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Editors

Revisiting Course Coordination in Instructional Contexts: A Flexible, Instructor-Centered Approach

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Abstract

Coordinating large, multi-section courses presents a persistent challenge in higher education, creating a tension between the need for standardization for quality assurance and the desire for pedagogical flexibility to foster instructor engagement. This paper addresses this challenge by proposing and evaluating a replicable, instructor-centered coordination model of "flexible standardization." Developed and implemented in a required undergraduate Information Systems course at a private U.S. college, the model integrates shared learning goals and common assessments within a framework that empowers instructors with the autonomy to adapt and innovate their teaching materials and methods. The model's effectiveness was assessed over six academic years (2019–2025) using student performance data from standardized Assurance of Learning (AoL) exam questions. The findings demonstrate that this flexible approach successfully maintains curricular coherence and meets accreditation benchmarks, with student performance consistently exceeding goals and showing low variability across sections. By fostering a culture of collaboration, professional trust, and shared ownership, the model provides a scalable, evidence-based alternative to rigid standardization that allows instructor agency while ensuring the integrity of student learning outcomes.

Keywords: Course Coordination, Flexible Standardization, Assurance of Learning (AoL), Instructor Agency, Accreditation.

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Revisiting Course Coordination in Instructional Contexts: A Flexible, Instructor-Centered Approach

Wenqi Zhou and Carlos Salazar-Betancourth

1. INTRODUCTION

Coordinating large, multi-section college courses is challenging in higher education, particularly when those sections are taught by instructors with diverse academic backgrounds, teaching philosophies, and employment statuses. Balancing the competing demands of quality assurance, pedagogical consistency, and faculty autonomy becomes crucial in foundational courses that are vital for student success. This paper addresses this challenge by presenting a replicable, instructor-centered model of course coordination that supports consistency in student learning outcomes without compromising instructional flexibility and creativity.

In today's higher education landscape, flexibility is increasingly recognized as a necessary feature of both student-centered and faculty-driven pedagogical design to improve accessibility for the students, adaptability to different learning styles, and creativity from the instructors (Barua & Lockee, 2024; Brekke & Zhang, 2024; Lübke et al., 2021). However, large-scale coordination efforts often lean toward rigid standardization to ensure fairness and accountability, inadvertently undermining the instructor engagement and innovation that contribute to meaningful learning. Moreover, resistance to top-down Assurance of Learning (AoL) systems, often seen as organizational compliance, complicates the development of effective, scalable course coordination frameworks (Bennett et al., 2017; Tham et al., 2023). Assurance of learning (AoL) refers to "*demonstrating, through assessment processes, that students achieve learning expectations for the programs in which they participate.*"

This study is best characterized as a longitudinal evaluation and case study of a course coordination model implemented over six academic years which addresses the debate on flexibility vs. standardization. This study proposes an alternative to more rigid approaches: a flexible standardization model built on the principles of collaboration, transparency, and shared governance. Developed through the lens of a course coordinator at a private U.S. college, the model incorporates curated teaching materials, shared assessments, and clearly defined yet adaptable structures. At its core, the system emphasizes faculty empowerment through well-supported autonomy and structured collaboration, anchored by common learning goals and assessment practices aligned with AACSB accreditation standards.

Drawing on literature related to pedagogy, assessment, and change management, this work situates such a model within a broader conversation about faculty agency, curriculum coherence, and institutional accountability. It then demonstrates how the model has been implemented, refined, and evaluated over multiple academic cycles in an introductory Information Systems course. Through student performance data, documented improvements in instructional engagement, and sustainable administrative practices, the model illustrates how academic rigor and pedagogical flexibility can coexist, producing a high-quality, inclusive learning experience across course sections.

By offering a practical framework grounded in both theory and practice, this paper contributes to efforts to reimagine course coordination as a participatory, faculty-led process. It provides institutions with a scalable, evidence-based alternative to rigid standardization—one that honors the professional judgment of instructors while preserving the integrity of student learning and accreditation standards.
The proposed model includes five key components: (1) forming a collaborative instructor team to share pedagogical ownership; (Couch et al., 2023; Moore et al., 2025) (2) distributing baseline materials to ensure consistency while avoiding redundancy; (Bennett et al., 2017; Brown et al., 2017) (3) administering shared assessments across all sections with centralized reporting; (Gibson et al., 2013; Miller et al., 2024; Tham et al., 2023) (4) offering weekly teaching plans as scaffolding tools; (Aga, 2023; Fortes & Tchantchane, 2010) and (5) allowing instructors to propose and integrate new teaching materials through a faculty-led process (Barua & Lockee, 2025; Brekke & Zhang, 2024; Lübke et al., 2021) .

2. LITERATURE REVIEW

Coordinating large courses remains a persistent challenge in higher education with most instructors still making key decisions independently and departments struggling to balance shared standards with instructor autonomy.(Couch et al., 2023; Fortes & Tchantchane, 2010; Miller et al., 2024). This situation persists even when these courses are divided into smaller sections for tutoring. While splitting a large class into sections—each led by a different instructor—reduces the number of students per group, it introduces the complex challenge of ensuring consistency in instructional quality and equitable learning outcomes across all sessions. A fundamental tension arises between the need for standardization, which supports fairness and facilitates accreditation processes, and the desire to preserve pedagogical flexibility, which fosters instructor engagement and enhances student learning (Barua & Lockee, 2025, 2024).

Prompted by the COVID-19 pandemic in 2019, recent shifts in course design have emphasized the value of flexibility to improve learning outcomes. Models such as HyFlex (i.e., Hybrid + Flexible so that students can choose to attend classes in-person, live online, or asynchronously) and modular formats allow instructors to tailor content delivery to student needs and teaching preferences, promoting critical thinking and learner engagement (Barua & Lockee, 2024; Koumpis et al., 2020). However, without guardrails, such autonomy can lead to inconsistent student experiences across sections, undermining curriculum coherence and assessment validity.

