Human Intelligence: Reclaiming Cognition in the Age of AI

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Abstract

Advancements in digital technologies are continuously reinventing human cognition, emotion and memory. While modern devices and platforms extend access to information and communication, they also present challenges such as cognitive overload, attention fragmentation, and memory decline, which can negatively impact well-being and educational objectives. Addressing these challenges requires a comprehensive approach that integrates cognition, emotion, and memory as interdependent systems for sustainable learning. The present report analyses the convergence of three emerging technological domains: digital phenotyping, digital therapeutics and neurotechnology, emphasizing their capacity to support cognitive enhancement, emotional regulation, and adaptive learning. Real-time behavioural and neural data is the foundation of the proposed system that will produce personalized interventions to strengthen memory, attention, decision-making and promoting emotional resilience. To improve the feasibility, ethical considerations, including privacy, equity, security and transparency, are critically discussed, alongside the model for practical application in an educational setting. This report aligns these technological tools within the framework of the United Nation's Sustainable Development Goals by positioning human cognition as the foundation for advancing quality education, mental well-being, and responsible technological development.

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Glossary

Term	Definition
Artificial Intelligence (AI)	A system that performs human-like cognitive tasks through algorithmic or adaptive models. In this report, AI includes any programmed or trained system that functions as an external cognitive tool, forming part of ReMind's digital layer.
Amygdala	A small, almond-shaped structure in the brain's medial temporal lobe involved in processing emotions such as fear, anxiety, and anger. It also influences how emotional experiences are stored as long-term memories.
Attention	A cognitive process that enables individuals to selectively focus on certain stimuli while ignoring others. Sustained attention is essential for learning, perception, and effective interaction with digital systems.
Brain–Computer Interface (BCI)	A technology enabling direct communication between the brain and external devices. Within ReMind, BCIs support adaptive neurofeedback and personalized cognitive training.
Cognitive	The set of mental processes that includes perception, thinking, learning, reasoning, and memory. Cognition forms the foundation of ReMind's approach to enhancing and repairing mental performance.
Cognitive Atrophy	The gradual weakening of cognitive abilities such as memory, reasoning, or problem-solving, often associated with underuse or overreliance on external aids like technology.
Cognitive Load	The total amount of mental effort being used in working memory during information processing. Excessive load reduces learning efficiency and is a key focus of ReMind's adaptive regulation.
Cognitive Offloading	The act of transferring mental tasks (e.g., remembering, calculating, navigating) to external tools like smartphones or AI systems to reduce mental demand.
Digital Health	An umbrella term for technology-based systems that support health monitoring, therapy, and intervention. ReMind operates within this space, integrating digital therapeutics and neuroadaptive feedback.
Digital Phenotyping	The continuous measurement of human behaviour, cognition, and physiology using data from personal digital devices such as smartphones and wearables.
Digital Therapeutics (DTx)	Clinically validated software-based interventions designed to prevent, manage, or treat health conditions through evidence-based digital programs.
Dual-Process Theory	A model of cognition that distinguishes between two types of thinking: fast, intuitive (System 1) and slow, analytical (System 2). ReMind aims to balance these processes through neuroadaptive training.
Electroencephalography (EEG)	A non-invasive neuroimaging technique that records electrical brain activity. ReMind uses EEG signals to assess cognitive load and deliver real-time neurofeedback.
Executive Function	A set of higher-order cognitive skills, including planning, decision-making, and self-control, governed by the brain's prefrontal cortex.
Fast Fourier Transform (FFT)	A mathematical algorithm that decomposes time-domain signals into their frequency components. In ReMind, FFT is used to analyze EEG data and estimate cognitive states.
Memory Consolidation	The process by which temporary memories are transformed into stable, long-term storage within the brain, often strengthened through emotional or repetitive reinforcement.
Neurofeedback	A self-regulation technique that provides real-time feedback on brain activity, allowing users to consciously modulate neural patterns. Integral to ReMind's adaptive learning and stress management features.
Neurotechnology	Any technology that interfaces with the nervous system to monitor, restore, or enhance brain function. This includes EEG, BCIs, and neurostimulation methods integrated into ReMind.
Power Spectral Density (PSD)	A measure of how the power of a signal is distributed across frequency, often used in EEG analysis to estimate cognitive load and attentional engagement.
Sustainable Development Goals (SDGs)	Global objectives established by the United Nations to promote social, environmental, and economic progress. ReMind aligns primarily with SDG 3 (Good Health and Well-Being) , SDG 4 (Quality Education) and SDG 9 (Industry, Innovation, and Infrastructure).

1. Introduction

Humans throughout history have defined their relationship with technology through cognition. From the invention of writing to the printing press, technological advancements have repeatedly reshaped how people think, learn and interact. As technologies grew in complexity so did the level of understanding required for their adoption. Yet, unlike the pioneers of earlier innovation, today's technologies are increasingly reaching inward, influencing the human brain more than ever. Today, in the era of the Fourth Industrial Revolution (4IR), technologies not only extend human cognition but also intervene directly in its processes, raising a critical question: can human cognition adapt to the pace of technological change, or are we at risk of being outpaced by our own creations? (Schwab, 2016).

Recent evidence highlights the stakes. Information overload, (see Appendix A.1) damages cognitive control, decision-making quality, and task efficiency (Arnold et al., 2023; Eppler & Mengis, 2004). Meanwhile, a study completed by McKinsey estimates that the average knowledge worker now spends 65% of their time managing incoming information rather than producing new insights (McKinsey, 2022). These patterns suggest that excessive digital input can hinder cognitive operations, emphasising the need for proactive tools to support the mind. UNESCO highlights that prolonged digital exposure, especially in learning environments, contributes to "*attention fragmentation and cognitive fatigue*" among students (UNESCO,2022). At the same time, technological tools are not inherently harmful. Smartphones, AI assistants, and automation have been enhancing learning, memory, and problem-solving, supporting the overall goal of this paper: restoring and refining cognition (Ward et al., 2017; Buchli & Storm, 2025).

