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AI-enhanced learning and cognitive processes in digital humanities: A systematic review of executive functions

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ABSTRACT

This systematic review synthesizes empirical evidence on artificial intelligence-enhanced learning interventions targeting executive function development across diverse populations and developmental stages within digital humanities contexts. Following PRISMA guidelines, a comprehensive search of five databases (PsycINFO, ERIC, Web of Science, Scopus, PubMed) from January 2020 through December 2024 identified 14 studies encompassing 1,810 participants aged 6 to 77 years. Included studies examined adaptive intelligent tutoring systems, virtual reality platforms, computerized cognitive training programs, computational thinking interventions, and machine learning-based assessment tools applied to humanities education and research. Results demonstrated consistent positive effects on inhibitory control (effect sizes: 0.11–0.62), cognitive flexibility, working memory (effect sizes: 0.09–0.18), and planning abilities, with machine learning models achieving high diagnostic accuracy (86.8%) for executive function impairments. Effectiveness was moderated by individual baseline cognitive capacity, particularly working memory constraints. Theoretical mechanisms underlying improvements included adaptive difficulty adjustment, cognitive load optimization, personalized scaffolding through Case-Based Reasoning and reinforcement learning algorithms, and neuroplasticity-driven neural efficiency gains. Despite promising findings, limitations include intervention heterogeneity, brief intervention durations, and limited long-term follow-up. Future research should prioritize longitudinal randomized controlled trials, neuroimaging studies elucidating neural mechanisms, and implementation science investigations supporting evidence-based integration of AI technologies in digital humanities pedagogy and clinical contexts.

KEYWORDS: adaptive learning, artificial intelligence, a systematic review, executive functions, cognitive training, neuroplasticity

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Introduction

Executive functions (EFs) represent a set of interrelated neurocognitive processes—including working memory, inhibitory control, cognitive flexibility, and planning—that enable individuals to regulate thoughts, emotions, and behaviors to achieve goals and adapt to novel situations (Ahmed et al., 2018; Friedman & Miyake, 2017; Zelazo, 2020). These higher-order processes, primarily associated with prefrontal cortex activity, are distinct from general intelligence and foundational for self-regulation and problem-solving (Blair, 2016; Friedman & Miyake, 2021). EFs develop rapidly from early childhood through adolescence, with foundational skills emerging in preschool years and reaching adult levels by late adolescence (Ferguson et al., 2021; Tervo-Clemmens et al., 2023). Critically, EFs are robust predictors of academic achievement, with working memory and inhibitory control showing strong associations with performance in reading, mathematics, and overall school success (Pascual et al., 2019; Spiegel et al., 2021).

Artificial intelligence has fundamentally transformed educational practices, evolving from static computer-assisted instruction (CAI) to sophisticated adaptive systems that respond dynamically to individual learner needs (Chen et al., 2020; Kamalov et al., 2023). Modern AI-powered platforms leverage machine learning and natural language processing to analyze student performance in real-time, enabling personalized learning pathways that adapt content, pacing, and feedback to each student's unique profile (Gligorea et al., 2023; Tapalova & Zhiyenbayeva, 2022). Intelligent tutoring systems now emulate one-on-one human tutoring at scale, providing individualized instruction and targeted interventions that significantly improve learning outcomes and student engagement (Lin et al., 2023; Seo et al., 2021). This paradigm shift from one-size-fits-all approaches to adaptive, personalized learning environments represents a critical advancement in educational technology.

The theoretical framework linking AI-enhanced learning to executive functions integrates four foundational principles: Cognitive Load Theory (CLT), which enables AI systems to monitor and optimize working memory dynamically demands through real-time instructional adjustments (Koc-Januchta et al., 2022; Paas & Van Merriënboer, 2020); Scaffolding Theory, whereby AI provides personalized, adaptive support that enhances self-regulation and metacognitive skills (Lim et al., 2022; Pozuelos et al., 2018); Zone of Proximal Development (ZPD), allowing AI to maintain optimal challenge levels that promote problem-solving and cognitive flexibility (Gehlot, 2021); and Neuroplasticity Principles, through which multisensory, adaptive interventions drive structural brain changes in prefrontal networks associated with executive control (Gkintoni et al., 2025; Robledo-Castro et al., 2023). This convergence positions AI as an intelligent co-agent that continuously assesses cognitive states and leverages neuroscientific principles to enhance executive function development (Gibson et al., 2023).

The empirical evidence base for AI-enhanced interventions targeting executive function development demonstrates robust growth across diverse populations, though with notable variations in focus and rigor. Research concentrates primarily on children, adolescents, older adults, and clinical populations, particularly those with ADHD and autism spectrum disorders (Liang et al., 2021; Makmee & Wongupparaj, 2022; Qiu et al., 2023; Timaná et al., 2024). Among executive function domains, working memory and inhibitory control emerge as the most extensively studied targets, followed by cognitive flexibility, while planning remains substantially underexplored (Nguyen et al., 2019; Robledo-Castro et al., 2022; Wollesen et al., 2020). AI technologies employed span adaptive digital platforms, serious games, virtual reality environments, and machine learning-driven neuropsychological tools (Medina et al., 2020; Robledo-Castro et al., 2022). Despite consistent evidence supporting core executive function improvements, significant gaps persist regarding long-term maintenance, real-world transfer effects, and comparative effectiveness across different technological modalities (Napolitano et al., 2025; Sakai et al., 2024).

