WORKING DRAFT

AI-Enabled Metacognitive Scaffolding for Neurodivergent Learners in Higher Education: A Design-Based Research Plan

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EDIT 803: Introduction to Design-Based Research

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April 23, 2026

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Statement of the Problem

In higher education online learning environments, neurodivergent adult students with ADHD and autistic traits often experience ongoing difficulties with planning, following through, and adapting reflectively. These issues are not mainly due to a lack of content knowledge or motivation. Instead, they stem from the interaction between executive functioning (EF) impairments common to both conditions and the design of university systems that are built around neurotypical regulatory assumptions. Learning management systems like Canvas and Blackboard offer deadlines without supporting planning, break information into fragments without prioritization, and add unnecessary cognitive load for learners whose working memory is already under strain. This creates a structural mismatch between the demands of these platforms and the capacity of neurodivergent students to meet those demands reliably.

The evidence is clear and consistent. Dijkhuis et al. (2020) observed that self-reported EF challenges in planning and organizing predicted academic success in autistic university students, with a correlation of $r = -.57$ ($p < .001$), and that daily EF accounted for three times as much variance in academic results as autism severity alone. Rather than being solely issues within the learner, Butcher and Lane (2025) used ecological systems theory to show that barriers such as poor time management, multi-course coordination issues, and emotional dysregulation are structurally worsened by university systems. In 72% of universities, autistic students have below-average graduation rates, while students with ADHD score a full grade point lower than neurotypical peers and face higher academic probation risks (Butcher & Lane, 2025). These gaps can’t be explained just by differences in ability or motivation. Instead, they reflect planning and regulation deficits in environments that don’t support these students.

Existing interventions have not yet bridged this gap. Review-level evidence from Liao and Lee (2025) and Ronksley-Pavia et al. (2025) revealed that, despite the rapid rise of AI tools

in neurodivergent education, there is a lack of theoretically grounded, iteratively tested LMS-embedded interventions necessary for inclusive higher education. The prevalent approach (including reminder systems, generic planners, and standalone AI assistants) primarily supports isolated tasks, such as entering deadlines, and offers little support for the performance monitoring and self-reflection stages of self-regulated learning (SRL), which are most affected by EF dysregulation (Xu et al., 2025). Le Cunff et al.'s (2024a) qualitative focus group study with neurodivergent university students confirmed this structurally. Here, neurodivergent participants noted that issues such as poor content presentation, inaccessible transcripts, and unclear curricula deplete their working memory resources. Unlike neurotypical peers, who can focus on learning the material, these challenges create a cognitive bottleneck rooted in the environment rather than the individual.

This study rejects the notion that neurodivergent adult learners in digitally facilitated higher education must manage complex, overlapping academic demands through sustained SRL and EF-dependent planning without contextually aligned, proactive support. The intervention under development is an AI-enabled, LMS-embedded academic planning scaffold designed to (a) reduce extraneous cognitive load, (b) support all three phases of SRL, (c) preserve learner agency, and (d) function as a default environmental feature rather than a disclosed accommodation. This DBR plan describes how that intervention will be built, tested, and iteratively refined to generate both a working artifact and the transferable design principles the field has identified as the primary missing contribution (Liao & Lee, 2025; Ronksley-Pavia et al., 2025).

Literature Review

Executive Functioning Profiles in Neurodivergent University Students

Executive functions (EF) are advanced neurocognitive processes that regulate attention, emotion, and action toward goals. Most models include working memory, response inhibition, planning, cognitive flexibility, and sustained attention (Townes et al., 2023). In university

settings, students with ADHD and autism often face EF impairments that increase their academic challenges, as they are expected to independently manage multiple deadlines, self-study, and ongoing self-assessment as effectively as their neurotypical peers.

The link between executive function (EF) and academic success in autistic college students is well-defined. Dijkhuis et al. (2020), examining 54 autistic young adults in Dutch higher education, found that self-reported problems with planning and organization were significantly associated with academic performance ($r = -.57$, $p < .001$). Including daily EF assessments in a regression model along with autism symptom severity increased the explained variance in academic progress from 12% to 36%. After accounting for EF, symptom severity no longer significantly predicted academic outcomes. This suggests that EF plays a central mechanistic role in educational risk rather than autism diagnosis alone.