To address this, institutions rely on AoL systems, particularly in accredited programs. AoL provides a structured framework to define learning outcomes, collect assessment data, and use findings to improve curriculum (Tarnoff, 2023; Tham et al., 2023). Effective AoL practices emphasize "closing the loop" or completing the cycle of evaluation and improvement, using assessment evidence to implement meaningful instructional changes (Bennett et al., 2017; Borschbach & Mescon, 2021). Yet, faculty often view these processes as administratively burdensome and disconnected from teaching, particularly when imposed top-down (Brown et al., 2017; Harvey, 2024). Resistance is common when assessment efforts are perceived as surveillance rather than tools for improvement (Moore et al., 2025).

Research suggests that AoL systems are more successful when they engage faculty as collaborators rather than as passive data providers. (Moore et al., 2025; Tarnoff, 2023) Building assessment literacy, streamlining reporting, and integrating assessment into professional learning communities can transform AoL from a compliance exercise into a shared improvement process (Bennett et al., 2017; Moore et al., 2025). This shift is fundamental in large courses where alignment across instructors is critical, and the risk of fragmentation is high.

Consistency in evaluation is another key concern in multi-section environments. Institutions such as Capella and Nova Southeastern University (NSU) have shown that using shared rubrics and standardized exam questions can ensure comparability in student outcomes while supporting transparency and fairness (Gibson et al., 2013). These tools, when developed collaboratively, not only promote equity but also enhance trust among instructors. (Couch et al., 2023; Miller et al., 2024; Tham et al., 2023).

Crucially, the literature highlights that flexibility and standardization are not mutually exclusive. Structured autonomy, where faculty work within a shared framework while retaining the ability to customize instruction, has been linked to improved student outcomes and higher instructor satisfaction (Brekke & Zhang, 2024; Cardona et al., 2022). In this context, clearly defined roles, open communication, and strong leadership are essential. Moore et al. (2025) recommend providing professional development, time support, and resources to help faculty view assessment as a meaningful activity rather than mere compliance. When these efforts are supported by digital tools that reduce workload and enhance coordination, institutions are better positioned to scale quality instruction (Borschbach & Mescon, 2021).

Importantly, shared responsibility for AoL processes, such as rubric development, assessment alignment, and data review, must be formalized as part of faculty roles. Gibson et al. (2013) demonstrate how assigning these responsibilities to "Course Academic Leaders" improves coherence across sections and meets accreditation standards. Moreover, institutional alignment across departments, administration, and faculty enables adaptive teaching practices without sacrificing strategic objectives (Aga, 2023; Brekke & Zhang, 2024).

Despite widespread agreement on these principles, literature tends to treat faculty agency, bureaucratic burden, and instructional consistency in isolation. Our work responds by offering an integrated coordination model that directly addresses these intersecting issues. Developed from the perspective of a course designer managing a foundational business course at a private college, the model embeds assessment practices within a flexible yet structured framework that promotes faculty engagement and instructional relevance.

Rather than enforcing uniformity, this approach supports instructional innovation within clearly defined boundaries. It fosters a culture where faculty are trusted to experiment, students benefit from consistent learning outcomes, and institutions can meet accreditation requirements without overburdening instructors. As demonstrated in our implementation, this model not only improves student performance but also contributes to a sustainable and inclusive academic environment.

3. METHOD

Context

The course examined in this study is a core requirement within the undergraduate business curriculum at a four-year private college in the Northeastern United States. Typically taken by first-year students, many of whom have yet to declare a major, the course introduces fundamental concepts in Information Systems, with an emphasis on the strategic role of technology in contemporary business environments. Designed to establish baseline digital literacy and critical thinking about information systems, it serves as an entry point into more advanced coursework across business disciplines.

The course is offered in over ten sections each year, with approximately 35 students enrolled per section. Instruction is provided by a mix of full-time faculty members and adjunct instructors, most of whom hold advanced degrees and possess substantial professional experience in relevant fields. Adjunct faculty typically teach one or two sections, while full-time instructors teach the remaining classes. All courses are delivered in-person each semester. This instructional diversity enriches classroom perspectives but also introduces the challenge of maintaining consistency in learning outcomes and instructional quality across sections.

In addition, this course is embedded in the institution’s AoL framework, as required by the Association to Advance Collegiate Schools of Business (AACSB). It contributes directly to the school's formal assessment cycle and is subject to annual data collection, rubric-based evaluation, and continuous improvement reporting. Because of this strategic role, the course functions as both a pedagogical and administrative touchpoint, where faculty engagement, instructional design, and accreditation goals intersect.

Within this context, the development of a scalable, instructor-centered coordination model became a practical necessity. The model described in this paper emerged in response to these institutional demands, with the dual goals of enhancing instructional coherence and preserving faculty autonomy. It represents an effort to balance structured accountability with pedagogical flexibility in a way that aligns with both faculty values and accreditation expectations.

Constraints of the Standardized Model

Prior to 2019, the course had adopted a rigid standardized coordination model for nearly a decade. An extensive literature review and a reflective analysis of the limitations inherent in the previous rigid coordination model informed the development of the new coordination system. Prior studies, as referenced earlier, emphasize the importance of maintaining instructional flexibility and preserving instructor autonomy (Barua & Lockee, 2025, 2024; Brekke & Zhang, 2024; Cardona et al., 2022; Lübke et al., 2021). They are shown to contribute significantly to educator engagement and course effectiveness. However, the practical implementation of these principles in large, multi-section courses remains uneven and often constrained by rigid coordination models that prioritize standardization at the expense of innovation.

Our proposed framework directly addresses this gap by offering a faculty-driven model of course coordination that integrates assessment, planning, and instructional support within a shared but adaptable structure. By formalizing collaboration, distributing baseline materials, and streamlining evaluation practices, the model fosters both curricular coherence and individual teaching agency. In doing so, it reframes coordination not as a mechanism of control, but as a scaffold that enables instructors to teach more creatively, confidently, and consistently—all while meeting institutional standards for quality and accountability.