Despite increasing research on AI-enhanced learning and the recognized importance of executive functions, significant gaps remain in understanding how AI impacts their development. Existing studies often focus on isolated applications and specific populations, lacking a comprehensive evaluation across diverse interventions and executive function domains. The literature is fragmented, with varied designs and methods, making it hard to identify which AI approaches work best, for whom, and under what conditions. Key questions about how AI enhances executive functions, the influence of individual differences, and comparisons with traditional methods remain unanswered. This systematic review aims to fill these gaps by synthesizing empirical evidence on AI-based learning interventions and their effects on executive functions across different populations and developmental stages.

Given the transformative potential of AI technologies in education and the critical importance of executive functions for academic achievement and life outcomes, this systematic review aims to comprehensively synthesize empirical evidence examining the effectiveness of AI-enhanced learning interventions on executive function development across diverse populations and developmental stages. Specifically, this review seeks to: (1) evaluate the impact of AI-powered educational technologies on four core executive function domains—inhibitory control, cognitive flexibility, working memory, and planning—across pediatric, adolescent, adult, and clinical populations; (2) assess the diagnostic accuracy and predictive validity of machine learning-based assessment approaches for identifying executive function impairments using digital biomarkers and behavioral data; (3) identify key AI implementation mechanisms associated with positive cognitive outcomes; (4) examine individual difference factors and baseline cognitive capacities that moderate intervention effectiveness; and (5) establish an evidence-based foundation to guide future research directions, inform educational practice and clinical intervention strategies, and advance the integration of AI technologies in supporting executive function development and human cognitive potential across the lifespan.

Methodology

This systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological rigor and transparency. The review aimed to synthesize empirical evidence examining the effectiveness of AI-enhanced learning interventions on executive function development across diverse populations and developmental stages.

Search Strategy

A comprehensive literature search was conducted across five major academic databases: PsycINFO, ERIC, Web of Science, Scopus, and PubMed, covering publications from January 2020 through December 2024. This timeframe captured the contemporary era of AI-enhanced learning systems following widespread adoption of deep learning architectures. The search strategy employed three conceptual clusters connected by Boolean operators: artificial intelligence terms (including "machine learning," "adaptive learning," "intelligent tutoring," and "virtual reality"), executive function terms (including "inhibitory control," "cognitive flexibility," "working memory," and "planning"), and educational context terms (including "learning," "education," "training," and "intervention").

Eligibility Criteria

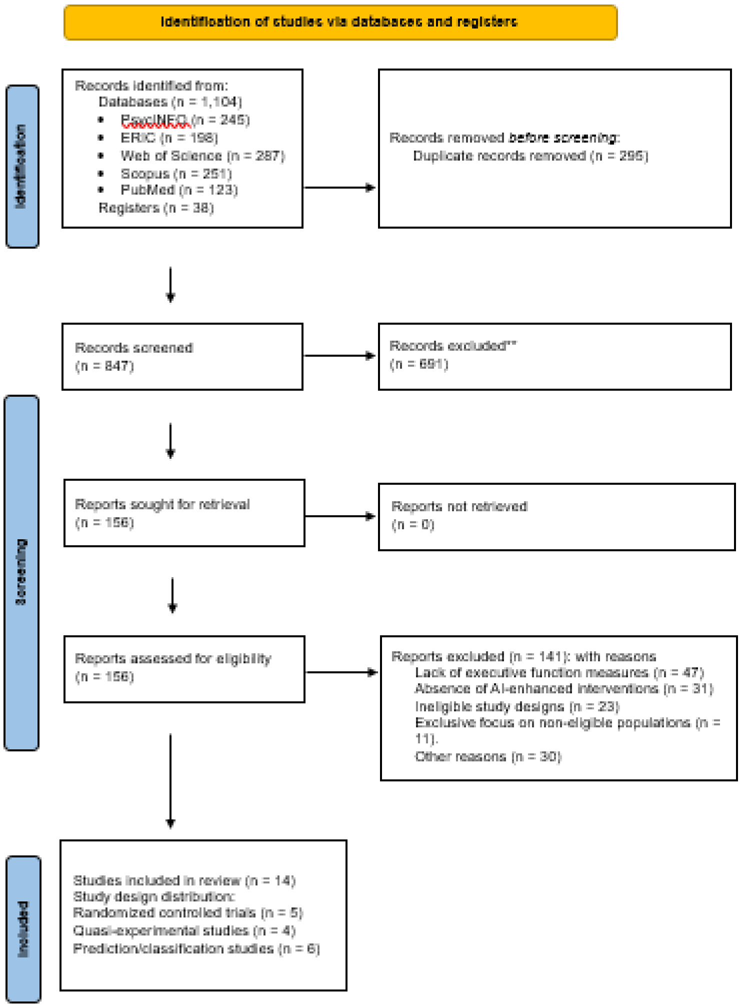
Studies were eligible for inclusion if they involved participants aged 6 to 77 years from diverse populations, including typically developing children and adolescents, healthy adults, older adults, and clinical populations such as individuals with ADHD, Down Syndrome, cognitive impairment, and other neurodevelopmental or neuropsychiatric conditions. Eligible interventions incorporated AI technologies for educational or cognitive training purposes, including adaptive intelligent tutoring systems, virtual reality platforms, computerized cognitive training programs, computational thinking interventions, and AI-based assessment tools. Intervention studies required a minimum duration of 3 to 12 weeks with multiple sessions. Studies must have employed appropriate comparison frameworks such as randomized controlled trials, quasi-experimental designs with baseline measures, or prediction studies with validation procedures. Crucially, studies were required to report at least one objective measure of executive function, including standardized neuropsychological tasks, validated rating scales, neuroimaging data, or machine learning-derived classifications. Exclusion criteria included non-empirical publications, purely qualitative research, studies lacking executive function measures, non-English publications, and studies without accessible full texts.