For ADHD, the EF–academic achievement pathway is equally well documented but expressed through distinct functional signatures. Southon (2022) analyzed 158 university students, including 21 with neurodevelopmental diagnoses, and found that ADHD traits significantly influenced the EF–achievement link, while ASD traits alone did not. Students exhibiting low EF and high ADHD traits experienced the most academic challenges. This aligns with known deficits in working memory and inhibitory control associated with ADHD. Crucially, since neurodevelopmental traits are not inherently harmful academically, their impact depends on the interaction with EF capacity. Therefore, intervention systems should be adaptable to individual EF profiles instead of relying solely on diagnostic categories.

Butcher and Lane (2025) corroborated this from a lived-experience perspective. Analyzed through ecological systems theory, their interviews with neurodivergent university students identified time management, organization, daily routine, and attentional regulation as the specific functional domains that made university life most challenging. As a result, the challenge was found to be the surrounding demands of navigating their coursework across the

intersecting microsystems of course structures, support services, and institutional expectations, rather than the content of the coursework.

The Case for a Transdiagnostic Design Approach

A key question for intervention design is whether ADHD and autism have distinct EF profiles that justify separate tools. The strongest evidence suggests against strict diagnostic separation. Townes et al. (2023), reviewing 58 direct comparison studies with 8,259 participants, found no significant differences between ASD and ADHD in core cognitive areas relevant for education: attention, cognitive flexibility, working memory, processing speed, and response inhibition. Additionally, comorbidity rates between ASD and ADHD range from 40% to 70%, which further questions the usefulness of strict diagnostic boundaries.

This does not mean that behavioral specificity is unimportant. Cromjongh et al. (2024) surveyed 64 university students and interviewed 6 autistic students. Their results suggested that autistic learners especially struggle with understanding overall tasks and estimating how long they will take. Additionally, when disruptions occurred, they found it to be particularly difficult to stay engaged with a plan through to completion. Twenty-eight percent of autistic students said they do not handle plan interruptions well, while none of the neurotypical students said the same. This finding points to evidence that autistic students have developed highly individualized planning strategies, such as intentionally using environmental cues and reducing barriers, that standard LMS designs do not accommodate. Southon's (2022) data offered additional insight: many autistic students with strong working memory and inhibitory control perform well academically. However, those with more significant EF difficulties are at higher risk, suggesting that AI should be tailored to individual EF profiles rather than relying solely on categorical ADHD or ASD labels.

This evidence collectively supports a transdiagnostic design that targets the shared EF demands across both profiles while adding behavioral specificity through personalized AI adaptation, rather than using separate tools for each diagnosis.

Theoretical Frameworks

Self-Regulated Learning

Self-regulated learning (SRL) theory, as outlined by Zimmerman (2002) and Pintrich (2004), conceptualizes effective learning as a recurring cycle with three stages: forethought (setting goals, analyzing tasks, planning strategies), performance (applying strategies and self-monitoring), and self-reflection (evaluating oneself and adapting). For students with intact executive functions (EF), these stages occur smoothly with little conscious effort. However, for those with EF dysregulation, the cycle often breaks down during the forethought stage because the cognitive processes necessary for planning and working memory are impaired, preventing initiation. SRL theory clarifies what this dysregulation looks like by explaining that the student's capacity to learn remains, but the regulatory system that triggers and sustains learning does not reliably activate.

The implications for AI-mediated environments are complex yet impactful. Xu et al. (2025), in a four-week quasi-experiment with 68 college students, found that providing explicit metacognitive support aligned with SRL phases led to significant improvements in task strategy and self-evaluation compared with unscaffolded AI use. Importantly, students who used AI without metacognitive scaffolding risked a decline in SRL from their baseline levels. Lan and Zhou (2025), in a review of 14 AI-SRL studies, highlighted the importance of agency structure. They indicate that in AI-focused systems, where AI makes regulatory decisions for students, the outcomes differ from human-centered systems, where students retain regulatory control with AI support. The benefits of SRL with AI depend less on the technology itself and more on whether the design frames AI as a tool to support students' regulatory processes or as a replacement for them.

