

Learner Agency, Motivation, and the Use of Personal Learning Data

A Rapid Literature Scan

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About Digital Promise

Digital Promise is a global nonprofit working to expand opportunity for every learner. We work with educators, researchers, technology leaders, and communities to design, investigate, and scale innovations that support learners, especially those who have been historically and systematically excluded.

Our mission is to shape the future of learning and advance equitable education systems by bringing together solutions across research, practice, and technology.

Guided by three Impact Goals, we are working to ensure the following by 2031:

1. 75% of historically and systematically excluded learners in America are learning in education systems with the knowledge and tools to create the conditions for them to succeed.
2. 30 million historically and systematically excluded learners have sustained and meaningful experiences of Powerful Learning, putting them on a path to postsecondary completion.
3. 30 million historically and systematically excluded learners are enabled to achieve postsecondary credentials that offer economic security, well-being, and agency.

The Center for Learner Pathway Innovations at Digital Promise reimagines education R&D by resourcing the creative ingenuity of communities to create liberatory education innovations rooted in self-determination for students furthest from opportunity. This brings together developers, entrepreneurs, researchers, educators, and also students, families, and community members to define challenges and build pathway innovations.

Purpose and Framing

Why Agency and Motivation Matter for LearnKit

The LearnKit concept aims to address a fundamental barrier in modern education: the fact that learners' accomplishments and skills are scattered across disconnected digital silos, making it nearly impossible for them to see a complete picture of their own progress. By building an integrated tool that puts the individual in the driver's seat of their own data, LearnKit aims to transform passive records into an evolving, actionable profile that follows the learner from K-12 through their professional life. However, providing access to data dashboards is not a silver bullet for success. For this idea to move from a technical framework to a transformative experience, the design must be rooted in how agency (an individual's ability to act and cause change during the learning process) and motivation (psychological force that causes the student to move toward a goal, the fuel for agency) function to drive persistence in pursuing a goal in the face of challenges. Understanding these psychological drivers is critical for responsible investment and ethical design. This document is intended to guide high-level strategy and prioritize future research investments by surfacing key psychological factors that point to design guardrails. It is a targeted scan of meta-analyses and literature reviews meant to inform decision-making, rather than an exhaustive academic review.

Framing the Question: What We Need to Understand Before Building

The key proposition underlying LearnKit is that a single platform that integrates the spectrum of a learner's data can provide learners with control over how they understand their own progress and apply it to their journeys between school and work. It assumes (in part) that learners are motivated to use the data, exercise agency in using the data to achieve their career and life goals, and have the skills to do so.

Agency and motivation are not fixed traits; they are states influenced by how an environment is designed and how information is presented. The following questions serve as the framework for this scan, surfacing the tensions and design guardrails identified in current research:

- What types of experiences are associated with building a sense of agency as they relate to learning?
- How is agency linked to motivation, persistence, and goal-oriented behavior in learning contexts?
- How do developmental stage, context, and support structures shape these dynamics (agency, motivation)?
- In what ways, if any, can choice architecture (i.e., how user choice is presented and embedded in a tool) support agency for learning and behavioral change?

What the Research Suggests About Agency, Motivation, and Learning

Experiences Associated with Building a Sense of Agency as They Relate to Learning

Research shows that agency is not a fixed personality trait, but rather a dynamic state shaped by a learner's environment and the design of the tools they use. Agency is most often supported through experiences that give learners meaningful control over goals, actions, and how they interpret progress. Across the literature, four recurring, research-backed mechanisms emerge as central to how learning environments cultivate a sense of agency:

1. **Prioritizing Autonomy Support**

Autonomy refers to feeling like you are the author of your own actions—doing something because you want to. When learners act out of interest, personal value, or meaning, they are autonomously motivated. Research consistently shows that this form of motivation is the strongest driver of deep learning, well-being, and persistence over time. In this sense, autonomous motivation is the fuel for agency. Agency reflects a learner's capacity to take charge of their learning, but motivation is what activates that capacity. Without motivation, agency remains dormant; without opportunities to exercise agency, motivation often stalls. Autonomy support is how learning environments help keep this cycle alive—by acknowledging learners' perspectives, explaining why tasks matter, and offering meaningful choices within clear structures (Bureau et al., 2022; Lintner, 2024).