Study Selection Process

The study selection process was executed in two stages by two independent reviewers using the Covidence platform. Initial database searches identified 1,142 total records (1,104 from databases, 38 from other sources). After removing 295 duplicates, 847 unique records underwent title and abstract screening. Following this phase, 691 records were excluded, and 156 full-text articles were assessed for eligibility. Full-text screening excluded

141 studies for the following reasons: lack of executive function measures (n = 47), absence of AI-enhanced interventions (n = 31), ineligible study designs (n = 23), exclusive focus on non-eligible clinical populations (n = 11), and other reasons including duplicates and inaccessible texts (n = 29). Ultimately, 14 studies met all inclusion criteria and were retained for data extraction, quality appraisal, and synthesis. Discrepancies between reviewers were resolved through discussion, with a third reviewer consulted when necessary. Inter-rater reliability was substantial at both screening stages: Cohen's kappa = 0.85 at abstract screening and κ = 0.91 at full-text screening. The PRISMA flow diagram (Figure 1) documents the progression of records through each screening phase.

Figure 1. PRISMA Flow Diagram



Data Extraction

Data extraction was conducted independently by two reviewers using a standardized form developed in Microsoft Excel and pilot-tested on 5 studies before formal implementation. Two reviewers independently extracted data across seven core domains: study characteristics (author, year, country, design), participant demographics (age, sample size, clinical status), intervention details (AI system type, platform, duration, frequency), comparison conditions, executive function domains assessed (inhibitory control, cognitive flexibility, working memory, planning), assessment instruments, and outcome metrics (effect sizes, statistical significance, ML accuracy rates).

Quality Assessment and Risk of Bias

Methodological quality was systematically appraised using validated tools tailored to study design. For randomized controlled trials (n = 5), the Cochrane Risk of Bias Tool Version 2 assessed five domains: randomization process, deviations from intended interventions, missing outcome data, outcome measurement, and selection of reported results. Each domain was rated as low risk, some concerns, or high risk. For quasi-experimental studies (n = 4), the ROBINS-I tool evaluated seven domains including confounding, participant selection, and intervention classification, with ratings ranging from low to critical risk of bias. For prediction and classification studies (n = 6), a custom framework assessed sample representativeness, feature validity, model validation procedures, and reporting transparency. Two independent reviewers conducted all assessments with Cohen's kappa = 0.82, indicating strong agreement. Quality ratings were used to inform interpretation of findings, with greater weight assigned to higher-quality studies when drawing conclusions.

Data Synthesis and Analysis

Data synthesis employed a narrative approach due to substantial heterogeneity in AI intervention types (adaptive tutoring, VR training, computerized cognitive training, computational thinking, ML assessment), population characteristics (age ranges 6-77 years, diverse clinical and non-clinical samples), executive function assessment methods, and study designs (RCTs, quasi-experiments, prediction studies). Given this heterogeneity, quantitative meta-analysis was not conducted. The synthesis was organized systematically by executive function domain: inhibitory control, cognitive flexibility, working memory, and planning. Within each domain, results were stratified by study type, distinguishing between intervention studies that examined training effects and prediction studies that used machine learning for assessment or diagnosis.

Results

Study Selection and Characteristics

The systematic search and screening process identified 14 studies that met all inclusion criteria for this review. **Table 1** presents the descriptive characteristics of included studies, encompassing publication years from 2020 to 2024, with participants ranging from 6 to 77 years of age across diverse geographical contexts including Spain, France, Germany, South Korea, Thailand, Colombia, China, Taiwan, Argentina, and the United States. The sample comprised 1,810 total participants across all studies, with individual study samples ranging from 12 to 509 participants. The review incorporated multiple population types: typically developing children and adolescents in educational settings, healthy younger and older adults, and clinical populations including individuals with ADHD, Down Syndrome, Mild Cognitive Impairment, Alzheimer's Disease, psychotic disorders, and PTSD. Study designs included randomized controlled trials, quasi-experimental designs, comparative field experiments, cross-sectional studies, and prediction studies employing machine learning methodologies.