Cognitive Load Theory

Cognitive Load Theory (CLT; Sweller, 1988) explains why conventional LMS architectures often fail neurodivergent students. CLT distinguishes three types of cognitive load:

intrinsic load (difficulty of the material), extraneous load (how the material is presented, such as navigation challenges, fragmented information, and irrelevant elements), and germane load (productive effort in building cognitive schemas). For neurodivergent learners, cognitive load is experienced in two ways. First, their working memory acts as a chokepoint since all three load types compete for its limited capacity. Second, high extraneous load consumes their cognitive resources that should be dedicated to learning.

Gunawardana et al. (2025) provided direct evidence of this division in a three-condition LMS comparison involving 22 adult students with ADHD. AI-generated interfaces scored higher on usability but lower on educational effectiveness than human-designed ones. This finding analytically separates interface optimization from learning effectiveness by showing that reducing extraneous load through AI-generated design is achievable, whereas educational effectiveness requires deliberate pedagogical design. The design challenge isn't about removing all friction, but about strategically reducing it to lessen unnecessary load on working memory while preserving the beneficial cognitive effort that fosters self-regulatory skills.

Providing insights into lived experiences that cannot be captured by Gunawardana et al.'s quantitative comparison, Le Cunff et al. (2024a) conducted focus group research with 12 neurodivergent and 14 neurotypical university students. In their study, neurodivergent participants saw extraneous load not as a difficulty but as a fundamental difference. They explained that neurotypical students primarily see content comprehension as their main challenge. In contrast, neurodivergent students consistently report difficulties such as navigation, inaccessible captions, unclear curricula, and rapid content delivery, which strain their working memory before they can even engage with the material. This qualitative reversal, in which the format of the learning environment becomes the primary cognitive obstacle rather than the content, explains why traditional LMS architectures tend to worsen rather than support neurodivergent working memory profiles.

A PRISMA-compliant review of 90 studies on cognitive load from 21 countries offered a structural reason for the slow integration of these findings into instructional design literature. Le Cunff et al. (2024b) found that 92% of CLT studies in online education did not consider neurodiversity and mostly assumed participants were neurotypical. The few studies including neurodivergent learners showed effects that contradict standard CLT guidance: subtitles, usually recommended for removal under the coherence principle because redundant info can add extraneous load for neurotypical students, actually lowered cognitive load for students with ADHD but increased it for neurotypical students. This problem suggests that current CLT-based instructional recommendations might be systematically misaligned with the targeted population.

Universal Design for Learning

Universal Design for Learning (UDL; CAST, 2018) redefined the design approach by making accessibility an integral environmental feature rather than an after-the-fact accommodation for students with disabilities. It emphasized proactive support for the broadest range of learners by grounding design in its three core principles: multiple means of engagement, representation, and action and expression. In doing so, UDL established requirements for adaptable methods of accessing information, demonstrating understanding, and sustaining motivation. For neurodivergent students, UDL's key implication is that support should be embedded as a default feature within the environment, with intelligent, ongoing adaptations to individual needs, without requiring students to disclose their profiles.

Dumitru et al. (2026) reviewed 27 papers on AI-powered assistive technologies for students with disabilities in higher education and found that cognitive and neurodevelopmental disabilities remain among the most underserved populations, as most tools are designed for sensory or physical accessibility rather than cognitive accessibility. They also identified a systemic ethical concern, namely a misalignment between the training data and the intended population. Because AI systems trained on neurotypical behavioral data may not effectively

adapt to neurodivergent interaction patterns, they may produce scaffolding that is systematically miscalibrated for the population they are intended to serve.

The SRL–CLT–UDL Framework Trifecta

These three frameworks collectively define the criteria for a valid intervention: (a) lessen unnecessary cognitive load on working memory while preserving the essential regulatory challenge that fosters self-regulatory skills; (b) support SRL stages affected by EF dysregulation without replacing student agency with AI-driven decisions; and (c) integrate support seamlessly as a default environmental feature rather than a personal accommodation. So far, no current intervention meets all three criteria simultaneously within the daily LMS setting for neurodivergent adult learners.