This aligns with the feedback collected from instructors who have collectively taught the

coordinated freshman-year course over the past decade. According to their experiences, the previous system's rigid standardization—originally designed to ensure equity across multiple sessions—ultimately stifled innovation and discouraged pedagogical personalization tailored to each classroom's needs.
Under the earlier model, all course sections were required to adhere strictly to unified instructional materials, including identical lecture slides, in-class activities, assignments, deadlines, and grading rubrics. While this uniformity aimed to prevent perceived inequities among students enrolled in different sessions, it inadvertently introduced several systemic challenges:

1) Detachment from Grading and Student Assessment

Instructors were not directly involved in grading, as this responsibility was delegated to graduate student graders. Although instructors could review graded submissions, they often had to invest significant time deciphering grading rationale, such as interpreting rubrics and justifying point deductions, instead of focusing on identifying learning gaps or patterns in student understanding.

2) Inconsistent Grading Quality

While graduate graders received basic training from course coordinators, their relative inexperience compared to seasoned instructors resulted in variability in grading quality. This inconsistency was especially evident when comparing feedback and scores across different graders or sessions.

3) Delays and Tensions in Grade Dispute Resolution

When students contested their grades, instructors had to act as intermediaries, relaying concerns to the course coordinator, who in turn consulted the graders. This multilayered process not only delayed resolution but also created friction among students, instructors, and course administrators, undermining trust and collaboration.

4) Limited Instructional Autonomy

The uniform structure prevented instructors from designing original assignments, adjusting deadlines, or modifying content to suit the pace and dynamics of their specific sessions. This was particularly problematic in cases where students, even within the same instructor's multiple sessions, demonstrated varied learning progressions.

5) Erosion of Instructor Motivation and Ownership

Over time, the inability to shape course content or respond dynamically to classroom needs led many instructors to disengage from course development processes. Lacking a sense of ownership, instructors were less inclined to contribute new ideas or engage in continuous course improvement.

The shortcomings of the previous model underscored the need for a more balanced approach, i.e., one that preserves consistency where necessary but empowers instructors to adapt their teaching to evolving classroom realities. The new coordination system, grounded in empirical research and years of practical feedback, embodies this shift. It aims to foster a culture of instructional ownership, professional trust, and pedagogical innovation, which are essential components for creating a more equitable and enriching learning experience for students.

4. RESULTS

The New Flexible Model for Consistent Quality

Implemented in 2019, the new coordination system was designed to place instructor agency and pedagogical personalization at its core, while maintaining the consistency and accountability expected of a multi-section foundational course. Rather than enforcing rigid uniformity, the system offers a structured yet adaptable framework that supports instructional innovation without compromising quality standards.

At the core of the model is a centralized collection of sample teaching materials accompanied by clearly defined requirements and an approval process for customized alternatives. Curated by the course coordinator, these resources include lecture slides, in-class activities, assignments, syllabus templates, and sample course calendars. Rather than imposing restrictions, these materials function as a flexible instructional framework, supporting faculty while allowing room for creativity and adaptation. Each resource specifies essential requirements, including intended learning outcomes, topic coverage, relevant technical competencies, and software usage.

Instructors are encouraged to tailor or replace materials to suit their teaching styles and the needs of their student cohorts, as long as the core requirements are fulfilled. To adopt alternative materials, faculty members simply submit their proposed content along with a brief rationale demonstrating alignment with the required learning objectives. Each semester, approximately half of the instructors contact the coordinator to request customized approaches, such as new tools or assignments. These instructors typically seek approval once or twice per term.

To ensure standardization for quality assurance and accreditation compliance, the system incorporates several institutional safeguards:

1) Assessment Alignment

A set of common final exam questions is administered across all sessions. Instructors are required to report student performance on these standardized items to the course coordinator, providing the primary dataset for annual AoL reporting.

2) Faculty Collaboration and Feedback Loops

The academic year begins with a kick-off meeting and concludes with a reflection session, both of which are structured to foster shared understanding of course expectations, exchange best practices, and collect feedback for continuous improvement. These forums help instructors remain aligned while also encouraging dialogue about pedagogical strategies, course content, and student engagement.

3) Defined Flexibility with Guardrails

While final exam items are standardized and selected learning outcomes are fixed for AoL reporting, instructors retain substantial control over most elements of the course. This includes the design and sequencing of instructional materials, formative assessments, deadlines, and weekly pacing. Importantly, instructors are actively encouraged to adapt their course content and delivery methods to reflect the specific learning profiles of their students.

This “flexible standardization” model offers a thoughtful compromise between consistency and autonomy. It enables diverse instructional approaches while supporting curricular coherence and data-driven quality assurance. As a result, instructors are more empowered, student learning is better contextualized, and accreditation requirements are more meaningfully addressed.

Student Performance & Faculty Feedback

In Fall 2019, this introductory Information Systems course was relaunched with a new textbook, revised master syllabus, and a redesigned coordination framework emphasizing instructor autonomy and pedagogical flexibility. The course continued to participate in the institution’s AoL assessment, which provides the appropriate setting for assessing the effectiveness of this new coordination model, particularly in supporting student learning outcomes while maintaining consistency.

Each academic term, instructors reported AoL data based on a shared set of standardized exam questions embedded within the course’s final assessment. These common questions were designed to align with core course learning objectives across all sessions, which are mapped to the learning goals of the undergraduate business program. Instructors submitted performance data at the session level, reporting (1) the total number of students enrolled and (2) the number who correctly answered each AoL question. These measures provided a consistent and comparative snapshot of student learning across all sections and instructional formats, summarized by the following Figure 1. We analyzed aggregated, de-identified AoL data, ensuring no student-level identifiers were used. This analysis was conducted after all grades were posted, so no intervention could have affected student grades.