Table 1. Descriptive characteristics of included studies: age ranges, geographical contexts, sample sizes, educational levels or clinical status, and study designs.

Study (Year)	Age Range / Mean Age	Geographical Context	Sample Size (N)	Educational Level / Clinical Status	Study Design / Methodology
Chevalère et al. (2021)	Mean 12.82 years (SD = 0.44)	France	509 middle-school students	Typically developing middle-school students. Focus on academic performance (Science and Technology).	Comparative Field Experiment (CAI vs. IBL); Multi-level Random Intercept Models.
Escolano-Perez & Losada (2024)	12–17 years old (Mean 13.81 years, SD = 1.4)	Spain	173 secondary school students	Compulsory secondary education students. Profiled based on cognitive and emotional EFs deficits.	Cross-sectional study; Machine Learning (Decision Tree/CART regression) for profile identification.
Jeun et al. (2022)	Adults over 20 years old (all subjects in their twenties)	South Korea	13 training group (45 for algorithm development)	Healthy younger adults/college students.	Personalized Cognitive Training Intervention using VR/fNIRS; Machine Learning (Logistic Regression) for difficulty classification
Jojoa-Acosta et al. (2021)	19–62 years old (Mean 33.63 years)	Spain	188 adults with Down Syndrome	Adults with Down Syndrome (DS) exhibiting mild or moderate Intellectual Disability (ID)	Prediction Study using Machine Learning (Random Forest, Logistic Regression, SVM) to predict inhibitory capacity
Kim et al. (2024)	Mean ages range from 20.9 to 26.2 years across groups	Korea	408 total (FEP, CHR, OCD, HC groups)	Patients with First-Episode Psychosis (FEP), Clinical High Risk (CHR) for psychosis, Obsessive-Compulsive Disorder (OCD), and Healthy Controls (HC).	Deep Learning Classification (LSTM + Attention) of impaired executive function based on eye movement data (RCFT)
Krupitzer et al. (2022)	Mean 19.34 years (SD=2.99 years)	Germany	37 for user study (110 for RL simulation)	Users (implied athletes/young adults) participating in VR executive function training.	Exploratory system evaluation; Intervention/ Training using Immersive VR; Reinforcement Learning (Q-learning) for adaptive difficulty.
Makmee & Wonguppparaj (2022)	Mean 65.87 years (SD = 4.18), range 60–77 years	Thailand	60 community-dwelling older adults	Community-dwelling older adults with normal cognitive function (assessed via MMSE-Thai).	Randomized Controlled Trial (RCT) (Pretest-Posttest Control Group); VR-based Cognitive Intervention.
Medina et al. (2021)	Mean ages 9.2 to 9.71 years	Spain	29 children with ADHD-C (15 Exp, 14 Control)	Children diagnosed with Attention Deficit Hyperactivity Disorder (ADHD-C). Intervention involved an AI-driven digital therapeutic.	Single-blind Randomized Controlled Trial (RCT) (Proof-of-concept); AI-driven digital intervention (Case-Based Reasoning/CBR).

Study (Year)	Age Range / Mean Age	Geographical Context	Sample Size (N)	Educational Level / Clinical Status	Study Design / Methodology
Menu et al. (2022)	Children (9–10 years); Adolescents (15–17 years)	France	137 healthy children (77) and adolescents (60)	Healthy, typically developing participants from public schools	Randomized Controlled Trial (RCT) (Longitudinal Design); Cognitive Training (Inhibitory Control vs. Active Control)
Robledo-Castro et al. (2023)	Ages 10 and 11 years (Fifth-grade children)	Colombia	30 children (17 Exp, 13 Control)	Primary school students receiving a Computational Thinking (CT) intervention	Exploratory Pilot Randomized Experimental Design (Double-blind analysis); Computational Thinking (CT) intervention
Schultebraucks et al. (2020)	Mean 37.86 years (SD = 13.99)	USA	81 trauma survivors	Trauma survivors, including those screened positive for provisional PTSD (31.6%) and depression (41.8%) diagnoses	Prediction Study using Machine Learning (XGBoost) applied to passive visual and auditory digital biomarkers.
Tsai et al. (2021)	Age not explicitly detailed	Taiwan	12 total (6 MCI/ early AD, 6 Healthy Controls)	Small groups of individuals with Mild Cognitive Impairment (MCI) or early Alzheimer's Disease (AD) and healthy controls	Classification Study using VR (supermarket task); various Machine Learning methods (LR, SVM, DT, RF, XGBoost)
Vladisauskas et al. (2022)	6-to-7 years old	Argentina	73 typically developing children (6-to-7 y.o.)	Typically developing children participating in a cognitive training intervention.	Proof-of-concept study; Supervised Machine Learning (SVC classifier) predicting individual cognitive training effectiveness
Wu et al. (2023)	Mean ages 65.52 to 67.68 years	China	50 participants (25 CCT, 25 Control)	Older adults receiving computerized cognitive training (CCT).	Randomized Controlled Trial (RCT); Multidomain Computerized Cognitive Training (CCT)

