

SCALING PERSISTENCE THROUGH STRUCTURED GOVERNANCE: INTEGRATING AI-ENABLED DIAGNOSTICS IN A HIGH-ENROLLMENT GATEWAY COURSE

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Abstract

Gateway courses function as critical persistence junctures in higher education, yet prevailing intervention models remain reactive, atheoretical, and insufficiently integrated into instructional decision-making. This paper introduces the Structured Governance Integration Model (SGIM), a domain-specific instantiation of the Human-Governed AI Operating Architecture™ (HG-AIOA), which embeds AI-enabled diagnostics within a four-layer governance structure to transform AI insight into authorized, equitable, human-executed instructional action. The study was conducted across four consecutive quarters of BUS100: Introduction to Business at Strayer University ($n > 2,700$ records) using a mixed-methods longitudinal design. SGIM deployment was associated with ~90% course completion rates sustained across three terms as enrollment tripled from approximately 500 to 1,400 students. The Learning Archetype Assessment (Carroll, 2023), anchoring the SGIM Diagnostic Layer, predicted persistence with high accuracy: in Quarter 3, only six students completing both intake instruments failed to finish the course. These findings reframe AI effectiveness in education as a governance property rather than a technological one, establishing HG-AIOA and SGIM as scalable, institutionally viable frameworks for aligning AI capabilities with human oversight in real-world learning environments.

Keywords: *AI governance, student persistence, gateway courses, learning archetypes, higher education.*

1. Introduction

Gateway courses occupy a structurally significant position in higher education: simultaneously entry points to degree progression and the most common sites of attrition. Research consistently demonstrates disproportionately high withdrawal and failure rates in introductory courses, particularly when students lack meaningful academic and social integration (Tinto, 1993). At Strayer University, BUS100: Introduction to Business enrolls more than 1,000 students per quarter and has historically exhibited strong early-term engagement followed by significant late-term attrition, with submission rates declining sharply in Weeks 7–10 when major writing assignments cluster.

The dominant institutional response has been technological: dashboards, early alert flags, and at-risk reports. Tools such as the Faculty Action Center (FAC) describe who has missed assignments. What they do not provide is diagnostic insight into why students disengage, nor a governance mechanism for translating AI signals into timely, equitable instructional action. The result is a reactive model: intervention arrives too late, is undifferentiated, and is unsupported by the governance structures needed to sustain it at scale.

This paper argues that the core problem is the absence of governance architecture at the point of instructional execution. Drawing on the Human-Governed AI Operating Architecture™ (HG-AIOA) — which holds that AI must inform but humans must govern, at the moment of action — this study introduces SGIM as the domain-specific implementation framework for higher education. Deployed in BUS100 across four quarters using the Learning Archetype Assessment, SGIM sustained ~90% completion rates as enrollment tripled, providing empirical support for HG-AIOA as a scalable model for governed AI deployment in real-world learning environments. The paper proceeds as follows: Section 2 reviews relevant literature; Section 3 presents the governance frameworks; Section 4 describes methodology; Sections 5–6 report results and discussion; Section 7 concludes with recommendations.

2. Literature review

Tinto's (1993) model of student departure remains the most cited persistence framework, establishing academic and social integration as primary retention drivers — an imperative operationalized in BUS100 through faculty-led live sessions (Coffee & Conversations, Momentum Tuesdays, Saturday Know-How). Studies on early alert systems (Arnold & Pistilli, 2012; Essa & Ayad, 2012) report variable effects, with intervention quality — not prediction accuracy — as the primary outcome determinant. This is precisely the gap SGIM addresses: not better AI prediction, but better governance of AI-informed instructional action.