The institutional AoL benchmark targets at least 75% correctness per program learning goal as a threshold for adequate mastery. As shown in Figure 1, the data from Academic Years (AY) 2019 through 2025 demonstrate consistent achievement of this benchmark across nearly all sessions and assessment items.

In AY 2019–2020, the initial year of implementation, performance fell slightly below the AoL target, which was expected given the transition to new course materials and coordination procedures. Following this baseline year, faculty engaged in targeted course refinements, including revisions to in-class activities, assignment designs, and wording of assessment questions. These adjustments were informed by feedback gathered during end-of-year reflection meetings and individual instructor reports.

From AY 2020–2021 onward, the course consistently exceeded the AoL benchmark in both aggregate and session-level performance during most semesters, reflecting stronger alignment

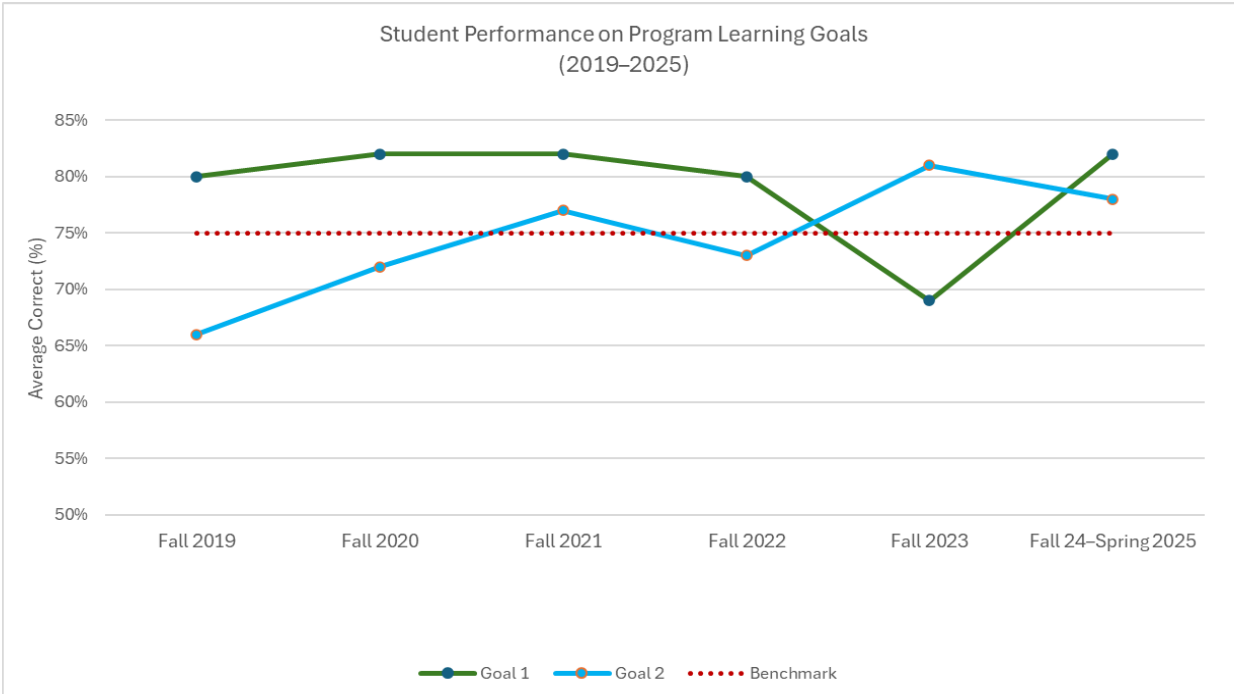

Figure 1 Student Performance Assessment under the New Coordination Model

between instruction, course objectives, and assessment instruments. In addition, the variability among course sections was minimal. In Academic Year 2024–2025, a total of 10 course sessions were delivered. The standard deviation of student performance was relatively low showing strong consistency across sections, 7.3% for Goal 1 (Business Functional Knowledge) and 3.7% for Goal 2 (Analytical & Critical Business Thinking), indicating a high level of uniformity in learning outcomes across instructors and formats.

During annual feedback sessions, the instructo team consistently praise the flexibility to tailor their sessions. They note that unlike the previous tightly controlled model, this approach fosters a sense of ownership that encourages both creativity and engagement.

To summarize, in a "flexible standardization" model, this study demonstrates a successful balance between instructor autonomy and consistent student outcomes. Furthermore, this model's emphasis on instructor agency has had a tangible, positive impact on overall student performance. Following an initial transition period, student scores on AoL assessments consistently surpassed the 75% benchmark from Academic Year 2020 onward. This finding suggests that a shift away from rigid uniformity and towards a more adaptable framework did not compromise educational quality.

5. DISCUSSIONS AND IMPLICATIONS

This study demonstrates that a structured, yet adaptable course coordination model can effectively balance autonomy for instructors with institutional accountability for learning outcomes. Consistent with Barua and Lockee (2025), the redesigned coordination system anchors the course in shared objectives, standardized assessment tools, and a curated suite of exemplary materials. However, it departs from rigid standardization by deliberately encouraging faculty to modify and build upon the base materials in a way that reflects their own pedagogical approaches and the unique needs of their student cohorts, which is supported by Brekke & Zhang (2024). This blend of structure and flexibility allows the course to maintain curricular coherence across multiple sections while fostering instructor ownership and creativity.

After implementing a new flexible teaching model in 2019, our study found that it successfully balances instructional autonomy with consistent learning outcomes. While instructors were empowered to personalize their teaching methods, the model's institutional safeguards, such as common final exam questions and faculty collaboration, ensured that all sections remained aligned with core learning goals. The student performance data confirms this success, showing a consistent achievement of the AoL benchmark and minimal variability in outcomes across different course sections. This demonstrates that empowering faculty through a "flexible standardization" framework can lead to measurable gains in student performance while ensuring curricular coherence and compliance with accreditation standards.