The Current AI Intervention Landscape

An increasing body of empirical and design research explores how generative AI and adaptive technologies address planning, organizational, and self-regulatory challenges faced by neurodivergent students in higher education. This literature falls into four categories, each with its own methodological characteristics and limitations.

In the first category, self-directed use of standalone generative AI tools, Mittler's (2025) qualitative longitudinal case study of a neurodivergent student across five semesters provides the most detailed evidence. The key finding was not which tools the student used but how they used them. Through their journal entries, participants revealed a shift from passive acceptance of AI outputs to systematic critical evaluation and strategic prompting. The student's metacognitive relationship with the tool, rather than the tool's features, determined whether the outcomes supported self-regulation or cognitive reliance. This, the most theoretically significant finding, has yet to be formalized as a design principle in the wider literature.

In the second category, AI-enhanced LMS platforms, Gunawardana et al. (2025) showed that usability and educational effectiveness are distinct design goals, with direct implications for the study's design logic. Gadzhimusieva et al. (2026) created SpectrumSphere, an AI-driven

LMS with VR, AR, and augmentative communication for autistic learners, evaluated using the Technology Acceptance Model with 30 special education teachers. The study focused on teachers' willingness to adopt rather than student outcomes and found that results in a K–12 setting do not necessarily apply to adult higher education. Their findings reflect a broader trend in this category, where technological sophistication often exceeds the specific needs of the population.

The third category, co-designed planning and task management applications, involves the most participatory approach. Zhu et al. (2026), using co-design workshops with 20 ADHD university students and interviews with five ADHD specialists, identified four key metacognitive challenges: lack of awareness of task sources and time demands; barriers to starting tasks, such as perfectionism and motivation issues; difficulties maintaining attention during interruptions; and emotional dysregulation that worsens procrastination into avoidance. Specialists consistently flagged cognitive outsourcing, the fully automated task breakdowns that eliminate the metacognitive effort that effective ADHD interventions aim to promote, as the primary long-term risk. This expert-student dynamic echoes the AI-versus-human-agency debate discussed in Lan and Zhou (2025). Cromjongh (2023) described a participatory design process at Utrecht University for an adaptive, context-aware planning system for autistic students that incorporated features such as time and task management, stress monitoring, and sensory stimulation. Parmar et al. (2026) used a Design-Based Research (DBR) approach to assess an app combining augmented reality and generative AI for 15 undergraduates with ADHD. Consistent with an early-stage prototype, they observed signs of improved task initiation and lower cognitive load, though no statistically significant quantitative results were observed.

The fourth category, AI-generated SRL scaffolding systems, is represented by Qian et al. (2025), who examined the technical reliability of SRL scaffolds generated by large language models using a multi-agent evaluation framework. They found that miscalibrated scaffolding, including prompts that target the wrong regulatory process or activate at the wrong moment, is a

systemic risk that is especially harmful for neurodivergent learners with atypical regulatory profiles. An AI scaffold tuned to neurotypical regulatory patterns will systematically misalign with ADHD and autistic interaction patterns, thereby increasing cognitive load rather than reducing it.

The Design Gap

Across all four categories, the pattern remains consistent and can be summarized in four ways. First, the most theoretically coherent and educationally meaningful results preserve student agency in the regulatory process (Mittler, 2025; Zhu et al., 2026). Second, embed metacognitive scaffolding in the environment rather than automating regulatory decisions (Xu et al., 2025; Lan & Zhou, 2025). Third, combine AI interface efficiency with human-led pedagogical design (Gunawardana et al., 2025). Finally, address authentic planning demands of real academic life rather than isolated task performance (Cromjongh, 2023; Cromjongh et al., 2024). None of these approaches has integrated these principles into an LMS used daily by neurodivergent adults in higher education, across a full academic semester, with a population spanning the ADHD–ASD diagnostic continuum, in a process that generates transferable principles rather than a single-context prototype.