The solution is not the eradication of these technologies. Abandoning innovation is not a viable strategy; historical patterns show that each innovation is quickly succeeded by another. Instead, this new landscape demands new tools and practices for understanding and intervention, rather than avoidance. Education presents a high-impact domain for such interventions. In this context, cognition forms the foundation of all learning processes. Bloom's Taxonomy, first proposed in 1956 and later revised by Anderson and Krathwohl (2001), offers a structured model for understanding how learners progress from basic recall to higher-order thinking, remembering, understanding, applying, analysing, evaluating, and creating. As shown in Figure 1, this framework remains widely used across educational institutions for designing curricula and assessing cognitive engagement (Technology for Learners, 2023).

In a digitally saturated world, many students struggle to move beyond the lower tiers of this hierarchy, reflecting a broader decline in sustained attention and critical thinking. Thus, restoring these higher-order cognitive skills is not merely an academic concern but a necessary adaptation for learning in the digital age.

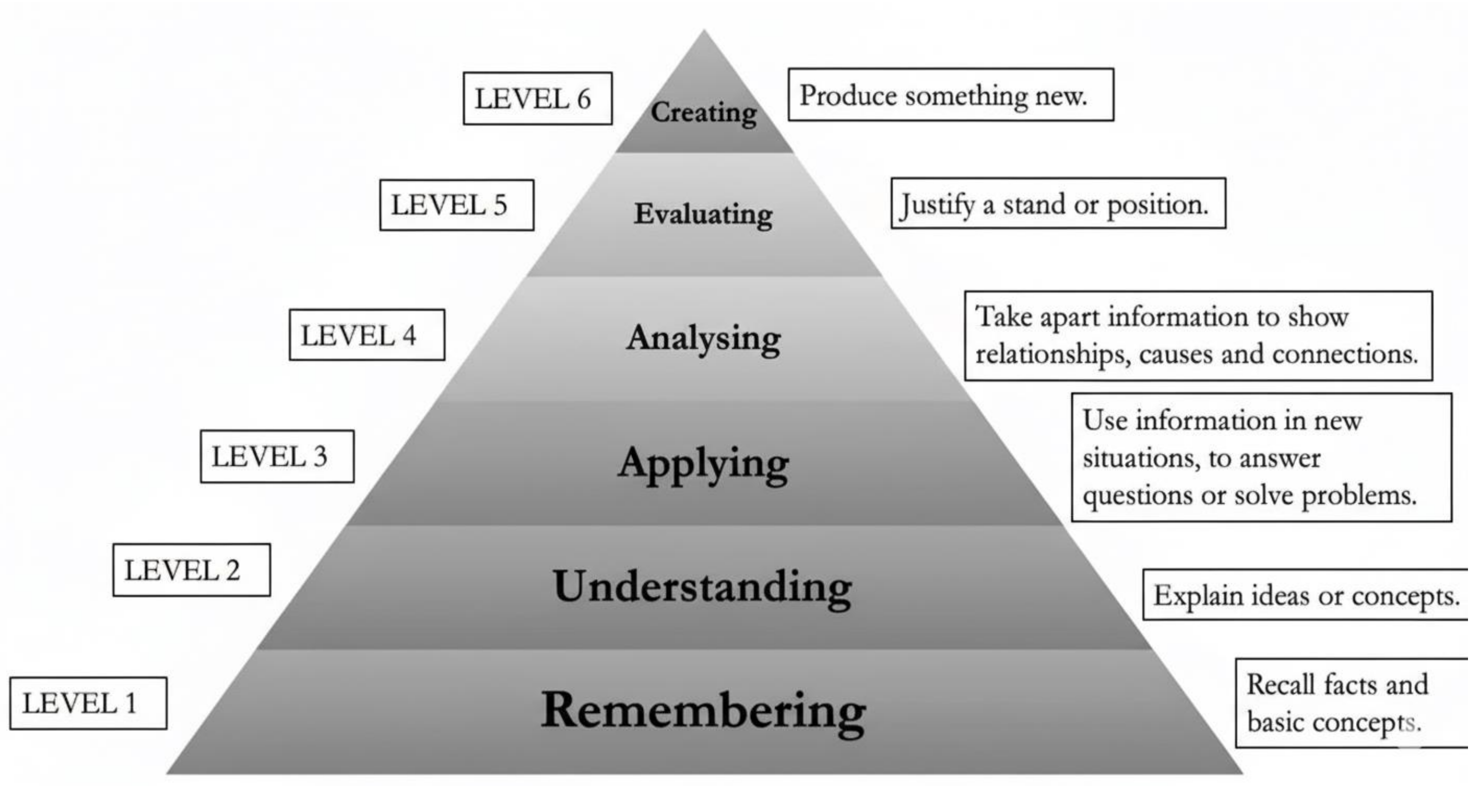

Figure 1. Bloom's Revised Taxonomy of Cognitive Processes (adapted from Technology for Learners, 2023; based on Anderson & Krathwohl, 2001; Bloom B. S. 1956). Created using Gemini.

UNESCO's research on digital learning and the United Nations' Sustainable Development Goals (SDGs) allows the identification global urgency in addressing the subject. The present report aligns with:

- SDG 3: Good Health and Well-Being.
- SDG 4: Quality Education.
- SDG 9: Industry, Innovation and Infrastructure.

SD3 and SDG9 are brought in as supporting goals to aid the primary goal: improving education quality through improved cognition. Therefore, throughout this report the brain is treated as the central piece where technology and human cognition converge. Three emerging approaches are especially salient:

- Digital phenotyping (DP)
- Digital therapeutics (DTx)
- Neurotechnology

Together, they form a triadic model that creates a framework for continuous brain support that offers adaptive and personalized guidance. This comprehensive model, which will be discussed later in subsequent sections, emphasizes enhancing human cognition while considering emotional and memory factors as essential contributors to learning and well-being.

2. Literature Review

2.1 Theoretical Foundations of Human Cognition

Human cognition represents one of the most complex and adaptive systems known to science. To analyse how the selected emerging technologies shape cognition, it is first necessary to construct a conceptual understanding of the brain itself. Cognitive neuroscience defines the brain as the central organ for consciousness as well as the primary interfaces between perception, action, and internal thought processes. Core states such as memory, attention, and control allow people to process stimuli, formulate rational reasoning and adapt to dynamic environments (Baddeley, 2003; Gazzaniga, 2018).