The role of instructor agency proved to be a central force in the success of the model. Teacher flexibility is crucial for addressing diverse student needs in inclusive settings. Flexible teachers are more likely to adapt to varied classroom situations and support both academic and social skill development in students (Lübke et al., 2021). Empowering faculty to revise course materials, contribute new resources, and shape in-class strategies cultivated a climate of continuous instructional innovation. Rather than enforcing uniformity, the coordination model created an environment in which faculty felt empowered to take initiative, experiment with delivery approaches, and iterate on their classroom practices. As a result, the course evolved organically based on insights from those directly involved in teaching, rather than through top-down mandates. This participatory model reinforces the idea that sustainable improvement in undergraduate education hinges on respecting and leveraging faculty expertise.

In terms of outcomes, the performance data strongly supports the effectiveness of this flexible model. Across six academic cycles, students consistently met or exceeded the AoL benchmark of 75% accuracy on standardized questions mapped to key learning goals. Importantly, this trend persisted despite notable variation in instructors, delivery modes, and classroom formats, underscoring the model's resilience and adaptability. The coexistence of strong student performance with pedagogical diversity suggests that coherence does not require conformity. When paired with thoughtful scaffolding and clear expectations, instructional freedom can be an asset rather than a liability.

Faculty collaboration was another emergent strength of the model. Scheduled kickoff meetings before each term and post-semester reflection sessions enabled faculty to align on expectations, share classroom insights, and iterate collaboratively on teaching strategies. These gatherings cultivated a culture of professional development in which teaching quality was not left to individual effort alone but enhanced by collegial discourse and shared stewardship of the course. This sense of community is especially valuable in large multi-section courses where instructors often operate in silos.

Moreover, the coordination system offers potential for scaling across disciplines and programs. Its key strengths, including standardized assessment anchors, curated yet modifiable resources, and transparent approval structures, make it well-suited for foundational or core courses that require consistency without sacrificing instructional relevance. The ability to disaggregate student performance by learning goals, section, and instructional strategy also enables data-driven refinement. Program leaders are now better positioned to identify performance gaps, test pedagogical interventions, and provide targeted faculty support based on real-time feedback.

While the findings of this study are grounded in a single institutional context, the proposed coordination model demonstrates strong potential for generalization across similar educational settings. Its successful implementation relies on several key conditions, including institutional support for shared governance, a structured Assurance of Learning (AoL) framework, and a culture that values faculty collaboration and instructional autonomy. Although the model was developed in a private college environment with moderate class sizes, its core principles—such as standardized assessment anchors, flexible instructional design, and faculty-led innovation—are adaptable to larger and more complex institutions. In particular, the role of leadership in facilitating coordination, maintaining alignment, and fostering trust among instructors is critical to successful replication. Future research should explore the implementation of this model in diverse institutional contexts, including large public universities and fully online programs, to further assess its scalability and external validity.

6. CONCLUSIONS

This study affirms the pedagogical and operational value of a flexible, instructor-centered coordination model in large, multi-section courses. By allowing instructors to exercise agency within a structured framework of shared goals and assessments, the system successfully navigates the tension between consistency and customization. The sustained achievement of learning benchmarks, paired with minimal variation across sessions, illustrates the model's capacity to maintain quality while honoring instructional diversity.

The implications of this model extend beyond the immediate context of a single course or program. For institutions operating in decentralized teaching environments, particularly those under pressure to demonstrate AoL compliance, this approach offers a compelling alternative to rigid standardization. The hybrid design facilitates alignment with institutional goals while supporting instructors' professional judgment and instructional creativity.

Moreover, the model's emphasis on autonomy has potential ripple effects on faculty engagement and retention. Allowing instructors to tailor content according to their pedagogical style and student demographics not only fosters greater investment in teaching but may also mitigate burnout and turnover, especially in high-enrollment or high-demand course areas. Future research should focus on systematically gathering faculty feedback about their experiences with the coordination model. From the student perspective, the flexibility inherent in this model contributes to more responsive and inclusive instruction. Instructors can better align course content with the modalities, backgrounds, and expectations of diverse student populations, whether teaching in-person, online, hybrid, or across varying regional contexts.

Importantly, the model also strengthens institutional positioning in accreditation and curriculum review cycles. By pairing structured learning objectives with standardized assessment items and transparent reporting, programs are better equipped to present clear, evidence-based narratives about student learning, curricular coherence, and continuous improvement.
Finally, while the system requires initial investments in coordination labor, shared content development, and instructor onboarding, these costs can be amortized over time through improved instructional alignment and more efficient assessment management. As institutions seek scalable solutions to meet evolving pedagogical and accreditation demands, this model presents a sustainable, adaptable framework with broad potential for replication.

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Student Engagement in IT Programs: What NSSE Captures and What It Misses

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Abstract

Are IT students truly disengaged, or do our assessment tools fail to recognize their unique modes of engagement? This work examines how well the National Survey of Student Engagement (NSSE) captures student engagement in Information Technology (IT) programs. The NSSE emphasizes group work, class discussions, and cross-disciplinary assignments, activities that diverge sharply from the common practices in IT, which often include solo work, lengthy periods of concentration, and complex system design. IT students also differ in how they interact with technology, engage with peer students, and learn, but NSSE does not account for these differences. As a result, NSSE data tends to underrepresent the real engagement of IT students. This misalignment underestimates the support and challenges IT students experience and motivates IT educators to change teaching practices to match the survey instead of the students. As a discipline, we need new measures that reflect how our students actually learn and work. Better tools will support improved teaching, more accurate engagement data, and higher rates of degree completion.

Keywords: National Survey of Student Engagement (NSSE), Information Systems Education, Computer Science Education, Student Engagement Measurement, ABET, Higher Education.

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Student Engagement in IT Programs: What NSSE Captures and What It Misses

James Wolf and Pruthikrai Mahatanankoon

1. INTRODUCTION

Results from the National Survey of Student Engagement (NSSE) and similar international instruments suggest that information technology (IT) students consistently self-report low student engagement scores (Butler et al., 2016; Morgan et al., 2018a, 2018b), leading some IT educators to suggest the need to strengthen student engagement as a key component in solving many of computing education's well-known troubles (Morgan et al., 2018a, 2018b). Yet the unique nature of IT learning itself offers plausible explanations for the low NSSE scores among IT students. This context leads to an intriguing question: Are IT students truly disengaged, or have our assessment tools failed to accurately measure their unique modes of engagement?