The gap exists both empirically and conceptually. While there is general consensus that personalization is important and that learner agency must be preserved, the field has yet to define neurodiversity-affirming AI scaffolding as a specific design guideline. This conceptual void also undermines the theoretical basis itself. Because the CLT evidence base underpinning current instructional design recommendations was primarily derived from neurotypical populations, the principles considered universal may not be applicable to neurodivergent learners and, in some cases, could even be counterproductive (Le Cunff et al., 2024b). Researchers such as Ronksley-Pavia et al. (2025) and Liao and Lee (2025) have noted that the key missing element is transferable design principles. This study aims to develop those principles.

Implications for a Design-Based Research Approach

This gap also represents a design problem, which is why Design-Based Research (DBR) is necessary. A descriptive survey could collect preference data, but would not create an artifact, as preferences alone cannot define it. A controlled experiment would need a stable intervention that iterative design has yet to establish. Descriptive qualitative research would provide experiential insights without producing generalizable principles. Therefore, DBR is appropriate (and arguably the only appropriate methodology) when the problem is urgent, existing theory has not been operationalized in the specific context, the design space is still developing, and the goal is to develop a functional artifact along with a generalizable understanding of why it works (Bannan-Ritland, 2003; McKenney & Reeves, 2019). All four conditions are met in this case.

Theoretical Conjectures and Research Questions

The five theoretical conjectures below are derived from the SRL–CLT–UDL framework trifecta and from the design pattern analysis conducted in Phase 1 of this research program. Each conjecture follows Sandoval's (2004) conjecture mapping format, specifying the expected mechanism, the conditions required for it to operate, and the observable outcome that would constitute evidence for or against it. Research questions follow directly from the conjectures and are scoped to be answerable within a single DBR cycle.

Theoretical Conjecture 1: SRL Scaffolding

If an AI scaffold explicitly structures the forethought, performance, and self-reflection phases of SRL within a daily planning interface, then neurodivergent learners with ADHD and/or autistic traits will show greater alignment between stated intentions and enacted planning behaviors than with unscaffolded or generic AI use, because structured phase prompts externalize the regulatory initiation that EF dysregulation disrupts.

Research Question 1 (RQ1). To what extent does explicit SRL phase scaffolding embedded in an LMS-based AI-enabled planner support planning follow-through and adaptive regulation in neurodivergent adult learners?

Theoretical Conjecture 2: Cognitive Load Reduction

If the planner's interface reduces extraneous cognitive load by limiting visible daily tasks to 3–5 items, auto-populating course deadlines from the LMS or provided syllabi, and providing explicit priority-ranking support, then learners will report less planning overwhelm and demonstrate fewer task-abandonment behaviors compared to their unscaffolded baseline, because a bounded display reduces the working-memory competition that degrades engagement in both ADHD and autistic profiles.

Research Question 2 (RQ2). How does a cognitively bounded planning interface affect task initiation and completion behaviors in neurodivergent university students?

Theoretical Conjecture 3: Agency Preservation

If the AI scaffold flags, suggests, and alerts rather than deciding, sequencing, or completing planning work on the learner's behalf, self-regulatory competence will be maintained or improved throughout a full academic semester, without evidence of the cognitive outsourcing that ADHD specialists identify as the primary long-term risk of automated planning support (Zhu et al., 2026).

Research Question 3 (RQ3). What design features of an AI planning scaffold preserve neurodivergent learner agency while reducing planning burden?

Theoretical Conjecture 4: Accessibility as Environmental Default

If planning supports are embedded as default features within the LMS interface (accessible without self-disclosure, disability services registration, or separate tool configuration), then neurodivergent learners will demonstrate higher sustained tool engagement across a full academic term compared to opt-in accommodation models, because proactive accessibility removes the disclosure burden that currently mediates tool adoption.

Research Question 4 (RQ4). How does embedding planning support as a default LMS feature, rather than a disclosed accommodation, affect sustained tool engagement and academic planning outcomes for neurodivergent learners?