The AI-enhanced interventions and assessment tools exhibited substantial heterogeneity in their implementation approaches. **Table 2** summarizes the specific AI systems, platforms, intervention durations, and implementation contexts across all included studies. Intervention studies utilized diverse AI mechanisms including adaptive intelligent tutoring systems driven by Case-Based Reasoning algorithms, personalized cognitive training platforms leveraging machine learning and functional near-infrared spectroscopy for real-time difficulty adjustment, virtual reality environments enhanced with reinforcement learning for adaptive challenge presentation, computational thinking programs employing block coding, and multidomain computerized cognitive training systems. Intervention durations ranged from 3 to 12 weeks, with session frequencies varying from twice weekly to daily, and individual session lengths spanning 10 to 60 minutes. Several studies employed AI and machine learning exclusively for assessment and prediction purposes rather than intervention delivery, utilizing technologies such as Random Forest classifiers, Support Vector Machines, deep learning architectures with Long Short-Term Memory networks and attention mechanisms, and extreme gradient boosting algorithms applied to digital biomarkers including eye-tracking data, passive visual and auditory markers, and behavioral performance metrics.

Table 2. AI systems and intervention characteristics: specific platforms, mechanisms, intervention

durations, and implementation contexts across included studies.

Study (Year)	AI System/Mechanism	Specific Platform/Program	Intervention Duration	Implementation Context (Population & Setting)
A. Adaptive Intelligent Tutoring/Training Systems (ML/CBR-Driven)				
Medina et al. (2021)	Children (8–11 years) diagnosed with Attention Deficit Hyperactivity Disorder (ADHD) combined presentation. Delivered on a mobile device (telematically monitored) in Spain.	12 weeks, 3 sessions per week, 15–20 minutes per session.	KAD_SCL_01 digital cognitive stimulation program	Case-Based Reasoning (CBR) Algorithm
Jeun et al. (2022)	Machine Learning (ML) / Logistic Regression (for difficulty classification)	VR-based Spatial Cognitive Training. Used PFC activity (via fNIRS) to predict customized difficulty level.	3 weeks, 4 times a week (12 sessions total), 30 minutes per session	Healthy younger adults (in their twenties) recruited from a local college in Asan-si, South Korea
Menu et al. (2022)	Adaptive Cognitive Training Algorithm (Real-time adaptation)	Computerized EF training (Inhibitory Control/IC training vs. Active Control/AC training).	5 weeks, 5 days a week (25 sessions total), 15 minutes per day	Healthy children (9–10 y.o.) and adolescents (15–17 y.o.).
Vladisauskas et al. (2022)	Adaptive Computerized Games (fixed protocol, predictive ML used for analysis)	Mate Marote online cognitive training software. Focuses on working memory, planning, and inhibitory control skills.	10 weeks (weeks 2–10), sessions were 10–15 minutes, one-to-three times per week	Typically developing children (6-to-7 years old). Note: Supervised Machine Learning (Support Vector Classifier) was used ex-post as a proof-of-concept to predict who benefited from this fixed protocol.
B. Virtual Reality (VR) Enhanced Training with Adaptive Elements				
Krupitzer et al. (2022)	Reinforcement Learning (RL) / Q-learning (for difficulty adaptation)	CortexVR Immersive Virtual Reality System. Used for analysis and training of Executive Functions (EFs).	User study involved training sessions, but the main evaluation was technical analysis and user experience. Long-term study was identified as future work.	Soccer players (professional domain). Collaboration with a German Bundesliga club
Makmee & Wonguppa-raj (2023)	VR-Based Cognitive Intervention (Visuospatial WM and Visuomotor adaptation)	Proprietary VR system utilizing Oculus Quest HMD and Unity3D engine. Focuses on inhibition, updating, and shifting.	4 weeks, 8 sessions total (twice a week), 60 minutes per session	Community-dwelling older adults (60–69 years) in Thailand
C. General Digital/Computational Interventions				
Chevalère et al. (2021)	CAI (Adaptive/Intelligent Tutoring System generation)	Tactileo tool. Compared against Inquiry-Based Learning (IBL)	Varied from four to ten weeks	Middle-school students (seventh graders) in Science and Technology subjects in France.