Understanding how emerging technologies engage with these cognitive systems requires distinguishing cognition from intelligence, two terms often used interchangeably but conceptually distinct. Cognition refers to the mental processes that enable perception, learning, memory, and reasoning, the mechanisms through which humans interpret and act upon the world. Intelligence, in contrast to this, reflects the capacity to apply those processes adaptively toward goals, integrating reasoning, problem-solving, and decision-making (Neisser et al., 1996; Sternberg, 2019). Thus, intelligence utilizes cognitive functions.

Artificial intelligence (AI) therefore does not possess cognition in the biological sense; rather, it simulates certain cognitive operations through algorithms and data-driven models. For clarity in this paper, “AI” denotes any computational system that performs tasks requiring human-like cognitive functions: from search and recommendation engines to large language models. This definition moves beyond conversational LLMs to include any trained or programmed system functioning as an external cognitive tool. Artificial general intelligence (AGI) moves forward to more human cognitive operations but this subsect remains conceptual.

The operations of the brain can be modelled through the lens of dual-process theory, popularized by Daniel Kahneman in Thinking, Fast and Slow (Daniel, 2011). He distinguishes between these two modes of thought: System 1 thinking is fast, intuitive, and based on automatic responses, while System 2 operates more slowly, engaging deliberate and analytical reasoning. System 1 enables quick reactions to everyday stimuli but is also vulnerable to cognitive biases and heuristic shortcuts. In contrast to this, System 2 supports deeper reflection and critical thinking, though it requires greater mental effort and concentration. This dual-process framework demonstrates that cognition is not simply a matter of rational thought; it is deeply interlinked with emotion and memory, forming an integrated foundation for adaptive behaviour.

Emotion and memory, though secondary in analysis, are identified and viewed as still integral to brain functions. Emotions are often fast automatic responses that are facilitated by the brain’s amygdala and influence attention and decision-making process through System 1 pathways (Lindquist et al., 2012; LeDoux, 2019). Memory is classified into short-term and long-term states that underpin cognition by retaining and retrieving information. Remembering is the lowest level of Bloom’s Taxonomy, requiring the least level of cognition. Emotions directly influence the efficiency of memory consolidation through activities measured by the hippocampus (Squire & Kandel, 2021; McGaugh, 2022). Thus, because memory retrieval is reconstructive in nature, the act of remembering reshapes cognition (Dudai, 2021).

Cognition, emotion and memory, interlinked brain functions that act under a unified system that interprets, evaluates, and stores experiences. Cognitive processes allow individuals to navigate and respond to the environment, emotions guide decisions, and memory retains these experiences to inform future actions (Shanmugasundaram & Tamilarasu, 2023). Together, these processes form a holistic framework for understanding the potential impact of emerging technologies on human mental functioning, laying the foundation for examining digital phenotyping, digital therapeutics, and neurotechnology in subsequent sections.

2.2 Digital Phenotyping

The term digital phenotyping originates from the biological concept of a phenotype, the observable traits shaped by an organism's genetic composition and its interaction with the environment. In the digital context, the term has been extended to be defined as the continuous quantification of human behaviour, cognition and physiology through data collected from personal devices such as Internet of Things sensors, wearables and smartphones (Onnela & Rauch, 2016). The practice reinvents how behavioural measurement is achieved through dynamic, continuous and data-rich understanding of human functioning rather than static and episodic forms.

Traditionally, the study of behaviour and cognition was dependent solely on structured surveys, laboratory assessments, and clinical interviews. While these approaches were invaluable for establishing the foundational psychological theory, they were inherently limited in scope. Behavioural data were often self-reported, retrospective, and context-dependent, introducing recall bias, temporal gaps and lack of personalization. To readjust this process, digital phenotyping was introduced to close these gaps, offering an ecological and temporally dense view of human activity that is closely more parallel to how people think, feel, and act in real life.

Digital phenotyping operates on two main streams of data: passive data and active data, as seen in Figure 2. Passive data is automatically captured from digital sensors such as accelerometers, Global Positioning System as well as screen usage logs. Active data on the other hand requires manual user input, collected from tasks or questionnaires. In conjunction with each other, these data types provide highly valuable insights into subtle behavioural actions that may reflect underlying cognitive or emotional states (Jilka et al., 2024). Digital phenotyping is mainly underpinned by machine learning models, often detecting patterns and correlations to predict outcomes such as stress, depression or cognitive decline. The advancement of deep learning and feature extraction has allowed for more nuanced interpretations of complex multimodal data (dos Santos et al., 2024).

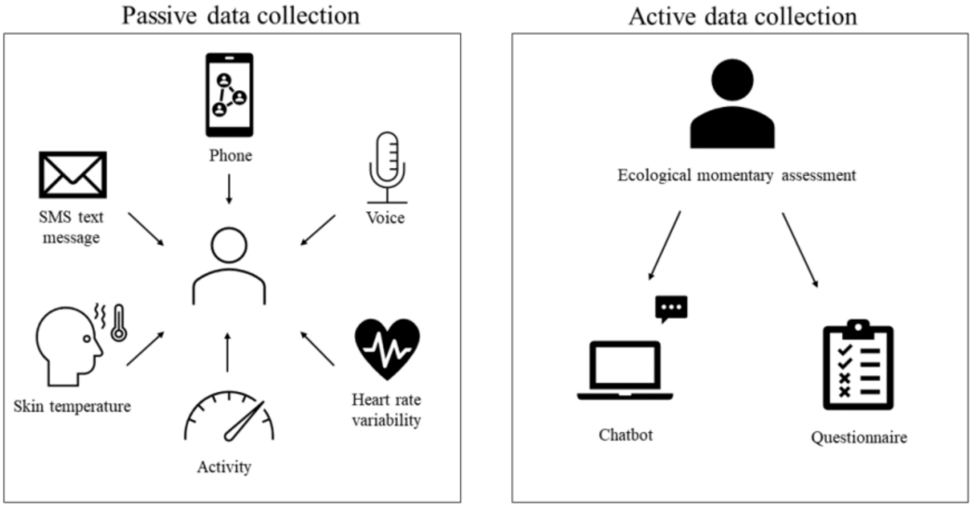

Figure 2. Passive and Active Data Collection Methods in Digital Phenotyping (Adapted from "Digital Phenotyping: Data-Driven Psychiatry to Redefine Mental Health") by R. R. Jagesar, F. M. M. A. van der Heijden, and T. Esko, 2020, JMIR Mental Health, 7(6), e17533 (https://doi.org/10.2196/17533). CC BY 4.0.