2. **Fostering Trust Through Co-design and Transparency**

Agency is strengthened when learners are treated as partners rather than passive recipients. This includes involving learners in co-designing analytic tools and being transparent about how their data are collected, interpreted, and used, particularly in systems that use learning analytics or AI. Transparency and explainability help build trust, which in turn supports learners' willingness to engage and self-regulate (Hooshyar et al., 2023).

3. **Shifting from “Quantified” to “Qualified” Selves**

While performance metrics such as grades, scores, or usage count are common, the literature suggests that agency is better supported when tools promote sense-making rather than simple quantification. Helping learners interpret patterns, reflect on progress, and understand the “why” behind their data supports meaning-making and self-direction, rather than passive self-surveillance (Bennett & Folley, 2020).

4. **Customization as Control**

Agency is reinforced when learners can meaningfully customize their learning tools, goals, and representations of progress. Customization functions as a form of control, allowing learners to adapt systems to their needs, preferences, or developmental stage. Research suggests that such flexibility supports ownership and engagement, particularly when customization extends beyond cosmetic changes to influence how learning goals and feedback are structured (Bennett & Folley, 2020; Hooshyar et al., 2023).

How Agency Relates to Motivation, Persistence, and Goal-Directed Behavior in Learning Contexts

Across the research, a consistent pattern emerges: agency-supportive practices—especially goal-setting paired with progress monitoring— increase motivation, persistence, and goal-directed behavior. These practices work together: goals give learners direction, while monitoring helps them adjust their effort and strategies over time. When aligned, they reliably increase engagement and follow-through.

Evidence is especially strong for progress monitoring. While both actively seeking progress information and passively receiving it (e.g., via alerts) support goal attainment, the effects are strongest when learners physically record or externalize their progress rather than tracking it mentally. This suggests that the benefit of monitoring lies not only in being visually presented with the data, but in the cognitive work required to process and internalize that information (Harkin et al., 2016).

The literature draws a clear distinction between engagement and academic performance. Reviews of learning analytic dashboards show substantial increases in participation and interaction, but only small or inconsistent effects on grades or test scores (Kaliisa et al., 2024). This suggests that agency-supportive tools tend to move engagement first, while learning outcomes depend on additional supports and conditions.

Perceived competence is the strongest driver of sustained motivation. Motivation research helps explain why. While autonomy and belonging matter, perceived competence (i.e., learners' sense that they are developing skills and making progress) is the strongest predictor of sustained motivation and persistence over time (Bureau et al., 2022). Without signals of growing capability, increased choice or data access alone may not translate into meaningful learning gains.

Taken together, the literature suggests that agency-supportive approaches are most effective when they help learners set clear goals, actively track progress, and see evidence of their growing competence rather than assuming increased engagement will automatically lead to improved academic outcomes.

Key Variations, Boundaries, and Risks

Agency-supportive approaches do not work equally well for all learners. A clear pattern across the research is that agency-supportive approaches do not work equally well for all learners. Effectiveness varies substantially by developmental age, prior ability, subject matter, and learning context, making “one size fits all” approaches poorly aligned with evidence. Design features that support agency for some learners may have neutral or negative effects for others, particularly when differences in skill level or developmental stage are not accounted for.

Limits of the current evidence base for K-12 contexts. Most studies examining agency-supportive systems such as learning analytics and dashboards are conducted in higher education settings (Hooshyar et al., 2023). This matters because agency is experienced differently across developmental stages. Younger learners are more influenced by parental support, while teacher-provided autonomy support becomes a stronger driver of motivation as students age (Bureau et al., 2022). Findings from university settings, therefore, do not always generalize to K-12 contexts, where cognitive development, instructional structure, and adult influence differ substantially.

Equity-related risks are especially pronounced in agency-supportive system designs. A recurring warning in the literature is centered around the **Mathew Effect**— the tendency for motivational interventions to benefit learners who are already performing well.

- Disproportionate benefits for high-performing learners: Motivation-focused interventions often increase engagement among higher-performing learners while offering little benefit, or even discouraging, learners who are already struggling.
- Amplification through competitive, norm-referenced design: Features such as leaderboards or rewards for top performance make success feel attainable for high-achieving learners, while lower-performing learners may feel that goals are out of reach for them.
- Risk of disengagement and withdrawal: When success feels unattainable, lower performing learners are more likely to disengage or withdraw, contributing to widening achievement gaps (Lintner, 2024; Sailer & Homner, 2020).
- Greater vulnerability outside STEM contexts: Some evidence suggests these equity risks may be more pronounced in non-STEM subjects, where progress and success criteria are less clearly defined (Law et al., 2024).