Robledo-Castro et al. (2023)	Computational Thinking (CT) / Block Coding	"Programming for Children" educational program (MinTic, Colombia). Included plugged activities (block coding via MakeCode for micro:bit) and unplugged activities	8 weeks, 2 sessions per week (16 sessions total), approximately 2 hours per workshop	Fifth-grade children (10 and 11 years old) from a Colombian public educational institution
Wu et al. (2023)	Computerized Cognitive Training (CCT)	Multi-domain CCT program	Not explicitly stated, described as repeated measures	Older adults

Executive Function Outcomes by Domain

Table 3 presents a comprehensive synthesis of findings organized by executive function domain, including overall effects, key AI implementation mechanisms, and quantitative evidence summaries. The results demonstrate domain-specific patterns of effectiveness across the four core executive function components examined in this review.

Table 3. Executive function outcomes by domain: overall effects, AI implementation mechanisms, and quantitative/qualitative evidence summaries with effect sizes and statistical significance.

Executive Function Domain	Overall Effect and Consistency	Key AI/Digital Implementation and Mechanism	Quantitative / Qualitative Evidence Summary (APA-7 Citations)
Inhibitory Control	Consistent Positive Gains. Digital training effectively improves IC performance across pediatric (ADHD), adolescent, and aging populations.	Adaptive Training (CBR/VR): Algorithms (CBR) dynamically increase cognitive load to foster neural network reconfiguration. Digital Assessment (ML): Used for classification/prediction.	Significant improvement in IC: AI-driven treatment for ADHD showed significant improvement in CPT-III commission score ($g=-0.62$) (Medina et al., 2021). VR intervention in older adults enhanced inhibitory ability (Go/NoGo RT) with a moderate effect size ($\eta 2p = .11$) (Makmee & Wongupparaj, 2023). Computational Thinking (CT) training improved cognitive inhibition (Stroop test execution time/correct answers) in children, yielding large effect sizes (rb >.50 in absolute value) (Robledo-Castro et al., 2023). Prediction: Machine Learning models predicted inhibitory capacity in adults with Down Syndrome with 86.8% accuracy (Jojoa-Acosta et al., 2021).
Cognitive Flexibility	Positive Effects observed, both directly on shifting tasks and as near transfer from inhibition training.	VR Intervention: Supports multi-component training and performance. Adaptive Training: Ensures continued challenge requiring flexible strategy switching.	Significant Improvement in Shifting: VR intervention in older adults enhanced shifting ability (BCST Percentage of Correct Responses) with a moderate effect size ($\eta p2 = .09$) (Makmee & Wongupparaj, 2023). The AI-driven digital intervention for ADHD resulted in significant improvement in the parent-reported BRIEF Shifting score ($P = .03$) (Medina et al., 2021). Computerized Inhibitory CSignificant Improvement in Shifting: VR intervention in older adults enhanced shifting ability (BCST Percentage of Correct Responses) with a moderate effect size ($\eta p2 = .09$) (Makmee & Wongupparaj, 2023). The AI-driven digital intervention for ADHD resulted in significant improvement in the parent-reported BRIEF Shifting score ($P=.03$) (Medina et al., 2021). Computerized Inhibitory Control training showed "tendential" improvement in switching (TMT) in children, suggesting positive transfer (Menu et al., 2022). ML Analysis: Flexibility deficits were not included as a primary predictor of poor academic outcomes in Language/Literature (Escolano-Perez & Losada, 2024).
Working Memory	Significant Gains, but effectiveness is strongly moderated by individual baseline WM capacity (risk of cognitive overload).	Neural Efficiency Adaptation (ML/fNIRS): Adaptation based on physiological signals (PFC activity) optimizes load. Cognitive Load Management: The nature of digital environments (CAI) imposes high WM demands.	Significant Improvement in Updating: VR intervention for older adults significantly enhanced updating (FDS Memory span) with a large effect size ($\eta p2 = .18$) (Makmee & Wongupparaj, 2023). AI-driven treatment for ADHD significantly improved Visuospatial Working Memory (VSWM) (Corsi backward span score, $P=.03$) (Medina et al., 2021). Personalized VR training based on ML prediction of PFC activity improved EF performance and led to a significant decrease in PFC activity (neural efficiency) (Jeun et al., 2022). Critical Limitation: CAI provided no academic benefit for students with below-average WM capacity due to cognitive overload risk (Chevalère et al., 2021).

Planning	Positive on Sequential Planning, but transfer to visuospatial planning is inconsistent. AI utilized effectively for diagnosis and strategy assessment.	Computational Thinking (CT): Enforces sequential/algorithmic planning. Deep Learning Assessment: Analyzes spatial organizational strategy via gaze fixation sequences.	Gains in Sequential Planning: CT training in children significantly improved performance on the Tower of Hanoi (movements and time), demonstrating large effect sizes (rb >.50 in absolute value) (Robledo-Castro et al., 2023). The AI-driven intervention for ADHD resulted in significant improvements in the parent-reported BRIEF Planning score (Medina et al., 2021). Assessment: Deep Learning (LSTM + Attention) models successfully discriminated between impaired and normal executive function based on significantly lower Planning scores and Organization T scores (e.g., Planning score 1.1±1.5 vs 3.4±0.8) derived from RCFT eye-tracking (Kim et al., 2024,). Inconsistent Transfer: CT training produced no significant effects on visuospatial planning (labyrinth test errors) (Robledo-Castro et al., 2023).