Theoretical Conjecture 5: Transdiagnostic Design

If a planning scaffold addresses the shared EF profile underlying ADHD and autistic traits, as characterized by Townes et al. (2023), rather than designing separate tools for each diagnosis, it will serve the combined ADHD–ASD population effectively without requiring categorical diagnostic disclosure, because the main planning issues are functionally similar even when behavioral presentations differ.

Research Question 5 (RQ5). Can a unified, transdiagnostic AI planning scaffold effectively address planning support needs across the ADHD–ASD diagnostic continuum in adult higher education learners?

Program of Study

This research program is structured according to Bannan-Ritland's (2003) Integrative Learning Design Framework (ILDF), which organizes design research into four progressively scaled phases: Informed Exploration, Enactment, Evaluation of Local Impact, and Evaluation of Broader Impact. This structure is complemented by McKenney and Reeves' (2019) generic model, which specifies that each phase must produce both artifact outputs and theoretical knowledge outputs simultaneously. The research questions and methods described below derive directly from the five theoretical conjectures in Section 3 and are designed to generate evidence to support, revise, or refute each conjecture through iterative cycles.

Phase 1: Informed Exploration

Purpose. Establish and extend the evidence base, identify design requirements, and conduct formative co-design with neurodivergent adult learners.

Research Questions. What EF demands most severely impair academic planning for neurodivergent students in higher education? What planning features do neurodivergent adult learners identify as essential versus burdensome or counterproductive? What design principles does the current literature support for AI-enabled planning tools serving this population?

Methods. Systematic literature review and evidence synthesis (evidence inventory to include primary sources, ASD design patterns, and ADHD continuity patterns derived through cross-source synthesis); co-design interviews (5–10 neurodivergent adult learners at George Mason University recruited through the Disability Services Office); expert consultation (ADHD specialist, instructional designer, LMS administrator); preliminary design pattern validation through structured review.

Artifact Output. Evidence inventory table with inference-labeled design patterns (evidence-backed, evidence-backed with design inference, or design inference).

Theoretical Output. Initial design principle set with confidence-level annotations and evidence basis; revised problem statement.

Current Status. Literature review, problem statement, and initial design pattern extraction are complete. Co-design interviews are the immediate next methodological step.

Phase 2: Enactment

Purpose. Build, test, and iteratively refine the AI planner prototype through structured mini-cycles of design and evaluation.

Research Questions. To what extent does the initial prototype instantiate the design principles derived from Phase 1 evidence? What usability barriers, unintended effects, or design conflicts emerge in early testing?

Methods. Iterative prototype development using a React-based web application with LMS integration via API; think-aloud usability sessions with 3–5 neurodivergent student co-designers; expert review panels (ADHD specialist, UDL-trained instructional designer); structured mini-cycles with conjecture logs documenting what triggered each iteration, what changed, and how the inference label of the affected design pattern was revised.

Artifact Output. Working prototype of the AI-enabled LMS-embedded planner with documented component map tracing each feature back to its design pattern and evidence basis.

Theoretical Output. Revised design pattern table with updated inference labels; conjecture log recording each mini-cycle and the theoretical claim it addressed.

Phase 3: Evaluation — Local Impact

Purpose. Conduct a semester-long pilot study to evaluate the refined planner's effect on planning follow-through, SRL alignment, and learner agency in authentic institutional use.

Research Questions. RQ1, RQ2, RQ3, and RQ4 are the primary targets of this phase. To what extent does the AI scaffold support SRL follow-through? Does it preserve learner agency? Does embedded default access increase sustained engagement? What design elements require further revision?

Methods. Semester-long pilot study (target: 10–15 neurodivergent adult learners enrolled in at least one digitally facilitated course); mixed-methods data collection including LMS usage logs, ecological momentary assessments, pre/post SRL surveys (e.g., the Motivated Strategies for Learning Questionnaire or equivalent), and end-of-semester semi-structured interviews; conjecture-mapped analysis tying each finding to a specific theoretical or design conjecture; formal conjecture revision at Phase 3 close.

Artifact Output. Revised planner incorporating changes identified through pilot analysis; conjecture revision log.