Emerging Variability in the use of generative AI. Similar variability appears in emerging research on generative AI. Evidence points to “variability engagement,” in which the same tool can either support or undermine agency, depending on how learners use it. Some learners engage reflectively, using AI to critique ideas, extend thinking, or support self-regulation (i.e., a learner’s ability to use information to plan, adjust, and persist toward a goal over time). Others rely on AI to offload cognitive effort entirely, reducing skill development and increasing dependency. Access to

AI tools is also uneven, introducing additional variability in the experience of agency-supportive technologies (Roe & Perkins, 2024).

Mechanism that Helps Learners Follow Through on Their Goals

Goals alone are rarely enough to change behavior. Research shows that intentions and goals, on their own, have only a modest impact on behavior. Without supporting processes such as monitoring, feedback, and structured guidance, learners often struggle to translate intentions into action, creating a persistent gap between goals and follow-through. **Choice architecture** describes how learning environments are designed to help close this gap by supporting decision-making. By shaping how decisions are presented, through mechanisms such as nudges (i.e., defaults, timing, framing, and feedback), choice architecture reduces friction and supports follow-through without removing learner agency.

Nudges help overcome common behavioral barriers— but only when well designed. Nudges influence decision-making by addressing common behavioral barriers, such as procrastination and decision fatigue. While nudges are often intended to support motivation, planning, and self-efficacy, not all nudges work equally well.

- Nudges are most effective when they are **personalized** and **timed to moments of likely disengagement**.
- Generic, one-size-fits-all nudges show little impact.
- Evidence suggests that nudges tend to support learners with lower motivation and weaker self-regulation.
- Overuse of the same prompts can frustrate or demotivate highly motivated learners (Pedrami, 2025).

Feedback turns action into learning. Feedback functions as a key mechanism for turning action into learning. Rather than simply signaling performance, well-designed feedback helps learners understand *how* to improve. The literature distinguishes between:

- **Low-information feedback**, such as rewards, punishments, or simple knowledge of results, and
- **High-information feedback**, which provides guidance on the task, learning process, or self-regulation.

High-information feedback is associated with meaningful changes in learner behavior and supports agency by clarifying how to improve, rather than merely how one is doing (Hooshyar et al., 2023; Wisniewski et al., 2020).

Framing and defaults matter most when learners are tired or overloaded. When motivation or cognitive capacity is low, learners do not evaluate options neutrally; they respond to how choices are presented in the moment. Research shows that emphasizing potential losses, such as losing progress, time, or momentum, often motivates action more strongly than promising equivalent rewards (Pedrami, 2025). Paired with defaults and simplified pathways, loss-framed signals help sustain follow-through by making the cost of inaction clear when learners are least able to deliberate, explaining why some designs prompt action under conditions of fatigue, while others do not.

Synthesis: What the Evidence Suggests About Agency and Action

Agency is shaped, not possessed. Taken together, the literature suggests that learner agency is not something students simply have, but rather something shaped by environments, tools, and the design decisions that surround them. Agency emerges when learners experience meaningful control, understand their progress, and trust the systems designed to support them. At the same time, agency alone does not guarantee action or improved outcomes.

Agency primarily influences behavior before performance. Research consistently shows that agency-supportive experiences primarily influence behavior first, such as engagement, persistence, and goal-directed-effort, rather than immediate academic performance. Practices like goal-setting and progress monitoring reliably increase follow-through, especially when learners actively track their behavior and can see evidence of progress. Whether these behavioral gains translate into learning outcomes depends on whether learners also experience growing competence and receive guidance on how to improve, rather than being presented with data or choice in the absence of guidance.

Agency-supportive approaches are highly context-dependent. At the same time, the literature makes clear that agency-supportive approaches are highly context-dependent. What motivates one learner may discourage another. Differences in age, prior ability, subject matter, and access to technology shape how agency is experienced, and poorly designed incentives or competitive features can unintentionally widen existing gaps. Emerging research on generative AI further underscores this point: the same tools can either strengthen or undermine agency, depending on how they are used and who has access to them.