Inhibitory control demonstrated the most consistent positive gains across diverse populations and AI-enhanced intervention modalities. The AI-driven digital therapeutic employing Case-Based Reasoning algorithms for children with ADHD showed significant improvement in objective inhibitory control as measured by the Conners' Continuous Performance Test commission score, yielding a medium-to-large effect size of -0.62 (Medina et al., 2021). Virtual reality-based cognitive intervention in community-dwelling older adults enhanced inhibitory ability on the Go/NoGo reaction time task with a moderate effect size of 0.11 (Makmee & Wongupparaj, 2023), while computational thinking training in fifth-grade children produced large effect sizes exceeding 0.50 in absolute value for cognitive inhibition as assessed by Stroop test execution time and correct responses (Robledo-Castro et al., 2023). Machine learning applications for assessment demonstrated high classification accuracy, with predictive models combining Random Forest, Logistic Regression, and Support Vector Machine algorithms successfully predicting inhibitory capacity in adults with Down Syndrome with 86.8% accuracy (Jojoa-Acosta et al., 2021).

Cognitive flexibility and working memory showed positive effects, though with important qualifications. Virtual reality intervention in older adults significantly enhanced shifting ability as measured by the Berg Card Sorting Test with a moderate effect size of 0.09 (Makmee & Wongupparaj, 2023), while the AI-driven digital intervention for children with ADHD resulted in significant improvement in parent-reported shifting ability ($p = 0.03$) (Medina et al., 2021). Working memory interventions yielded significant gains, including large effect sizes of 0.18 for updating ability in older adults (Makmee & Wongupparaj, 2023) and statistically significant improvements in visuospatial working memory for children with ADHD ($p = 0.03$) (Medina et al., 2021). However, a critical limitation emerged: computer-assisted instruction in middle-school students provided no academic benefit for learners with below-average working memory capacity due to cognitive overload risk (Chevalère et al., 2021), underscoring the importance of cognitive load management in AI-enhanced learning environments.

Planning abilities demonstrated positive gains following computational thinking interventions targeting sequential and algorithmic planning skills, though transfer effects to visuospatial planning tasks were inconsistent. Computational thinking training in fifth-grade children significantly improved performance on the Tower of Hanoi sequential planning task, with reductions in both movements required and completion time yielding large effect sizes exceeding 0.50 in absolute value (Robledo-Castro et al., 2023). Deep learning models combining Long Short-Term Memory networks with attention mechanisms successfully discriminated between impaired and normal executive function based on planning and organization scores derived from eye-tracking data during the Rey-Osterrieth Complex Figure Test (Kim et al., 2024). However, transfer of sequential planning gains to visuospatial planning tasks was inconsistent, with computational thinking training producing no significant effects on labyrinth test errors (Robledo-Castro et al., 2023), suggesting domain-specific learning effects that do not readily generalize across planning task modalities.

Discussion

This systematic review synthesized evidence from 14 studies examining AI-enhanced learning interventions and executive function outcomes across 1,810 participants spanning childhood through older adulthood. The findings demonstrate that AI-powered educational technologies consistently improved inhibitory control across diverse populations, with effect sizes ranging from moderate to large (Medina et al., 2021; Makmee &

Wongupparaj, 2023; Robledo-Castro et al., 2023). Cognitive flexibility showed positive gains both directly and through transfer effects from inhibitory control training (Medina et al., 2021; Menu et al., 2022). Working memory interventions produced significant improvements, particularly when adaptive algorithms optimized cognitive load based on individual capacity constraints (Jeun et al., 2022; Makmee & Wongupparaj, 2023). Planning abilities improved following computational thinking interventions, though transfer to visuospatial tasks remained inconsistent (Robledo-Castro et al., 2023). Machine learning assessment approaches achieved high diagnostic accuracy, with models successfully classifying executive function impairments based on digital biomarkers (Jojoa-Acosta et al., 2021; Kim et al., 2024; Schultebraucks et al., 2020). These convergent findings establish AI-enhanced learning as a promising avenue for executive function development across the lifespan.

The theoretical mechanisms underlying observed improvements integrate cognitive and neurobiological principles. Adaptive algorithms dynamically adjusted task difficulty based on real-time performance metrics, maintaining optimal challenge within each learner's zone of proximal development while preventing cognitive overload (Medina et al., 2021; Menu et al., 2022). Case-Based Reasoning systems and reinforcement learning architectures personalized instruction by continuously assessing cognitive states and modifying scaffolding accordingly (Krupitzer et al., 2022; Medina et al., 2021). Neuroplasticity-driven changes were evidenced by decreased prefrontal cortex activation following personalized training, indicating enhanced neural efficiency (Jeun et al., 2022). The multisensory nature of virtual reality interventions engaged multiple neural pathways simultaneously, potentially accelerating executive function development through enriched sensory-motor integration (Makmee & Wongupparaj, 2023). Computational thinking interventions strengthened planning through algorithmic decomposition and sequential reasoning practice (Robledo-Castro et al., 2023). These converging mechanisms suggest that AI's capacity for continuous assessment, personalized adaptation, and theoretically grounded intervention delivery drives executive function enhancement through optimized cognitive load management and targeted neural engagement.