Theoretical Output. Revised design principles table with updated confidence levels based on empirical evidence; local instructional theory statement specifying conditions under which identified mechanisms operated as expected.

Phase 4: Evaluation — Broader Impact

Purpose. Examine the transferability of design principles derived from Phase 3 across varied institutional contexts and populations.

Research Questions. RQ5 and cross-institutional options of RQ1 and RQ4. Do the design principles hold under different institutional conditions (course types, LMS platforms, population variation)? What scope conditions limit or enable transfer?

Methods. Multi-site pilot expansion (two to three institutions with varied LMS platforms and neurodivergent student populations); cross-site comparative analysis; stakeholder dissemination sessions with instructional designers and disability services professionals; final design principle statement specifying conditions of transfer.

Artifact Output. Dissemination-ready planner; implementation guide for LMS integration.

Theoretical Output. Transferable design framework for neurodiversity-affirming AI planning scaffolds; conditions-of-transfer statement specifying which principles generalize and under what circumstances.

Alignment of Learning Targets, Task Analysis, Intervention Features, and Research Questions

Table 1 maps the learning targets addressed by the proposed AI planner to the executive function demands they engage, the planning behaviors they require learners to perform, the specific intervention features that scaffold those behaviors, and the research questions that govern how those features will be evaluated.

Table 1

Alignment of Learning Targets, Task Analysis, Intervention Features, and Research Questions

Learning Target	EF Demand Addressed	Task Analysis	Intervention Feature	Research Question(s)
Generate goal-aligned weekly plans	-Initiation -Goal-setting -Working memory	Identify weekly priorities and convert goals into daily task commitments	AI-guided weekly goal-entry with auto-populated LMS deadline view and priority-setting prompts	RQ1, RQ3
Monitor task progress during performance phase	-Sustained attention -Self-monitoring	Check off completed tasks; flag incomplete or blocked items in real time	Daily progress check-in with visual task-status display and optional checkpoint prompt	RQ1, RQ2
Manage cognitive load across multiple courses	-Working memory -Inhibitory control	Filter and prioritize tasks from multiple concurrent courses	Daily task cap of 3–5 items with course-color-coded priority ranking	RQ2, RQ5
Initiate task engagement without prior replanning	-Initiation -Response inhibition	Start work directly from the task view without reorganizing or re-sequencing	Low-friction "Start now?" trigger that activates without requiring prior sorting or setup	RQ2, RQ3

Learning Target	EF Demand Addressed	Task Analysis	Intervention Feature	Research Question(s)
Adapt plans in response to changing conditions	-Cognitive flexibility -Self-reflection	Reschedule or deprioritize tasks when energy, load, or circumstances shift	One-tap task deferral with optional reason-tagging for pattern analysis	RQ1, RQ3
Sustain engagement without alert habituation	-Sustained attention -Motivation regulation	Respond to AI reminders across a full academic term without progressive disengagement	Rotating reminder format with frequency decay after repeated ignore events and optional opt-out	RQ3, RQ4
Navigate task transitions with predictability	-Predictability -Transition management (ASD)	Move between planning phases and tasks with minimal unstructured transition demands	Stable daily layout with explicit visual pre-transition cues and bounded next-step guidance	RQ4, RQ5
Access planning support without self-disclosure	-Accommodation burden -Autonomous access	Use embedded planning features as part of the standard LMS interface	Default LMS-embedded planner requiring no separate opt-in, disability documentation, or disclosure	RQ4, RQ5
Reflect on weekly performance and adapt strategies	-Self-evaluation -Metacognition	Complete end-of-week reflection prompt and review outcomes to inform next-week plan	Structured end-of-week reflection with auto-generated progress summary and adjustment prompt	RQ1, RQ3

Note. EF = executive functioning. Learning targets map to the SRL–CLT–UDL framework trifecta established in Section 2 (p. 9). RQ = Research Question as numbered in Section 3 (pp. 12-14). Intervention features are design inferences unless noted otherwise in the design pattern library.