Despite the presented strengthens, digital phenotyping introduces critical challenges (De la Fabián et al., 2023). The sensitive nature of data collection, often involving personal aspects of daily life, raises profound ethical questions regarding consent, ownership and surveillance (Martinez-Martin et al., 2021). The lack of standardisation across devices, sensors, analytical methods make replication difficult which may apply these findings to other general groups (Alam et al., 2025). These limitations showcase the need for clinically validated and outcome driven interventions that can translate this behavioural data collected into measurable improvement. Digital therapeutics emerge as natural extension of digital phenotyping, refining insights into cognitive and emotional care.

2.3 Digital Therapeutics

Digital therapeutics represent a clinically validated subset of digital health interventions designed to prevent, manage or treat diseases and disorders through software applications-based delivery. These systems differ from wellness applications by being grounded in rigorous clinical evidence, undergoing regulatory evaluation, and are intended to deliver measurable therapeutic outcomes (Digital Therapeutics Alliance, 2023). Digital Therapeutic systems converge behavioural science, cognitive psychology, and digital technology to deliver structured interventions through mobile devices, computers, or connected platforms.

Therapeutic interventions once relied on in person consultations, static treatment plans and self-reported adherence, factors that created challenges in maintaining consistency, scaling and long-term monitoring. These approaches, though effective in a controlled setting, lacked the dynamic ability to change and accommodated for personalized nature of human behaviour. Digital therapeutics were constructed to target these flaws, enabling health professionals to offer continuous, adaptive, and personalized care that extends beyond the clinical environment. Interactive modules, gamified exercises, and real-time feedback loops not only differentiate digital therapeutics from traditional therapeutic interventions, they empower patients to actively engage in their treatment and allow medical professionals to monitor progress remotely (Torous et al., 2021).

Digital Therapeutic systems draw upon computational models and, in some instances, integrate data insights from digital phenotyping. Passive and active data collected through sensors or self-assessments can inform machine learning algorithms that tailor therapeutic content dynamically. This creates a feedback mechanism where behavioural data refine the intervention in real time, bridging the gap between clinical prescription and lived behavioural patterns (Biskupiak et al., 2024). Such adaptability allows for unprecedented precision in addressing mental and cognitive health conditions, marking a shift from one-size-fits-all treatment to personalised digital medicine.

These systems are subject to rigorous regulatory evaluation, often by agencies such as the U.S. Food and Drug Administration (FDA) or the European Medicines Agency (EMA**)**. FDA-approved applications like *reSET* and *reSET-O*, developed by Pear Therapeutics, demonstrated improved adherence and relapse prevention in substance use disorder treatment. Similarly, *EndeavorRx* the first prescription video game to treat paediatric ADHD, showcased measurable cognitive improvements in attention control (Akili Interactive, 2020). These examples highlight that these digital therapeutics can preserve clinical efficacy while significantly expanding accessibility and patient engagement (Gerke et al., 2022).

Despite these advances, digital therapeutics face challenges of data privacy, interoperability, and equitable access. Ethical concerns persist around data ownership, standardisation of outcome metrics, and the digital divide between patient populations (Smith et al., 2023). Furthermore, while digital therapeutics excels in behavioural and cognitive intervention, they remain limited to software-based interaction of the mind. The next section, neurotechnology**,** moves beyond behavioural interfaces to interact directly with the brain's physiological processes. As such, Neurotech represents not a replacement but a further extension of digital therapeutics, which already build on digital phenotyping, enabling interventions at the neural level to enhance, restore, or interface with human cognition.

2.4 Neurotechnology

Human cognition, emotion and memory are no longer studied only through behavioural observation but also through direct interaction with the brain's physiological activity. Neurotechnology refers to the discipline that encompasses methods and devices, designed to record, monitor and influence neural activity (Yuste et al., 2017). Brain-Computer Interfaces, neurotechnological tools that enable bidirectional communication between neural signals and computational systems, have emerged as one of the most prominent tools. BCIs are typically divided into two holistic categories: invasive and non-invasive technologies.

Invasive BCIs, such as those developed by Neuralink, Synchron, and Blackrock Neurotech, involve the surgical implantation of electrodes directly into the brain tissue. As these interfaces operate in direct contact with brain tissue, invasive BCIs offer high-resolution data and precise control. As a trade-off, these BCIs raise significant ethical, medical and societal concerns related to safety, privacy and autonomy (Ienca & Andorno, 2017). In contrast to these, non-invasive BCIs rely on external sensors and most notably electroencephalography (EEG), functional near-infrared spectroscopy (fNIRS), and transcranial magnetic stimulation (TMS) to detect and influence neural signals through the scalp. These approaches avoid surgical risks while allowing scalable and ethically acceptable applications in healthcare, education, and cognitive enhancement (He et al., 2020).

Non-invasive BCIs function on detecting the brain's electrical activity associated with cognitive states such as attention, stress, or fatigue. These signals are then translated by AI models into actionable data which can then trigger adaptive responses in digital systems such as digital therapeutics. Current applications include the use of electroencephalography to detect reduced beta-wave activity indicating mental fatigue. Similarly, neurofeedback mechanisms enable users to observe their brain activity in real time and learn to regulate it, improving focus and emotional control (Arns et al., 2020).

The growing convergence of digital phenotyping, digital therapeutics and neurotechnology presents a promising opportunity for creating integrated, adaptive, and ethically guided systems that enhance cognitive and emotional well-being. This convergence will form the basis of the proposed system discussed in the following section.

3. Proposed System: ReMind

3.1 Theoretical Convergence

Now that a holistic understanding of these three technological domains has been established, it becomes possible to consider their convergence in relation to our central point: the brain. Digital phenotyping, digital therapeutics, and neurotechnology represents not merely a technological synthesis but a strategic response that can be applied to the challenges identified in the beginning of this paper. Cognitive overload, emotional fatigue and erosion of autonomous mental function, digital age issues that can be mitigated with the proposed system: a triadic model. The proposed system aligns these technologies into complementary roles.