AI-enhanced learning interventions offer distinct advantages over traditional instructional approaches for executive function development. Unlike conventional classroom instruction that proceeds at a fixed pace for all learners, adaptive AI systems provide individualized difficulty adjustment and immediate feedback tailored to each student's cognitive profile, potentially addressing the heterogeneity in executive function capacity that traditional methods struggle to accommodate. The comparative field experiment demonstrated that computer-assisted instruction outperformed inquiry-based learning among students with adequate working memory, though traditional approaches proved superior among learners with below-average working memory capacity (Chevalère et al., 2021). Virtual reality and game-based AI interventions provide engaging, ecologically valid contexts that may enhance motivation and transfer compared to traditional paper-and-pencil exercises (Krupitzer et al., 2022; Makmee & Wongupparaj, 2023). However, AI systems lack the social-emotional scaffolding, contextual sensitivity, and flexible responsiveness that skilled human instructors provide. Optimal outcomes likely emerge from hybrid models combining AI's adaptive precision with human guidance, relationship-building, and nuanced pedagogical judgment.

These findings carry significant implications for educational practice, clinical intervention, and technology design. Educational institutions should consider integrating adaptive AI tutoring systems to support executive function development alongside academic content mastery, particularly for learners with attentional or working memory difficulties. Clinicians may leverage AI-driven digital therapeutics as scalable, accessible interventions for executive dysfunction in ADHD and other neurodevelopmental conditions, potentially addressing treatment access barriers. Technology developers should prioritize adaptive algorithms that account for individual working memory constraints and incorporate physiological feedback mechanisms to optimize cognitive load dynamically. Policymakers should support evidence-based implementation of AI learning technologies while ensuring equitable access across socioeconomic contexts. Assessment practices could benefit from machine learning-powered diagnostic tools that utilize digital biomarkers, enabling earlier identification of executive function impairments. Importantly, AI interventions should complement rather than replace human instruction, leveraging technology's adaptive capabilities while preserving essential social-emotional dimensions of learning.

Several limitations warrant consideration when interpreting these findings. The substantial heterogeneity in intervention types, population characteristics, assessment instruments, and study designs precluded quantitative meta-analysis, limiting the precision of effect size estimates across studies. Sample sizes ranged widely, with some studies employing small samples that may limit generalizability. The temporal scope focused on recent literature, potentially excluding earlier foundational work on computerized cognitive training. Most interventions were relatively brief, ranging from three to twelve weeks, leaving long-term retention and transfer effects uncertain. Publication bias may inflate reported effect sizes if null findings remain unpublished. The review excluded non-English publications, potentially missing relevant international research. Individual difference factors such as motivation, prior technology experience, and socioeconomic status were inconsistently reported, limiting understanding of moderating variables. Finally, mechanistic neurobiological evidence remained limited, with few studies incorporating neuroimaging to validate proposed neural pathways.

Future investigations should address critical knowledge gaps through methodologically rigorous designs. Longitudinal randomized controlled trials with extended follow-up periods are needed to establish durability of executive function gains and far-transfer effects to real-world outcomes including academic achievement and occupational functioning. Research should systematically examine individual difference moderators, particularly baseline executive function capacity, working memory constraints, and sociodemographic factors that influence intervention responsiveness. Neuroimaging studies combining functional and structural measures would elucidate neural mechanisms underlying AI-driven executive function enhancement and identify biomarkers predicting treatment response. Comparative effectiveness research should directly contrast different AI implementation approaches to determine optimal intervention components. Studies should investigate optimal dosing parameters including session frequency, duration, and intensity. Research examining implementation science factors such as scalability, cost-effectiveness, and real-world feasibility would inform widespread adoption. Finally, investigations should explore potential risks including technology dependence and diminished intrinsic motivation.

Conclusion

This systematic review provides evidence that AI-enhanced learning interventions effectively improve executive functions across diverse populations and developmental stages. The convergence of adaptive algorithms, personalized learning pathways, and neuroscience-informed design principles positions AI as a powerful tool for cognitive enhancement. Inhibitory control, cognitive flexibility, working memory, and planning all demonstrated significant gains following AI-driven interventions, with machine learning assessment approaches offering promising diagnostic capabilities. However, effectiveness depends critically on thoughtful implementation that accounts for individual cognitive constraints, particularly working memory capacity. As AI technologies continue to advance, their integration into educational and clinical practice must be guided by empirical evidence, theoretical grounding, and ethical considerations of equity and access. Future research addressing current limitations will further refine our understanding of how AI can optimally support executive function development and, ultimately, human cognitive potential across the lifespan.

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