Choice architecture helps bridge the gap between agency and action. Research in behavioral economics and the learning sciences helps explain how these pieces connect. Even motivated learners face cognitive limits, especially in complex learning environments. Choice architecture, through nudges, timing, feedback, defaults, and framing, functions as a bridge between agency and action by reducing friction (e.g., mental load, decision fatigue, information overload) and supporting

follow-through. These mechanisms are most effective when timely, personalized, and when they provide high-information feedback (i.e., feedback that provides actionable guidance on how to improve) to help learners adjust their strategies, and account for real-world decision fatigue rather than assuming sustained motivation.

Design matters more than access alone. Across the literature, a consistent message emerges: agency is more likely to support follow-through and engagement when it is intentionally designed, guided, and supported, rather than assumed to work on its own. Tools that simply provide access to data or choice are unlikely to drive meaningful change on their own. Instead, the evidence points to the importance of aligning agency-supportive tools with structures that guide behavior and decision making, clear signals of competence, and sensitivity to learner differences and equity risks. Together, these findings clarify both the promise of agency-supportive tools and the conditions under which they are likely to succeed—or fall short.

Implications for LearnKit: Design and Research Priorities

Implications for Foundational Research

The literature suggests that while agency, motivation, and access to information are often assumed to support learning and persistence, the underlying mechanisms linking these factors to sustained behavior change are neither uniform nor well understood. Across domains, increased access to personal data is frequently associated with higher engagement, but evidence is mixed regarding whether and how this engagement translates into durable progress over time. Before large-scale investment in learner-centered data systems, several foundational questions warrant further investigation.

Access to data does not guarantee effective use. Many studies implicitly assume that learners can interpret and act on personal performance data once it is made available. However, making sense of data requires skills such as prioritization, interpretation, and self-regulation (i.e., a learner's ability to use information to plan, adjust, and persist toward a goal over time), that vary widely across learners, developmental stages, and contexts. Learners may encounter detailed progress information without understanding its relevance or implications for next steps. Foundational research is needed to clarify what data-use skills are required for learners, how those skills develop, and under what conditions access to data supports effective action rather than increasing cognitive load or disengagement.

Motivation operates differently across learners and contexts. The literature highlights substantial variation in how learners respond to agency-supportive systems (tools and learning environments designed to give learners control over their goals, actions, and progress) depending on developmental stage, prior experience, confidence, and available supports. What motivates one learner may discourage another, particularly when feedback emphasizes comparison or normative benchmarks. While these patterns are well-documented, less is known about how different learners interpret information and how these factors shape motivation, persistence, and sense of control over time.

Equity considerations remain underexplored in learner-centered data systems. Research shows that systems emphasizing comparison or competition tend to advantage high-achieving learners while discouraging those who are struggling. However, there is comparatively little empirical work examining alternatives that emphasize individual growth relative to the learner's own baseline rather than an external benchmark or standard. Understanding how different approaches to feedback and data framing affect learners across contexts is a foundational concern for ensuring that agency-supportive systems do not inadvertently widen existing gaps.

Implications for LearnKit Design

The research implications outlined above suggest that the primary design challenge for LearnKit is not simply how to aggregate or display learning data, but how learners experience, interpret, and act on that information in practice. **Design decisions, therefore, matter less as isolated features and more as the conditions they create for sense-making, follow-through, and trust over time.** Rather than assuming that access to personal data will naturally lead to better decisions, LearnKits design should intentionally support interpretation, persistence, and learner control in ways that align with real-world constraints.

Interpreting the data should be treated as part of the user experience, not a given. Because learners vary widely in their ability to make sense of data, designs that prioritize aggregation or data access alone are unlikely to be sufficient. For LearnKit, this implies presenting information in ways that clarify meaning, relevance, and priority, rather than assuming learners can independently translate data into action. In this context, data is usable when it helps learners answer a concrete question and decide what to do next. Design choices that surface patterns over time, highlight what matters most, and reduce cognitive effort can support agency by easing the interpretive work required. Taken together, this suggests that LearnKit should consider how support for data interpretation and self-regulation skills can be embedded within the tool itself, rather than treating them as external knowledge or prior capacity that learners are expected to bring. This also suggests the importance of helping learners make sense of their data as a story over time, rather than as isolated numbers or metrics. Designs that support reflection on patterns, change, and context can help learners understand why progress occurs and what it means, thereby supporting agency rather than passive self-monitoring.