Digital phenotyping serves as the data-centric layer, continuously capturing behavioural and physiological patterns that reflect the cognitive states such as attention, stress, or fatigue. This real-time information which is often disjointed or unobservable through traditional methods, becomes the crucial foundation of the system. Once this data is collected, high functioning software applications, digital therapeutics, can be deployed to utilize this information. The objective at this layer of the model is to continuously apply interpretive and corrective measures that aid in brain health maintenance. Driven by clinically approved standards and validated algorithms, these programs will deliver adaptive feedback, micro-therapies and personalized cognition training, promoting better learning and well-being without replacing human judgment. To reinforce this closed-loop system that operates to cognition, emotion and memory, neurotechnology is added as an enhancement layer. Non-Invasive brain-computer interfaces enable the model to become more interactive, allowing direct observation of neural activity where behavioural or cognitive interventions are insufficient. Through electroencephalographic neurofeedback, attention can be restored, emotional states can be balanced and memory encoding can be strengthened in an ethically guided manner.

However, this integration of human and artificial systems also reflects a deeper cognitive principle. Recent theoretical work introduces the concept of System 0 thinking, a pre-conscious disturbed layer of human and machine interaction that operates beneath the dual-process theory of System 1 and System 2. System 0 acts as the connective substrate between human intuition and algorithmic inference, or the viewed AI systems, enabling continuous adaptation without explicit awareness. In this academic report, System 0 is adapted as the cognitive analogue of the triadic model: digital phenotyping, digital therapeutics and neurotechnology.

This model is underpinned by sustainability, accessibility, and ethical design, supporting key UN Sustainable Development Goals. SDG 3, Good Health and Well-being, is addressed through proactive mental health monitoring and intervention. SDG 4, Quality Education is the primary objective supported via adaptive, personalized learning platforms responsive to cognitive states. SDG 9, Industry, Innovation, and Infrastructure, is advanced by fostering responsible neurotechnology development and equitable access.

These objectives create the blueprint for ReMind, which applies the conceptual triad in practice, integrating digital phenotyping, therapeutics, and non-invasive brain–computer interfaces while considering real-world contexts, including societal and South African-specific factors.

3.2 Technical Foundation

3.2.1 The Concept

ReMind is a neuroadaptive system that integrates digital phenotyping, digital therapeutics, and non-invasive brain–computer interfaces to enhance cognitive performance, emotional regulation, and mental resilience. ReMind is designed to function safely for the general public audience seeking cognitive enhancement, while a more intensive, clinically-oriented version can be utilized under professional supervision for users with identified cognitive or mental health needs.

In an age where AI continues to accelerate, ReMind refocuses attention on the human mind itself, aiming not to replace intelligence, but rather to restore, reinforce, and retrain it. This bridges the growing divide between human cognition and machine efficiency, positioning technology as a tool for education rather than artificial intelligence dependency.

What once only existed in science fiction is now increasingly possible through a personalized mobile ecosystem that integrates digital activity monitoring with real-time neurofeedback. Through pairing a smartphone-based application with a lightweight electroencephalographic headset, ReMind aims to extend traditional mental health and learning tools into continuous, data-driven brain care.

3.2.2 System Architecture

Data Layer

At its foundation, ReMind collects ethically sourced and user-consented data through digital phenotyping and physiological signals. This includes metrics such as screen time, voice tone, facial micro-expressions, heart rate, and sleep cycles**,** gathered passively from the user's device. Users maintain full transparency and control over what is collected, with the option to toggle or restrict any data stream, whether this is screen time or sleep cycles, users maintain the control. This ensures adherence to privacy laws such as South Africa's POPIA Act, while also promoting digital trust. The resulting multimodal data allows ReMind to form a personalized neural and behavioural profile, the backbone of its adaptive feedback loops.

Software Layer

The software architecture of ReMind serves as the analytical and therapeutic core. Built around a hybrid AI model, the system combines algorithms based on cognitive behavioural and neuropsychological theory and machine learning models trained on pre-existing, clinically validated datasets. Unlike generative systems that scrape open internet data, which can often be malformed, ReMind's AI operates within a controlled knowledge base, verified by professionals in their respective fields, reducing the risk of misinformation or hallucination. This curated model supports personalized digital therapeutic interventions that adapt dynamically to user needs. To meet clinical credibility, the software would align with international digital therapeutics certification frameworks such as Digital Therapeutics

Alliance standards and has to be regulated by recognized health bodies, ensuring that ReMind's recommendations are not only intelligent but medically responsible.

Hardware Layer

The ReMind headset acts as the primary neural interface**,** capturing brain activity through non-invasive EEG sensors embedded in a comfortable, lightweight design suitable for extended wear. Constructed from comfortable polymer materials with flexible electrode placement, the headset is optimized for portability and accessibility. It records alpha (8–12 Hz) and beta (13–30 Hz) frequency bands, which correspond to emotional states, cognitive load, and alertness. Elevated beta activity is associated with active concentration and anxiety, while more alpha activity indicates relaxed alertness and improved retention.The alpha and beta signals collected are pre-processed through Fast Fourier Transform (FFT) algorithms for noise reduction and pattern recognition, ensuring accurate cognitive state estimation. The power spectral density $P(f)$ of the EEG signal is calculated as the squared magnitude of its Fourier Transforms, $P(f) = |FFT(x_t)|^2$ (Welch, 1967; Teplan, 2002). This represents the distribution of signal power across frequencies. By computing spectral energy ratios such as $\frac{\mathrm{P}\beta}{\mathrm{P}\alpha}$, ReMind estimates the user's cognitive load intensity, with higher ratios typically reflecting greater mental engagement or stress (Klimesch, 2012).

Processing Layer

ReMind's processing system combines therapeutic logic with adaptive cognition. The core algorithmic engine interprets neural and phenotypic data, comparing current readings against baseline metrics to identify cognitive or emotional deviations. When activated, the system's intervention module recommends evidence-based actions, such as revisiting a certain chapter, exercises, memory recall tasks, or adaptive learning prompts, curated to the user's state. In addition to this, the processing layer is also powered by a pre-trained machine learning model, fine-tuned on datasets derived from neuroscience, educational psychology, and digital behaviour analytics. ReMind would then require a large language model (LLM), fine-tuned for educational interaction. A suitable candidate we can consider for this layer is OpenAI's GPT-4 turbo or Anhtropic Claude 3 Opus, selected for their factual accuracy, scientific alignment, and interpretability in peer-reviewed evaluations (Bang et al., 2023; Chang et al., 2024). This design minimizes data drift and optimizes personalization, ensuring that ReMind acts as a reliable companion for real-time learning rather than a reactive study bot.