NSSE, pronounced "Nessie" like the mythical Scottish lake creature, is the most widely used benchmark for assessing North American undergraduate student engagement. Although the survey is respected and validated (Kuh et al., 2008), it is geared toward more traditional classes, with items covering the number of papers written, the length of papers, and the frequency of class presentations (Kuh, 2001). Meanwhile, IT classes focus less on the types of collaborations NSSE measures, such as including diverse political, religious, racial/ethnic, and gender perspectives or connecting learning to societal problems or issues. Indeed, many of NSSE's items have little to nothing to do with instruction or assessments commonly employed in IT classes, whose curriculum is typically skill- and logic-oriented, emphasizing technical skill acquisition over other forms of academic interaction. IT education is often characterized by more individualistic learning, with tasks like coding or system design demanding deep, solitary focus.

The distinctive nature of IT education and the narrow focus of the NSSE survey means that it, and other similar surveys, could present a misleading picture of the hours students spend in intense, solitary coding—a highly engaging activity for many IT students, particularly those with autistic traits conducive to "flow states"—as disengagement rather than productive forms of deep learning engagement (Heasman et al., 2024; Rapaport et al., 2024). Therefore, the low NSSE scores among IT students may not be evidence of a lack of engagement per se, but rather an indication that the instrument does not fully capture these students' modes of engagement.

An added degree of urgency to accurately measure IT student engagement comes from the push to use national student engagement surveys, like NSSE, as performance indicators that affect funding. In the U.S., Australia, and the UK, links between these surveys and tuition fees or funding have been proposed, tested, or dropped (Butler et al., 2016; Morgan et al., 2018b).

2. STUDENT ENGAGEMENT

Student engagement, which refers to a student's psychological commitment to acquiring, comprehending, and excelling in the skills and knowledge required for academic tasks (Lamborn et al., 1992), is one of the most extensively studied constructs in education due to its positive links with academic performance, retention, and graduation (Fredricks & McColskey, 2012; Morgan et al., 2018a, 2018b). Engaged students are more likely to stay in school, learn more, perform better academically, and reach their goals (Fredricks et al., 2004; Kuh, 2001; Morgan et al., 2018a; Morgan et al., 2018b). Student engagement has three distinct components: cognitive, behavioral, and emotional engagement (Fredricks & McColskey, 2012; Wong & Liem, 2022).

Cognitive engagement involves a willingness to invest effort to understand complex ideas and master difficult skills. It can range from "deep" engagement, which involves actively using prior knowledge and creating complex knowledge structures, to "shallow/surface" engagement, characterized by rote processing and mechanical actions such as verbatim memorization (Greene, 2015; Mahatanankoon & Wolf, 2021). Self-regulation, including goal-setting, planning, monitoring, and self-reflection, is also part of cognitive engagement (Greene, 2015; Greene et al., 2004; Greene & Miller, 1996).

Emotional engagement reflects how students feel about their learning experiences. It can include feelings of interest, enjoyment, enthusiasm, vigor, and alertness (Fredricks & McColskey, 2012; Wong & Liem, 2022). Emotional engagement also involves students' identification with their school, including a sense of belonging and valuing their education.

Behavioral engagement refers to students' active participation and involvement in academic, social, and/or extracurricular activities, characterized by their effort and adherence to school and classroom norms (Fredricks & McColskey, 2012; Wong & Liem, 2022). Examples include paying attention in class, exerting effort, persisting in carrying out tasks, completing homework, participating in discussions, attending school, and engaging in extracurricular activities.

The bulk of existing studies on instructional innovation in IT have focused on students' behavioral engagement, as it is the easiest of the three engagement components to observe and measure. Excellent examples of such behavioral work include Davies (2002), Hakkarainen and Palonen (2003), and Hew and Cheung (2008). Similarly, the majority of items in existing student engagement scales, such as NSSE, also capture student behavior (Butler et al., 2016).

NSSE

NSSE was launched in 2000 (Kuh, 2001) and was originally funded by a grant from the Pew Charitable Trusts. By shifting to web-based surveys and attracting more colleges, NSSE became self-sustaining through institutional user fees in 2003 (Kuh, 2009). NSSE was designed as an alternative to college rankings, which often provide little insight into the actual student experience (Kuh, 2001, 2009). Although most collegiate rankings focus on reputation and resources (e.g., student SAT scores, faculty credentials, library holdings), NSSE focuses on active participation in practices linked to enhanced learning and development (Kuh, 2001, 2003, 2009).

Each year, NSSE surveys first-year and senior students at four-year institutions to understand their behavior and experiences related to learning and personal development (Kuh, 2001, 2003). NSSE was adopted rapidly, administered to approximately 75,000 students at 276 schools in its first national administration in 2000, to more than 220,000 students from about 320 institutions by 2001, accumulating data from 285,000 first-year and senior students from more than 600 four-year colleges and universities in its first three years (Kuh, 2001, 2003). In 2023, 354,067 students at 543 American and Canadian institutions completed the survey (National Survey of Student Engagement, 2023).

Rather than directly assessing student learning outcomes, NSSE measures students' participation in practices associated with educational outcomes and groups the practices into five benchmarks: level of academic challenge, active and collaborative learning, student–faculty interaction, enriching educational experiences, and supportive campus environment (Kuh, 2001, 2003, 2009). These five benchmarks allow for institutional comparisons and the ability to pinpoint areas for improvement.