Design should prioritize follow-through, not just initial engagement. Engagement indicators such as logins, views, or goal-setting activity can overstate progress if they are not accompanied by sustained action. From a design perspective, this implies that success should not be defined by initial interaction alone, but by whether learners are supported in returning, adjusting, and persisting over time. Designs that emphasize completion, streaks, or one-time milestones without reinforcing longer-term engagement risk encouraging short-term activity without durable impact.

Supporting follow-through depends on whether meaningful signs of progress can actually be captured and shown in the tool. In many learning settings, especially outside of formal classrooms, clear indicators of growth or skill development may be limited, inconsistent, or hard to interpret. Although badging, certificates, and micro-credentials are increasingly available, their quality and validation vary. Moreover, in all likelihood, learners will identify skills they have earned and deem important, but data for which is not readily available (e.g., interpersonal skills with managers developed while working at a fast food chain). This means that designs must

account for the data learners can realistically see and understand when making sense of their progress and present their skills to others.

LearnKit should be designed for intermittent, purpose-driven use in real-world contexts.

Learners are unlikely to engage with LearnKit in continuous or linear ways. Instead, use is likely to be episodic and shaped by competing demands, fluctuating motivation, and a specific purpose or question tied to real-world decisions. Data use typically begins not with exploration of the system, but with a reason for engaging, for example, checking progress toward a goal, understanding a setback, or deciding what to focus on next. Design implications, therefore, include minimizing friction (e.g., mental load, decision fatigue, information overload), avoiding unnecessary complexity, and ensuring that learners can re-enter the system without having to reconstruct context or expend additional effort. Dense, poorly prioritized, or effort-intensive data presentations may undermine agency rather than support it.

Implications for Design and Implementation Research

The research gaps and design implications outlined above point to a small number of critical uncertainties that can only be addressed through the study of LearnKit in real-world use. Because LearnKit is intended to support learners across time, contexts, and purposes, design and implementation research should focus on how learners actually use data to guide decisions and sustain progress, rather than on surface-level engagement alone. We suggest several research questions necessary to substantiate that LearnKit has the intended effect, how, why, and under what conditions.

Data interpretation and sensemaking

- How do learners use the data available to them, why, and how? What primary purpose(s) or question(s) do learners aim to answer with the available data?
- What data are missing from learners' perspectives based on their primary purposes for using the data?

Follow-through under real-world constraints

- What constraints do learners experience in trying to use their data? Why?

Data-use and self-regulation skills

- What skills do learners need to use the available data?
- How do learners' data-use and self-regulation skills develop with repeated use?

Design support for skill and action

- What design elements build learners' data-use skills?

- What choice architecture features support learners in moving from viewing data to taking action?
- What approaches to tracking competence development help learners recognize progress and sustain effort over time?

Perceived Agency, Efficacy, and Impact

- What decisions about education, skill development, or career planning do learners feel better able to make because their data is visible and manageable in a single platform, rather than spread across multiple systems?
- To what extent, if at all, do learners feel increased agency, motivation, confidence, and efficacy in making decisions about education, skills attainment, and job seeking as a result of having access and control over their data in a centralized platform? Why? What design elements support these impacts?

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Appendices

Appendix A. Scope and Approach to the Literature Scan

This literature scan was intentionally scoped, question-driven, and design-oriented, rather than exhaustive or evaluative. The purpose was not to determine whether specific interventions work, nor to aggregate effect sizes across studies, but to surface patterns, mechanisms, risks, and design-relevant considerations that can inform LearnKit’s development and future research agenda.

The scan was organized around the core research questions articulated in the Statement of Work, rather than by theoretical tradition, disciplinary silo, or intervention type. In particular, the review focused on:

- What types of experiences are associated with building a sense of agency as they relate to learning?
- How is agency linked to motivation, persistence, and goal-oriented behavior in learning contexts?
- How do developmental stage, context, and support structures shape these dynamics (agency, motivation)?
- In what ways, if any, can choice architecture (i.e., how user choice is presented and embedded in a tool) support agency for learning and behavioral change?

Because meta-analyses, systematic reviews, and design-oriented studies operate at different levels of abstraction and often answer different kinds of questions, this scan did not treat all evidence as equivalent or summarize findings as a simple set of positive effects. Instead, studies were interpreted in relation to the mechanisms they illuminate (e.g., autonomy support, feedback interpretation, goal monitoring, choice architecture) and the design tensions they raise (e.g., participation versus achievement, meaningful versus superficial choice, growth versus comparison).

