, B., Liu, J., & Wegner, D. M. (2011). Google effects on memory: Cognitive consequences of having information at our fingertips. *Science, 333*(6043), 776–778. https://doi.org/10.1126/science.1207745
38. Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4
39. Ward, A. F., Duke, K., Gneezy, A., & Bos, M. W. (2017). Brain Drain: The mere presence of one's own smartphone reduces available cognitive capacity. *Journal of the Association for Consumer Research, 2*(2), 140–154. https://doi.org/10.1086/691462
40. Wilmer, H. H., Sherman, L. E., & Chein, J. M. (2017). Smartphones and cognition: A review of research exploring the links between mobile technology habits and cognitive functioning. *Frontiers in Psychology, 8*, 605. https://doi.org/10.3389/fpsyg.2017.00605

CORTEXPLORE Journal of CORTEXPLORE

41. Zimmerman, B. J., & Moylan, A. R. (2009). Self-Regulation: When Metacognition and Motivation Intersect. In Hacker, D.J., Dunlosky, J., & Graesser, A.C. (Eds.). (2009). Handbook of Metacognition in Education (1st ed.) (pp. 299-315). Routledge. https://doi.org/10.4324/9780203876428