Student engagement comprises two parts: one linked to the students and the other centered around the institution (Kuh, 2001; Wolf-Wendel et al., 2009). The organization-centered aspect relates to how higher education institutions allocate resources and structure learning opportunities to encourage student participation, whereas the student-centered aspect assesses students' time and effort in their studies (Kuh, 2001). NSSE captures both organization-centered and student-centered aspects of student engagement (Kuh, 2001, 2003).

Studies on the link between NSSE scores and academic success have produced mixed results. Although some find that higher institutional NSSE scores correlate with greater collegiate success (Kuh et al, 2008; Pike, 2013), critics have noted imperfect alignment between NSSE survey items and direct learning measures or student grade point averages (Campbell & Cabrera, 2011; Gordon et al., 2007; Porter et al., 2011; Price & Baker, 2012). Moreover, NSSE was designed for campus-level benchmarking, not for evaluating individual departments or majors (Kuh, 2001, 2003, 2009). For individual departments and programs, higher education relies on specialized accreditations—such as AACSB, ABET, or similar quality assurance processes. As a result, our concerns about the survey are not with NSSE per se, but with the way NSSE data are being misinterpreted by university administrators.

Student engagement matters; how we measure it matters more. Student engagement is widely viewed as central to learning. But it is unclear whether NSSE fits disciplines like IT, where pedagogy, outcomes, and student experience often differ from the norm.

3. UNIQUENESS OF IT EDUCATION

IT professionals, students, and faculty differ from their peers in other fields in how they think, work, and learn. The culture prizes technical skill, structure, and extended periods of individual effort. These traits contrast with the collaborative and discussion-based activities that dominate other disciplines, raising questions about whether current engagement measures fit the field at all. The following sections explore these differences by examining IT education from the perspectives of IT professionals and students.

IT Professionals are Different

IT professionals differ from others in their work culture, required skills, personal traits, and reasons for changing jobs. IT culture values technical skills and informal practices. Professionals rely heavily on jargon, enjoy a great deal of freedom, and deal frequently with change (Guzman et al., 2004; Jacks et al., 2018; Prommegger et al., 2020; Rao & Ramachandran, 2011). This autonomy brings constant pressure and tight deadlines, creating a sense of endless tasks (Ahuja et al., 2007; Armstrong et al., 2015; Joseph et al., 2011; Rutner et al., 2011; Zhang et al., 2012).

Another issue is rapid technological change. Rapid technological change means continuous learning is necessary to remain useful (Benamati & Lederer, 2001; Rong & Grover, 2009); thus, IT professionals must continually update their skills in technical areas, business knowledge, and communication (Gonçalves et al., 2024; Riemenschneider & Armstrong, 2021). In addition, IT jobs blend creativity with logic. Although IT professionals gain respect for their technical skills, they tend to face stereotypes about their poor social skills. They often prefer working with machines and speak in technical terms while ignoring social norms (Glen, 2002; Moore & Love, 2011). These mixed public perceptions—namely, admiration for technical expertise alongside criticism of individuals' poor communication skills—are further strengthened by the fact that the computing profession lacks widely accepted ethical standards or consistent certifications, unlike fields such as law or medicine (Denning, 2001).

Although many IT roles require teamwork, professionals typically have lower social needs but a strong motivation to succeed (Balijepally et al., 2006; Lounsbury et al., 2007; Prommegger et al., 2020). Different career paths and changing job prospects also motivate them to engage in continuous skill improvement (Joseph et al., 2011; Zhang et al., 2012). Indeed, experienced IT workers prefer roles offering growth, new technologies, and skill development (Niederman et al., 2016; Prommegger et al., 2020). However, heavy workloads drive them away from positions, particularly in agile environments requiring frequent interactions and tight deadlines (Chilton et al., 2010; Meske & Junglas, 2021; Tuomivaara et al., 2017; Zaza et al., 2023). IT workers often feel a loyalty to the profession that outweighs loyalty to an employer; as a result, they frequently switch companies (Jacks & Palvia, 2014; Joseph et al., 2012, 2015; Zaza et al., 2023). To help retain workers, companies should offer meaningful support, including effective tools and fair working conditions (DeConinck & Stilwell, 2004).

Personality also shapes IT professionals' experiences. Computing roles often suit neurodivergent people, particularly those with autism. Tasks tend to be logical, structured, and predictable, matching common autistic preferences (Grandin & Panek, 2013). Not surprisingly, many IT professionals show higher levels of autistic traits compared to the general population, leading them to experience increased stress and lower coping abilities. Such traits relate to lower emotional control and higher burnout risks (Hill, 2004; Hirvikoski & Blomqvist, 2015; Ilen et al., 2024; Jia et al., 2022, 2024).

Yet many IT jobs also involve less emotional labor compared to service roles, thereby reducing stress related to managing emotional expressions (Jia et al., 2024, 2025). Collaboration exists, but tasks like coding provide long periods for individual focus and minimal social interaction (Armstrong, 2012). This mix of structure, low emotional demands, and solo work may offer relief to people who find social ambiguity or emotional display exhausting.

IT Students are Different

Computing majors have historically faced gender and racial diversity issues (Mahatanankoon et al., 2012). Women and students from historically underrepresented backgrounds have lower representation and retention rates in computing programs than white and Asian men (Lehman et al., 2023; Salguero et al., 2021; Whitney et al., 2013). Despite enrollment numbers for women and underrepresented students increasing in recent years, these students leave computing majors at higher rates than their counterparts (Lehman et al., 2023).

IT draws people with specific thinking styles, communication habits, and work preferences. For example, people with autistic traits have higher intrinsic interest in computing technology (Jia et al., 2022). This interest may reflect neurological patterns that align with the nature of the work (Jia et al., 2022). IT students are motivated by innovative technologies, hands-on experiential learning, and skill development. Research on IT adoption suggests that individuals differ in their uniqueness. Personal Innovativeness in IT (PIIT) also explains why some people strongly engage with technology. Agarwal and Prasad (1998) defined PIIT as "the willingness of an individual to try out any new information technology" (p. 206). PIIT appears in major models, such as the technology acceptance model (TAM) (Davis, 1989) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). Rosen (2005) and Rosen and Kluemper (2008) found that traits linked to autism, such as deep focus and narrow interests, often predict higher PIIT, which plays a central role in technology acceptance. These traits often fall outside the norms assumed by standard surveys and evaluations. When those tools fail to reflect the reality of IT learning and teaching, the blame shifts to the people, not the instruments. While NSSE captures engagement for many students, it misses it for others, especially those in computing programs.