Positive Psychological Capital theory (Luthans et al., 2007) demonstrates that hope, self-efficacy, resilience, and optimism predict academic persistence, providing the motivational architecture for archetype classification. Cognitive load theory (Mayer, 2002) informs SGIM's Decision Layer governance rules for assignment sequencing, directly addressing the Weeks 7–10 overload condition. DISC (Marston, 1928), the Birkman Method (2013), and Bolles' career framework (1970/2021) supply differentiated communication strategies associated with each archetype. Maslow's hierarchy (1943) grounds the Readiness & Behavioral Questionnaire's assessment of environmental barriers as prerequisites to persistence intervention. Prior literature has not articulated a governance architecture resolving these threads at the execution layer; HG-AIOA and SGIM represent that contribution.

3. Governance framework: HG-AIOA and SGIM

The Human-Governed AI Operating Architecture™ (HG-AIOA) is predicated on the principle that AI must inform, but humans must govern, at the moment of action. Governance is reconceptualized as an execution-layer system property — not a post-hoc compliance function — embedded within the workflows through which AI-generated insights become authorized human decisions. Authority resides with human actors; AI holds no independent permission to act.

SGIM operationalizes HG-AIOA in higher education through four integrated layers, each resolving a distinct governance question at the point of instructional execution:

Layer 1 — Diagnostic Layer: AI analyzes multi-modal learning signals via the Learning Archetype Assessment and Readiness & Behavioral Questionnaire, generating archetype classifications and persistence-risk profiles. The layer produces insight but does not determine action.

Layer 2 — Decision Layer: Governance rules translate diagnostic outputs into allowable instructional actions, defining authorized interventions per archetype, escalation thresholds to institutional coaching, and equity constraints — embedding faculty autonomy within governed boundaries.

Layer 3 — Execution Layer: Faculty operationalize governed interventions in real time: archetype-informed personalized outreach, assignment scaffolding, resource referral, and timely feedback. This is the site of human accountability. AI informs; humans execute.

Layer 4 — Feedback Layer: Outcome data — submission rates, archetype-to-completion correlations, student voice — feed back into governance rule refinement each term, making SGIM a continuously learning system rather than a static deployment.

A Cross-Cutting Governance Layer operates across all four dimensions, enforcing policy compliance, bias and fairness monitoring, audit transparency, and risk management — ensuring that scale does not erode the equity and accountability properties of the system.

3.1. The five Learning Archetypes

The Learning Archetype Assessment classifies students into five profiles synthesizing PsyCap, Maslow, Tinto, cognitive load, DISC, Birkman, and Bolles frameworks into actionable instructional profiles:

Sleeper: Low engagement, low self-efficacy, minimal submission activity. Highest attrition risk. Requires immediate, consequence-informed outreach from both faculty and institutional coaches.

Crawler: Inconsistent engagement, moderate environmental barriers, low confidence. Benefits from structured scaffolding, step-by-step guidance, and encouragement-focused communication.

Walker: Capable but inconsistent. Responds to accountability nudges, deadline reminders, and clear consequence messaging rather than emotional support appeals.

Jogger: Motivated and generally consistent. Benefits from recognition, enrichment opportunities, stretch challenges, and community connection to sustain momentum.

Runner: High self-efficacy, strong persistence, proactive engagement. Benefits from leadership opportunities within the learning community and advanced application challenges.

By pre-defining authorized interventions for each archetype, the Decision Layer resolves a critical governance problem: it ensures faculty act on diagnostic signals in ways that are equitable, consistent, and theoretically grounded — rather than dependent on individual instructor judgment, bandwidth, or instinct. This is the governance logic that distinguishes SGIM from conventional early-alert models.

4. Methodology

A mixed-methods longitudinal design was employed across four consecutive quarters of BUS100 at Strayer University. Quantitative data: assignment submission rates, attendance records, archetype classification distributions, and course completion rates across 2,700+ student records. Qualitative data: open-text BUS100 Midterm Check-In responses and end-of-term S-Curve Reflections. Quarters 1–3 (Pilot: $n \approx 500$; Scaling: $n \approx 800$; Large-Scale: $n \approx 1,400$) provided pre/post implementation comparisons; Quarter 4 ($n \approx 1,200$) supplied ongoing validation. More than 60,000 external users completed the open-access instrument on the EmpoweredEd Pro platform, providing additional usability validation.