To support this approach, the literature was synthesized into a small set of analytic anchors aligned to the SOW questions:

1. Experiences associated with building agency,
2. Links between agency, motivation, and persistence,
3. Variation, boundary conditions, and equity considerations, and
4. Implications for tool design.

The final anchor was explicitly synthetic, drawing on the prior anchors to identify design considerations, unresolved questions, and areas warranting additional research or experimentation.

This scoped approach was chosen to ensure that the resulting synthesis moves beyond general claims about the benefits of agency and instead provides actionable insights into what LearnKit should prioritize, be cautious about, and explore next, given its goals and constraints.

Methods and AI-Human Collaboration

This literature scan combined AI-supported tools with human-led analysis and synthesis. AI was used strategically to support efficiency, organization, and iterative drafting, while all analytic judgement, interpretation, and final framing decisions were made by the author. Different AI tools were used at different stages of the process, based on the nature of the task and whether the material involved public literature or Digital Promise and partner-facing work.

AI-Supported Search, Tracking, and Organization

For early-stage exploration and review of public, non-proprietary literature, general-purpose AI tools were used to support search, triage, and organization.

ChatGPT Plus was used to

- Generate and refine interdisciplinary search keywords related to learner agency, autonomy support, motivation, learning analytics dashboards, nudging, and choice architecture.
- Rapid identification of relevant articles across education, psychology, behavioral science, and human-centered design.
- Support the development of a process tracker to document sources reviewed, emerging themes, and analytic decisions over time.
- Organized notes, excerpts, and provisional themes aligned to the evolving anchor framework.

Notebook LM was used to scan and summarize large bodies of literature. This tool supported:

- Generation of initial summaries of individual articles to support triage and comparison.
 - These AI-generated summaries were treated as starting points, not final representations of the literature.
- Extract key study attributes.
- Preliminary clustering of findings into provisional topic groupings (anchors).
- Creating the glossary.
- Generating the references in APA 7th ed.

Human Expertise, Verification, and Synthesis

All substantive analytic decisions were led by the author: This included:

- Defining the core framing question/ anchors for the scan.

- Defining and refining the final set of anchors, including decisions about scope, boundaries, and terminology.
- Verifying AI-generated summaries by returning to original resources, with close review conducted for a little more than half of the articles and spot checking for the remainder.
- Paraphrasing, reorganizing, and re-writing AI assisted text to ensure conceptual accuracy, clarity, and relevance.
- Reviewing all AI outputs → checking for accuracy.

During synthesis, particular attention was paid to identifying gaps, tensions, and boundary conditions in the literature. These judgements required disciplinary expertise and could not be derived solely from AI outputs.

AI Use for Digital Promise and Partner-Facing Interpretation

For tasks involving Digital Promise or partner-facing synthesis, including interpretation of findings in relation to LearnKit and implications for tool design, Gemini, under Digital Promise proprietary license, was used as the AI environment (per Digital Promise AI policy). Gemini supported:

- Interpreting synthesized findings in relation to LearnKit's goal and design direction.
- Supporting iterative drafting and tightening of language for partner-facing summaries.

Final interpretations, implications, and framing decisions reflect the author's analytic judgement and were refined through discussion with a colleague.

Documentation and Transparency

Throughout the process, a prompt log was maintained to document:

- Which AI tools were used at different stages.
- The types of prompts used (e.g., search refinement, summarization, drafting).
- Where AI-assisted outputs were saved.

This document ensures transparency around how AI supported the workflow and clarifies the boundary between AI-assisted generation and human-led synthesis.

All substantive claims, interpretations, and conclusions were grounded in human review or primary and secondary sources. AI outputs were treated as provisional and were continuously checked against the underlying literature for accuracy, nuance, and alignment with the evidence base. Final synthesis decisions, framing choices, and implications reflect the authors' analytic judgement rather than automated outputs.

This approach enabled greater efficiency and traceability while maintaining (analytic synthesis) rigor, methodological transparency, and interpretive accountability.

Appendix C. Glossary

Active Monitoring: A dimension of progress monitoring where the person makes deliberate efforts to attend to goal-related behavior, and/or seeks out information about goal-related outcomes (e.g., stepping on a scale).