3.2.3 Core Functions

Cognitive Calibration

ReMind continuously monitors the user's cognitive state through both electroencephalographic signals and behavioural cues. When indicators of mental fatigue, reduced attention, or cognitive overload are detected, the system provides personalized recommendations such as rest breaks, focus intervals, or targeted exercises to restore balance. As the system integrates digital phenotyping with neural data, ReMind can convert complex brain activity into actionable cognitive insights, enhancing both focus and productivity without compromising the user's mental well-being.

Emotional Regulation Assistance

The proposed system, named ReMind, translates physiological and neurological inputs into an understanding of emotional behaviour. Using the collected data correlated with digital interactions the system can identify emotional trends and triggers, offering users real-time insights into their mood fluctuations. Through continuous feedback, it assists users in developing emotional self-awareness and understanding, suggesting mindful routines, grounding techniques, or mood-specific interventions. Over time, ReMind compiles these patterns into a Mood Mirror Dashboard, allowing users to visualize emotional resilience, identify triggers, and track progress over time.

Memory Enhancement

To address the initial identified concerns of memory erosion and fragmented attention, ReMind introduces a Memory Enhancement Mode that integrates neuroscientific principles of spaced repetition and reinforcement learning. As it detects optimal learning windows via brainwave analysis, the system intelligently times memory recall prompts and adaptive learning activities, strengthening both short-term and long-term retention. This is complemented by gamified exercises that stimulate hippocampal engagement and neuroplasticity, effectively turning mental training into a measurable and rewarding process.

3.3 Implementation and Adoption

3.3.1 Scope

ReMind operates in a dual-model structure, adopted from dual-process theory, designed to evolve from a public cognitive enhancement tool into a regulated and verified clinical-grade system over time. While the main user market is students, ReMind is not limited to the classroom, rather used for general learning and cognitive restoration. This approach is feasible within the next five years, by 2030, aligning with the United Nations expected date for reviewing the Sustainable development goals plan. The public version of ReMind will focus on accessible cognitive support for everyday users such as students, seeking better mental resilience.

The long-term vision of ReMind, about 10 – 15 years, however is to expand the current public educational use into a more medically approved clinical ecosystem. This version will cater towards individuals with specific neurocognitive conditions such as ADHD, mild cognitive impairment or generalized anxiety disorder, following regulatory approval from internationally recognized bodies like the World Health Organization (WHO), U.S. Food and Drug Administration (FDA), and South African Health Products Regulatory Authority (SAHPRA). ReMind at this phase of development will more inclusive for students suffering from serve mental illnesses.

As evident, the clinically-graded digital therapeutic will require a large amount of time. Factors such rigorous testing, ethical vetting and longitudinal studies require special care, these processes are not immediately achievable within the current research cycle. Therefore, this section focuses on the user journey of the public educational system of ReMind, which establishes the groundwork for clinical expansion.

3.3.2 The User Journey

The ReMind journey begins with a calibration session, while using both the mobile application and the electroencephalographic headset, students can create a baseline cognitive profile. Once configured, the system collects phenotypic data passively through smartphone usage while also integrating neural feedback during active sessions, typically indoors or controlled environments. This hybrid design allows ReMind to maintain its accuracy and practicality: the headset being used during focused activities, while the mobile app maintains adaptive learning and emotional tracking in everyday contexts.

Cognitive Support and Learning Flow

During focused study sessions with ReMind, the headset monitors beta and theta brainwave activity, translating this into real-time insights on concentration and mental load. When the system detects higher brain activity that is associated with difficulty in comprehension, or supressed activity during prolonged engagement, indicating lack of learning adsorption, ReMind will automatically offer to simplify or rewrite digital notes.

For instance, ReMind may reformat dense paragraph into clearer summaries based on the exact point of interaction while reading. This is tracked through the current viewport coordinates. Example prompts include: "*It seems this concept caused high mental strain. Would you like a simplified version based on your past study sessions?* "

This adaptive learning process enables ReMind to serve as both a cognitive mirror and learning companion that understands the user better. Over time, the system's AI refines its rewriting precision, building a personal language and learning rhythm unique to each user.

Emotional Regulation and Mood Mirror

Emotional states are a bit more difficult to improve. As explained in the section 2.1, emotional states are subjective in nature. This is exactly why ReMind's personalized approach is required. Through the Mood Mirror, a built-in interface on the mobile app that recognizes and manages emotional states, ReMind equips the user to understand their behavioural patterns more deeply. This is not just simply analytics on the current mood, rather a personalized understanding and guided experience towards better cognitive abilities.

When negative affective spikes are detected, the app delivers suggestive, context-aware suggestions: "*You've been showing signs of tension for the past 20 minutes while using this app. Reflect on specific causes?"*

These insights are not only informatic data, rather a common ground for the user to engage in direct conversation with the ReMind AI, discussing emotional patterns and receiving guided interventions for negative emotions such as stress, anxiety, anger, depression.

Memory Reinforcement and Retention

Memory reinforcement in the ReMind systems works through neuroadaptive reinforcement cycles. The model identifies periods of optimal brain receptivity based on a high alpha-beta balance and introduces spaced recall prompts and short-term memory challenges during those windows.

An arbitrary example of this in action after a study session:

“Your neural activity suggests high consolidation potential, ready for a 60-second recall test?”

As the user engages with ReMind, the system model tracks which information is most frequently forgotten or easily recalled, refining its adaptive learning architecture. Enhancing this, gamified memory tasks are introduced to subtly stimulate the hippocampal engagement, transferring traditional memorization into measurable progress. While this approach is not designed for clinical memory rehabilitation, this mode enhances everyday retention and strengthens cognitive flexibility.

3.3.3 South African Context

The design of ReMind’s user experience not only defines its therapeutic and cognitive impact but also informs its long-term sustainability strategy, business model, and potential market positioning. In turn ReMind is now situated as a product under analysis in the South African context. Rather that implementing a subscription-based model, ReMind adopts a once-off purchase structure, allowing users to buy a complete “starter” kit that encompasses the ReMind EEG headest and the mobile application. This package is an estimated R9 000 to R10 000, a price derived from the market value of a basic EEG headset, approximately R5 000 for a basic version and a selling price for both the mobile application and services as an experience. This current structure allows users to have access to their ReMind unit overtime without recurring costs, ensuring that even offline or low-income users can benefit once the system is acquired.