Instruments: (1) Learning Archetype Assessment (Carroll, 2023) — a 12-item tool classifying students into five profiles (Sleeper, Crawler, Walker, Jogger, Runner), grounded in PsyCap, Maslow, Tinto, cognitive load theory, DISC, Birkman, and Bolles frameworks; (2) Readiness & Behavioral Questionnaire — assessing environmental barriers, operationalizing Maslow within the Diagnostic Layer; (3) BUS100 Midterm Check-In — five open-ended questions capturing structured student voice as a formal Feedback Layer input; (4) S-Curve Reflection — end-of-term growth narrative. Content validity was established by grounding each item in prior validated constructs. Predictive validity was confirmed by strong alignment of archetype classifications with observed persistence outcomes; formal psychometric analysis is planned for subsequent phases. Quantitative and qualitative data were triangulated to confirm alignment between attrition patterns and student voice themes.

5. Results

5.1. Engagement and persistence outcomes

Submission rates in Weeks 2–6 consistently exceeded 95% across all quarters, reflecting the effectiveness of Diagnostic Layer onboarding and early social integration. In Quarter 3 ($n \approx 1,400$), overall submission rates reached 90.4%, with 95.6% active course starts and 79.5% sustaining consistent attendance through midterm. Completion rates sustained near 90% across three terms as enrollment grew from ~500 to ~1,400 — a 180% increase — the study's most institutionally significant scalability finding. Of new students completing both intake instruments in Quarter 3, only six failed to complete the course. Priority and repeat students — significantly less likely to complete intake instruments — were disproportionately represented in the non-submission pool, validating the Diagnostic Layer's predictive function.

5.2. Weeks 7–10 attrition window

Non-submission spikes clustered predictably in Weeks 7–10: 234 students missed the Week 7 Business Functions paper; 251 missed the Week 9 SWOT Analysis; 209 missed the Week 10 S-Curve Reflection — nearly 3× the early-term baseline. Three consecutive quiz-heavy weeks (Weeks 4–6) depleted writing momentum and cognitive capacity at the onset of the high-stakes writing window, consistent with Mayer's (2002) cognitive load predictions. Post-implementation assignment rebalancing — SWOT moved earlier, Week 9 converted to scaffolded revision — produced measurable non-submission reductions in subsequent quarters, confirming the Decision Layer's governance value.

5.3. Student voice

Midterm Check-In qualitative analysis identified four consistent themes: (1) assignments, professor feedback, and live sessions as most helpful course elements; (2) time management and writing overload as primary challenges; (3) requests for clearer assignment templates and more frequent check-ins; (4) appreciation for personalized archetype-informed outreach. Themes aligned precisely with quantitative attrition patterns and directly informed Decision Layer governance rule updates each term — closing the bidirectional accountability loop between student experience and instructional governance.

6. Discussion

The central finding — that AI-enabled diagnostics sustain persistence at scale only within a structured governance architecture — challenges the prevailing EdTech assumption that better prediction yields better outcomes. SGIM's effectiveness derives not from the diagnostic precision of the Learning Archetype Assessment alone but from the governance logic surrounding it: Decision Layer rules ensuring equitable, archetype-consistent interventions; Execution Layer accountability requiring faculty action within authorized boundaries; Feedback Layer mechanisms enabling student voice to continuously refine governance rules. Remove the governance structure, and the instrument becomes another dashboard — generating insight that goes unacted upon or applied inconsistently across instructors and sections.

The Weeks 7–10 attrition window is reconceptualized as a governance failure: a predictable, preventable event when assignment sequencing exceeds cognitive capacity thresholds without triggering governed instructional responses. SGIM's incorporation of cognitive load theory directly into Decision Layer governance rules — defining assignment rebalancing and proactive scaffolding as authorized responses to approaching overload signals — transforms what a reactive crisis was into a governed, preventable event.