Justification and Rationale for Design-Based Research

Why Not Conventional Research Designs

The problem described in Section 1 is not adequately addressed by any single conventional research methodology. Descriptive methods can document the frequency and pattern of planning failures. They cannot produce the artifact that the evidence demands. Interpretive methods, including phenomenological and ecological systems approaches like Butcher and Lane's (2025) contribution, provide the essential emic depth and lived-experience evidence base that this design draws on. However, while interpretive work generates contextual understanding, it does not produce transferable design principles, which Liao and Lee (2025)

identify as the field's primary missing contribution. Controlled experimentation would require a stable, fully specified intervention that iterative design has not yet produced. The proposed study is not a pre-post comparison of a fixed treatment. Instead, it is the research process of discovering what that treatment should be.

Why Design-Based Research

DBR is appropriate when four conditions are held simultaneously: one, the problem is urgent and practically significant; two, relevant theory exists but has not been operationalized in the specific context; three, the design space is still developing; and four, the goal is to develop a functional artifact along with a generalizable understanding of why it works (Bannan-Ritland, 2003; McKenney & Reeves, 2019). All four conditions are met here. The SRL–CLT–UDL trifecta provides theoretical architecture. The evidence-based documents the population's needs precisely. The literature on AI intervention shows promise but is in its early stages, with limited duration and vague theoretical foundations. This makes it insufficient as a ready-to-deploy evidence base (Liao & Lee, 2025; Ronksley-Pavia et al., 2025). Therefore, the intervention must be built, and building must be governed by theory and shaped by evidence. That is the DBR commitment.

Why Iteration is Essential

Three empirically documented failure modes require iterative design rather than a single-cycle implementation. First, SRL behaviors are context-dependent (Xu et al., 2025). The fit of any planner with a specific course structure, LMS platform, or learner profile cannot be assumed in advance. What scaffolds planning in one course context may impose extraneous load in another. Iterative testing across varied contexts is the only way to identify and resolve these context–design conflicts.

Second, reminder-based supports (a core feature of AI planning tools) may habituate over time as users ignore or suppress alerts (Zhu et al., 2026). This is a dynamic that manifests only with sustained use, not in brief usability sessions or single-semester snapshots. Alert

format rotation, frequency decay after repeated ignore events, and learner control over reminder parameters are design responses to habituation that require empirical calibration across multiple cycles to find the best settings.

Third, AI scaffolding may weaken the metacognitive processes it aims to aid if it shifts the user's sense of agency to automation (Lan & Zhou, 2025; Zhu et al., 2026). The risk of cognitive outsourcing is not theoretical. It was identified empirically by ADHD specialists as the primary long-term concern with automated planning support. Guardrail mechanisms (AI that flags and suggests rather than decides), opt-in feature architecture, and over-reliance monitoring require iterative testing to determine which design configurations actually protect learner agency without undermining the support that makes the tool worthwhile.

Design Implications to Uncover

This research program is specifically designed to answer five design questions that current evidence cannot resolve. First, what is the optimal balance between AI suggestion frequency and learner control that avoids alert habituation while preventing dependency throughout a full academic semester? Second, considering Cromjongh et al.'s (2024) finding that 28% of autistic students struggle with plan interruptions, which transition cue formats most effectively minimize the planning disruptions caused by interrupted conditions for autistic learners? Third, how can accommodation-relevant features (such as energy-state tracking, sensory-load indicators, and masking flags) be incorporated into a universal default tool without requiring diagnostic labels or self-disclosure? Fourth, what level of AI-generated suggestion specificity causes the scaffold to move from supporting learner agency to replacing it, and how can that threshold be identified and highlighted in the interface? Fifth, which design principles are consistently effective across different institutional settings, and which need clear scope-condition definitions before they can be considered transferable?

These questions cannot be resolved through literature review, stakeholder interviews, or prototype usability testing alone. They require an artifact in authentic use, created

collaboratively with neurodivergent designers and participants, across a full academic term, within a methodological framework that yields transferable principles rather than a single-context prototype. Design-Based Research, structured around Bannan-Ritland's ILDF and guided by Sandoval's conjecture mapping, is the methodology that meets those requirements.

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