According to ICASA’s 2024 Communications Report, an estimate of 78% of South Africans are active internet users, with over 90% of households owning at least one smartphone (ICASA, 2024). This strong digital base supports ReMind’s hybrid design, which will function offline through the mobile app and EEG for local data processing and syncs automatically. ReMind aims to address the digital divide affecting rural or under-resourced areas through partnerships with local municipalities, community learning centres and technical colleges to subsidize hardware costs through shared learning hubs.

From a business viewpoint, the foundational rollout would focus on pilot deployments within universities and schools, supported by strategic partners such as the Department of Basic Education, the Department of Science and Innovation, and innovation hubs like Stellenbosch LaunchLab, The Innovation Hub, and Workshop17. In addition to these ambitions, ReMind will seek out support from private investors focused on impact-driven technology such as Naspers Foundry, Sibanye Stillwater iHub, or Telkom FutureMakers. In return, these partnerships will strengthen the project’s scalability and credibility while promoting job creation in the local neurotech manufacturing ecosystem.

The five-year plan is structured as follows:

- Years 1 - 2: Prototype development and small-scale trials in universities.
- Year 3: National rollout through partner institutions.

- Years 4 - 5: Public distribution and preparation for clinical model trials, which will require certification from SAHPRA and later international regulators such as the FDA or EMA.

Ultimately, ReMind is not only a product, it's an experience. An ecosystem built to strengthen South Africa's cognitive and educational infrastructure, aligning directly with the UN's SDG 3, SDG 4 and SDG 9 targets for 2030.

4. Discussion & Analysis

4.1 Limitations

While ReMind presents a necessary step towards converging technology and cognitive abilities to improve education, there are several limitations we must acknowledge.

From a technical standpoint, the reliability of EEG readings remains a challenge outside controlled environments. Factors such as hair density, user movement, and environmental noise can affect signal clarity. Similarly, digital phenotyping data may not always accurately reflect true emotional or cognitive states, as device interactions are often context-dependent. To mitigate these, ReMind's algorithms would need continuous calibration and contextual filtering to minimize false observations.

Privacy and data ethics represent another major concern. Neurological data is deeply personal, requiring strict adherence to POPIA, GDPR. Transparent consent systems and high device security will therefore be prioritized to ensure user trust.

Financially, the cost of producing EEG hardware may limit large-scale accessibility, particularly in lower-income communities in South Africa. To address this, as mentioned in section 3.3.3, ReMind will propose partnerships and partial subsidies with educational and health institutions.

Lastly, clinical oversight remains vital. Although non-invasive EEGs are generally safe, improper use without professional interpretation can lead to misjudgement of one's mental state. ReMind's public version will thus include clear usage guidelines and gradual rollouts, ensuring both ethical use and scientific integrity.

5. Conclusion

The convergence of digital phenotyping, digital therapeutics, and neurotechnology represents a defining shift in how society understands and supports mental health and cognition. This paper has examined how concepts once regarded as speculative are now actively shaping the ways we learn, regulate emotion, and preserve memory. Yet, as innovation continues to grow, our ultimate goal should not be to create more intelligent machines, but rather cultivate stronger, more capable minds. True progress lies in developing technologies that help us think and feel more deeply not those that begin to think or feel in our place.

Within this vision, ReMind emerges as a neuroadaptive digital health system designed to bridge the increasing gap between human cognition and machine efficiency. By combining user-consented digital behaviour data with non-invasive brain–computer interfaces, the system transforms abstract neural and emotional signals into practical insight. Through features such as cognitive calibration, emotional awareness, and memory reinforcement, ReMind aims to reintroduce technology as a partner in human growth, not a substitute for it. Its modular design allows for both general public use and future clinical adaptation, reflecting a pathway from accessible wellness support to regulated medical application.

While there are limitations in privacy, accessibility, and regulatory oversight, the framework outlined in this report demonstrates that ReMind's integration is both feasible and ethically grounded. ReMind's envisioned 2030 model aligns with the Sustainable Development Goals, particularly those promoting health, well-being, education and innovation. Ultimately, ReMind serves as a reminder both in name and purpose: technological advancement should coexist with human resilience, ensuring that the future of intelligence remains human.

6. Declaration Statement

In preparation of this paper, I have utilised a range of generative AI and language tools, primarily: ChatGPT(OpenAI), Claude(Anthropic), Gemini (Google DeepMind) and Grammarly. These tools were used as supportive aids in specific, transparent capacities.

1. ChatGPT and Claude were used during my ideation and information searching phases to assist with constructing research approaches, exploring cognition and refining structural coherence. All sources and factual materials obtained through these interactions were subsequently verified manually using primary and peer-reviewed literature.
2. Gemini was exclusively used for image creation, specifically the visual representation of Bloom's refined taxonomy, based on empirical and peer-reviewed theoretical models developed by Bloom (1956) and Anderson & Krathwohl(2001). The figure was produced in a black and white academic style to comply with academic standards.
3. Grammarly and ChatGPT were used to improve language structure, grammar, clarity and sentence flow. No automated paraphrasing, summarisation or direct content generation was used in place of my own academic abilities.

I further acknowledge that the AI tools were used to improve the literature review process and assist in synthesising complex ideas, mirroring my declared proposed system 0 cognition architecture, however all critical reasoning, analysis and interpretation remain entirely my own. Holistically the present paper remains inherently mine and I take full accountability for its intellectual integrity and academic accuracy. This declaration is made in accordance with Nelson Mandela University's Institutional Position Statement on Generative AI (LTC, 2024).