The 180% enrollment increase without completion degradation demonstrates that SGIM scales through governance rules — not individual faculty effort — preventing both the quality degradation (overwhelmed bandwidth) and consistency degradation (unstandardized responses) pathways that typically accompany rapid enrollment growth. For the broader EdTech field, the 60,000+ open-access users of the Learning Archetype Assessment demonstrate significant market demand for theoretically grounded, scalable persistence diagnostics. SGIM provides the governance architecture necessary to deploy such instruments responsibly at an institutional scale. For researchers, this study positions governance as an independent variable in AI effectiveness research — a productive new framing that opens directions not yet pursued in the literature.

7. Recommendations and conclusion

Five institutional recommendations follow: (1) Rebalance writing assignments to govern against cognitive overload — SWOT moved earlier, Week 9 as a scaffolded revision — embedded as a Decision Layer rule, not a discretionary design choice. (2) Mandate the Learning Archetype Assessment in Week 1 for all new, repeat, and priority students, with results integrated into faculty-coach governance huddles and archetype-informed outreach systematically embedded in course workflows. (3) Establish a dedicated coaching track for repeat and priority students as an Execution Layer governance protocol, with assigned coaches and consequence-informed weekly outreach. (4) Formalize the Midterm Check-In as a Feedback Layer input, with qualitative themes systematically translated into Decision Layer governance rule updates each subsequent quarter. (5) Define live sessions as governance-specified integration anchors with required recording and automated reminder sequences as governance-authorized accessibility provisions.

This study demonstrates that the effectiveness of AI-enabled diagnostics in higher education is not primarily a function of model capability — it is a function of governance. SGIM, deployed within HG-AIOA's architecture, sustained ~90% completion rates across three consecutive quarters as enrollment tripled, because governance architecture — defined authorized actions, embedded human accountability, continuously refined governance rules — ensured AI-generated insights became timely, equitable, and effective instructional action. The paper's central theoretical contribution is the articulation of SGIM as a domain-specific instantiation of HG-AIOA, establishing that governance must be embedded at the point of instructional execution rather than applied as a compliance overlay. Three future research directions follow: longitudinal tracking of SGIM completers through program graduation; refined coaching protocols for the highest-risk subgroups; and responsible integration of AI-governed nudges at tens-of-thousands-learner scale. SGIM and the Learning Archetype Assessment represent a scalable, governance-grounded contribution to one of higher education's most persistent challenges: ensuring that the students who begin a degree program have a governed, human-accountable pathway to completing it.

References

- Birkman, R. W. (2013). *The Birkman Method: Your personality at work*. Wiley.
- Bolles, R. N. (1970/2021). *What color is your parachute?* Ten Speed Press.
- Carroll, M. (2023). *The Learning Archetype Assessment*. Unpublished instrument, Strayer University.
- Carroll, M. (2023). *BUS100 Midterm Check-In*. Unpublished faculty instrument, Strayer University.

- Carroll, M. (2023). Readiness & Behavioral Questionnaire. Unpublished faculty survey, Strayer University.
- Carroll, M. (2024). Human-Governed AI Operating Architecture™ (HG-AIOA). Carroll Beck, LLC.
- Essa, A., & Ayad, H. (2012). Student success system: Risk analytics and data visualization using ensembles of predictive models. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, 158–161.
- Luthans, F., Avolio, B. J., Avey, J. B., & Norman, S. M. (2007). Positive psychological capital: Measurement and relationship with performance and satisfaction. *Personnel Psychology*, 60(3), 541–572.
- Marston, W. M. (1928). *Emotions of normal people*. Harcourt, Brace & Company.
- Maslow, A. H. (1943). A theory of human motivation. *Psychological Review*, 50(4), 370–396.
- Mayer, R. E. (2002). Cognitive load theory and the design of educational materials. *Journal of Educational Psychology*, 93(2), 187–198.
- Tinto, V. (1993). *Leaving college: Rethinking the causes and cures of student attrition* (2nd ed.). University of Chicago Press.