- *Defined by:* Harkin et al. (2016).

Agency (Student/Learner): A student's experience of having access to or being empowered to act through personal, relational, and participatory resources, which allow him/her to engage in purposeful, intentional, and meaningful action and learning in study contexts.

- *Defined by:* Jääskelä et al. (2017), as cited in Hooshyar et al. (2023).

Autonomy (Need for): The psychological need to experience a sense of volition, choice, and self-endorsement; the desire to be the origin of one's behavior.

- *Defined by:* Ryan & Deci (2017), as cited in Mammadov & Schroeder (2023) and Okada (2021).

Autonomy Support: What a student perceives significant others (such as teachers or parents) doing or saying to enhance their internal locus of causality and volition. This includes providing rationale, offering meaningful choices, and acknowledging perspectives.

- *Defined by:* Reeve et al. (2003), as cited in Mammadov & Schroeder (2023).

Behavioral Nudge: A non-coercive intervention in the choice architecture that guides behavior in predictable ways by leveraging cognitive biases, without forbidding any options or significantly changing economic incentives.

- *Defined by:* Thaler & Sunstein (2008), as cited in Pedrami (2025).

Bounded Rationality: The concept that an individual's ability to make rational decisions is limited by the information they have, the cognitive limitations of their mind, and the finite amount of time they have to make a decision.

- *Defined by:* Pedrami (2025).

Choice Architecture: The design of different ways in which choices can be presented to consumers (or learners), and the impact of that presentation on decision-making.

- *Defined by:* Pedrami (2025).

Competence (Need for): The human desire to efficiently interact with one's environment to feel competent in producing preferred outcomes; to explore and attempt mastery of skills.

- *Defined by:* Ryan & Deci (2017), as cited in Okada (2021) and Mammadov & Schroeder (2023).

Critical Digital Pedagogy (CDP): An approach stemming from Freirean pedagogy that focuses on offering students a notion of critical agency—the agency to know, understand, act on, or resist reality—while rejecting systems of surveillance and control.

- *Defined by:* Morris & Jessifer (2020) and Freire (1978), as cited in Roe & Perkins (2024).

Descriptive Analytics: A type of learning analytics that employs statistical methods to illustrate "the way things are and what has happened."

- *Defined by:* Hooshyar et al. (2023).

Diagnostic Analytics: Analytics using data mining and statistical methods to enable students to investigate the root causes of possible learning issues and difficulties.

- *Defined by:* Hooshyar et al. (2023).

Digital Badges: A digital display that acknowledges, recognizes, and validates the achievement of skills and competencies through explicit evidence.

- *Defined by:* Blackburn et al. (2016), as cited in Law et al. (2024).

Engagement: A construct often defined by three dimensions: Behavioral (effort and persistence), Cognitive (use of meta-cognitive skills/strategies), and Emotional/Affective (presence of positive emotions/interest during tasks).

- *Defined by:* Fredricks et al. (2004) and Skinner & Pitzer (2012), as cited in Mammadov & Schroeder (2023) and Okada (2021).

Explainability (Explainable AI / XAI): The degree to which the internal mechanics, decision-making processes, and outputs of an algorithmic system (such as a Learning Analytics Dashboard or Generative AI tool) can be understood and interpreted by human users. In educational contexts, explainability moves beyond "black box" predictions to provide the "why" behind a result—for example, detailing which specific behaviors or data points led a system to categorize a student as "at-risk" or recommend a specific resource. It is identified as a critical factor in building trust, ensuring ethical transparency, and supporting student agency by enabling learners to validate and act on data-driven insights.

- *Defined by:* Hooshyar et al. (2023)

External Regulation: The least autonomous form of extrinsic motivation, where an individual acts solely to obtain a reward or to avoid punishment.

- *Defined by:* Ryan & Deci (2017), as cited in Okada (2021).

Feedback: A dialogic process in which learners make sense of information from varied sources and use it to enhance the quality of their work or learning strategies.

- *Defined by:* Carless (2015), as cited in Matcha et al. (2020).

Feedback (High-Information): Feedback that contains information on the task, the processing of the task, or self-regulation, rather than simple reinforcement or punishment.

- *Defined by:* Wisniewski et al. (2020).

Game Fiction: A gamification element defined as the inclusion of a narrative context or the introduction of a game world (e.g., meaningful stories, avatars, or teammates).