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8. Appendices

Appendix Table A.1: Information Overload Situations

TABLE 1

Information overload situations

Context/overload situation	**Example**	**References**
Information retrieval, organization, and analysis processes	Searching on the Internet	Berghel, 1997
Information retrieval, organization, and analysis processes	Screening medical information	Bawden, 2001
Information retrieval, organization, and analysis processes	Financial distress analysis	Chewning and Harrell, 1990
Information retrieval, organization, and analysis processes	Evaluating the variety of product functions	Herbig and Kramer, 1994
Information retrieval, organization, and analysis processes	Analysis activities (strategic portfolio, environmental, new product analysis, service decisions)	Meyer, 1998
Information retrieval, organization, and analysis processes	Investment analysis	Tuttle and Burton, 1999
Information retrieval, organization, and analysis processes	Library management	Meier, 1963
Decision processes	Managerial decisions in general	Ackoff, 1967; Iselin, 1993
Decision processes	Management (project, strategic, production management)	Chervany and Dickson, 1974; Haksever and Fisher, 1996; Meyer, 1998; Sparrow, 1999
Decision processes	Supermarkets (choice of product)	Friedmann, 1977; Jacoby et al., 1974
Decision processes	Bankruptcy prediction process	Casey, 1980; Iselin, 1993
Decision processes	Capital budgeting process	Swain and Haka, 2000
Decision processes	Welfare assistance (decisions about type and amount)	O'Reilly, 1980
Decision processes	Innovation choice	Herbig and Kramer, 1994
Decision processes	Price setting	Meyer, 1998
Decision processes	Advertising media selection	Meyer, 1998
Decision processes	Strategy development	Sparrow, 1999
Decision processes	Physician’s decision making	Hunt and Newman, 1997
Decision processes	Financial decision making	Iselin, 1988; Revsine, 1970
Decision processes	Brand choice (consumer decision making)	Jacoby et al., 1974; Iyer, 1987; Malhotra, 1982; Owen, 1992; Scammon, 1977; Wilkie, 1974
Communication processes	Aviation	O'Reilly, 1980
Communication processes	Meetings	Schick et al., 1990
Communication processes	Telephone conversations	Schick et al., 1990
Communication processes	The use of groupware applications	Schultze and Vandenbosch, 1998
Communication processes	Bulletin board systems (BBS)	Hiltz and Turoff, 1985
Communication processes	Face-to-face discussions	Sparrow, 1999
Communication processes	Telephone-company services	Griffeth et al., 1988
Communication processes	Electronic meetings	Grise and Gallupe, 1999, 2000
Communication processes	Idea organization	Grise and Gallupe, 1999, 2000
Communication processes	E-mail	Bawden, 2001; Speier et al., 1999; Denning, 1982
Communication processes	Management consulting	Hansen and Haas, 2001
Communication processes	City interactions	Milgram, 1970
Communication processes	Disclosure law, contract complexity, legal disclaimers	Grether et al., 1986

Note. Adapted from “The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines” by M. J. Eppler & J. Mengis (2004), The Information Society, 20(5), 325–344. https://doi.org/10.1080/01972240490507974

Appendix Table A.2: Causes of Information Overload

TABLE 2

Causes of information overload

Category	**Cause**	**References**
Personal factors	Limitations in the individual human information-processing capacity	Herbig and Kramer, 1994
Personal factors	Decision scope and resulting documentation needs	Kock, 2001
Personal factors	Motivation, attitude, satisfaction	Muller, 1984
Personal factors	Personal traits (experience, skills, ideology, age)	Owen, 1992; Hiltz and Turoff, 1985; Muller, 1984; Schneider, 1987; Swain and Haka, 2000
Personal factors	Personal situation (time of the day, noise, temperature, amount of sleep)	Owen, 1992; O'Reilly, 1980
Personal factors	Screen senders outputting information insufficiently	Van Zandt, 2001
Personal factors	Users of computers adapt their way of interacting too slowly with technological development	Maes, 1994
Personal factors	Social communication barriers break down	Schultze and Vandenbosch, 1998
Personal factors	Number of items of information rises	Bawden, 2001; Herbig and Kramer, 1994; Jacoby et al., 1974; Jacoby 1977, 1984; Malhotra, 1982
Information characteristics	Uncertainty of information (info needed vs. info available)	Schneider, 1987; Tushman and Nadler, 1978
Information characteristics	Diversity of information and number of alternatives increase	Bawden, 2001; Iselin, 1988; Schroder et al., 1967
Information characteristics	Ambiguity of information	Schneider, 1987; Sparrow, 1999
Information characteristics	Novelty of information	Schneider, 1987
Information characteristics	Complexity of information	Schneider, 1987
Information characteristics	Intensity of information	Schneider, 1987
Information characteristics	Dimensions of information increase	Schroder et al., 1967
Information characteristics	Information quality, value, half-life	Sparrow, 1998, 1999
Information characteristics	Overabundance of irrelevant information	Ackoff, 1967
Task and process parameters	Tasks are less routine	Tushman and Nadler, 1975
Task and process parameters	Complexity of tasks and task interdependencies	Tushman and Nadler, 1975
Task and process parameters	Time pressure	Schick et al., 1999
Task and process parameters	Task interruptions for complex tasks	Spicer et al., 1999
Task and process parameters	Too many, too detailed standards (in accounting)	Schick et al., 1999
Task and process parameters	Simultaneous input of information into the process	Grise and Gallupe, 1999, 2000
Task and process parameters	Innovations evolve rapidly—shortened life cycle	Herbig and Kramer, 1994
Task and process parameters	Interdisciplinary work	Bawden, 2001
Task and process parameters	Collaborative work	Wilson, 1996
Organizational design	Centralization (bottlenecks) or disintermediation (searching by end users)	Schneider, 1987
Organizational design	Accumulation of information to demonstrate power	Edmunds and Morris, 2000
Organizational design	Group heterogeneity	Grise and Gallupe, 1999
Organizational design	New information and communication technologies (e.g., groupware)	Bawden, 2001; Schultze and Vandenbosch, 1998; Spicer et al., 1999
Information technology	Push systems	Bawden, 2001
Information technology	E-mails	Bawden, 2001
Information technology	Intranet, extranet, Internet	Bawden, 2001
Information technology	Rise in number of television channels	Edmunds and Morris, 2000
Information technology	Various distribution channels for the same content	Edmunds and Morris, 2000
Information technology	Vast storage capacity of the systems	Schultze and Vandenbosch, 1998
Information technology	Low duplication costs	Schultze and Vandenbosch, 1998
Information technology	Speed of access	Schultze and Vandenbosch, 1998

Note. Adapted from “The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines” by M. J. Eppler & J. Mengis (2004), The Information Society, 20(5), 325–344. https://doi.org/10.1080/01972240490507974