- *Defined by:* Sailer & Homner (2020).

Gamification: The use of game design elements in non-game contexts.

- *Defined by:* Deterding et al. (2011), as cited in Sailer & Homner (2020).

Goal Setting (Theory): A theory positing that specific, difficult task goals produce higher commitment and performance than vague goals that are easy to attain.

- *Defined by:* Locke and Latham (1990, 2002), as cited in Lazowski & Hulleman (2016).

Identified Regulation: A form of extrinsic motivation with greater autonomy, where a person identifies with the value of the activity and believes performing it is personally important.

- *Defined by:* Ryan & Deci (2017), as cited in Okada (2021).

Intervention (Educational): A manipulation implemented by an external agent (i.e., teacher, researcher) intended to change students' cognitions, emotions, and/or behaviors within an ecologically valid context.

- *Defined by:* Lazowski & Hulleman (2016).

Intrinsic Motivation: Engaging in an activity purely for the pleasure and satisfaction derived from performing it; the highest level of self-determination.

- *Defined by:* Ryan & Deci (2017), as cited in Okada (2021) and Bureau et al. (2022).

Introjected Regulation: An internally controlled form of extrinsic motivation in which an individual acts to avoid feeling guilty or anxious, or to assert pride.

- *Defined by:* Ryan & Deci (2017), as cited in Okada (2021) and Bureau et al. (2022).

Learning Analytics Dashboards (LADs): Displays that aggregate different indicators about learner(s), learning process(es), and/or learning context(s) into one or multiple visualizations.

- *Defined by:* Schwendimann et al. (2016), as cited in Kaliisa et al. (2024) and Matcha et al. (2020).

Loss Aversion: A cognitive bias where the fear of losing something (e.g., credits, opportunities) is a stronger motivator for behavior change than the pleasure of gaining an equivalent reward.

- *Defined by:* Pedrami (2025).

Micro-credentials: A term often used interchangeably with digital badges to describe the recognition of achievement of skills and competencies.

- *Defined by:* Berge & Muilenburg (2016) and Ellis et al. (2016), as cited in Law et al. (2024).

MULAS: A Model for User-centered Learning Analytics Systems consisting of four dimensions that are cyclically and recursively interconnected: theory, design, feedback, and evaluation.

- *Defined by:* Matcha et al. (2020).

Nudge Plus: An evolution of nudging that combines conscious (reflective) and unconscious (automatic) processes to foster sustainable behavioral modifications.

- *Defined by:* Banerjee & John (2021), as cited in Pedrami (2025).

Passive Monitoring: A dimension of progress monitoring where the person attends to information about progress that is readily available in the environment without deliberate effort (e.g., clothes feeling looser).

- *Defined by:* Harkin et al. (2016).

Performance-based Financial Incentives: Interventions that give students an opportunity to get some form of future financial incentive contingent on their academic performance (e.g., exam score, GPA, credits gained).

- *Defined by:* Lintner (2024).

Predictive Analytics: Analytics using machine learning and statistical modeling to provide predictions about future student outcomes (e.g., future agency profiles).

- *Defined by:* Hooshyar et al. (2023).

Relatedness (Need for): The desire to feel connected to and accepted by significant others (e.g., teachers, friends).

- *Defined by:* Ryan & Deci (2017), as cited in Okada (2021) and Mammadov & Schroeder (2023).

Self-Determination Theory (SDT): A framework positing that student motivation varies along a continuum of self-determination, dependent on the satisfaction of three psychological needs: autonomy, competence, and relatedness.

- *Defined by:* Ryan & Deci (2017), as cited in Bureau et al. (2022).

Self-Regulated Learning (SRL): The process whereby students activate and sustain cognitions, behaviors, and affects, which are systematically oriented toward the attainment of their goal.

- *Defined by:* Zimmerman (2008), as cited in Matcha et al. (2020).

Shannon Entropy (Method): A mathematical method from information theory used to measure the "surprise" or "news value" of a theme; in this context, it objectively determines a factor's importance based on how much it reduces uncertainty in the model.

- *Defined by:* Pedrami (2025).

System 1 vs. System 2 Thinking: A dual-process theory where System 1 represents fast, intuitive thinking, and System 2 represents slow, analytical thinking. Effective nudges can target both systems.

- *Defined by:* Pedrami (2025).

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