In sum, the professional demands of IT careers and the learning needs of IT students underscore the need for appropriate engagement measures in IT programs, centered on traits, interaction with technology, and skill development rather than interpersonal engagement.

4. NSSE ENGAGEMENT PATTERNS AMONG IT STUDENTS

Year in College	ALL	CS	IS
1	35.24	34.46	33.79
4	36.26	33.32	32.56

Table 1: 2023 Average Scores by Year and Major

This section reports annual results from the 2023 NSSE survey (National Survey of Student Engagement, 2023). Throughout this paper, we use "Information Technology (IT)" as an umbrella term that includes all computing majors. In the NSSE dataset, the reported categories that fall within IT are Computer Science (CS) and Information Systems (IS), so we treat them as proxies for IT students. Table 1 shows a summary of 2023 NSSE Engagement Indicator average scores across all measured constructs for students in all majors, Computer Science (CS) majors, and Information Systems (IS) majors. CS and IS majors tend to have lower average NSSE scores compared to other majors in both their first and fourth years, with the disparity appearing to be more pronounced for fourth-year students. While the average engagement for all majors increased from year 1 to year 4, the average engagement for both CS and IS majors decreased over the same period, further widening the disparity. The first to fourth year decrease in NSSE scores found in the 2023 survey is consistent with earlier findings (Morgan et al., 2018a, 2018b; Sinclair et al., 2015).

Engagement Indicator	All Majors	IS	CS
Collaborative Learning	30.3	20.7	30.8
Discussions with Diverse Others	38.5	34.2	38.0
Learning Strategies	38.7	39.5	36.4
Student-Faculty Interaction	22.7	19.9	20.5
Reflective & Integrative Learning	36.3	34.8	34.3

Table 2: 2023 First-Year IS and CS Students: Engagement Indicators with Large Performance Gaps

Table 2 shows that lower NSSE scores for CS and IS students are apparent even in their first year, though concentrated in specific areas. Information systems students have the largest gap in collaborative learning, scoring 9.6 points below the NSSE average (20.7 vs. 30.3), suggesting significant incongruence with NSSE's proxy for peer-to-peer learning activities. Both majors struggle substantially with student-faculty interaction, with CS students scoring 2.2 points below average and IS students 2.8 points below. CS students also show notably lower scores in NSSE items for learning strategies (-2.3 points) and reflective and integrative learning (-2.0 points). Curiously, IS students score lower on items involving diverse others (-4.3 points), while CS students perform at or near average in this area.

Table 3 shows increased NSSE score gaps by senior year, with both majors now showing substantial gaps across most indicators. The size of these gaps also increases, with reflective and integrative learning becoming the area with the largest gap for CS students (-6.2 points) and collaborative learning remaining the largest gap for IS students (-7.2 points). Student-faculty interaction deficits worsen for both majors, reaching -4.8 points for CS and -5.4 points for IS.

Perhaps most troubling, new areas of NSSE score gaps emerge by senior year, including learning strategies for CS students (-4.6 points), higher-order learning for both majors (CS: -3.8, IS: -2.0), and effective teaching practices (CS: -3.1, IS: -2.2). This pattern suggests one of two possibilities: either computing students grow less engaged across multiple dimensions of their educational experience, or the NSSE fails to capture important ways IT students engage as they progress through their computing degree programs.

Engagement Indicator	All Majors	IS	CS
Collaborative Learning	31.1	23.9	31.7
Reflective & Integrative Learning	39.3	34.6	33.1
Student-Faculty Interaction	25.1	19.7	20.3
Discussions with Diverse Others	39.0	34.2	36.9
Learning Strategies	39.5	38.3	34.9
Higher-Order Learning	41.1	39.1	37.3
Effective Teaching Practices	40.4	38.2	37.3
Supportive Environment	32.5	30.9	30.3

Table 3: 2023 Senior IS and CS Students: Engagement Indicators with Largest Performance Gaps

Engagement Indicator	All Majors	IS	CS
Quality of Interactions	43.5	45.5	43.2
Quantitative Reasoning	29.4	30.4	30.0
Effective Teaching Practices	38.7	40.0	38.5
Learning Strategies	38.7	39.5	36.4
Higher-Order Learning	38.8	39.3	38.3
Collaborative Learning	30.3	20.7	30.8

Table 4: 2023 First-Year IS and CS Students: Engagement Indicators with Strongest Relative Performance

Table 4 identifies several areas where first-year CS and IS students demonstrate competitive or superior NSSE scores compared to their peers. Both majors excel in quantitative reasoning, with CS students scoring 0.6 points above average and IS students 1.0 points above, reflecting the mathematical foundations of computing disciplines. Information systems students show particular strength in quality of interactions (+2.0 points), effective teaching practices (+1.3 points), learning strategies (+0.8 points), and higher-order learning (+0.5 points), suggesting they enter college with strong interpersonal and academic skills. Computer science students perform above average in collaborative learning (+0.5 points) during their first year. These relative strengths indicate that computing students possess important capabilities upon entry, particularly in analytical thinking and, for IS students, in several interpersonal and learning domains.

Engagement Indicator	All Majors	IS	CS
Quality of Interactions	43.2	44.7	41.7
Collaborative Learning	31.1	23.9	31.7
Quantitative Reasoning	31.4	31.3	29.7

Table 5: 2023 Senior IS and CS Students: Engagement Indicators with Strongest Relative Performance

Table 5 reveals a dramatic reduction in areas of relative strength by senior year, with only three indicators where either major performs competitively compared to NSSE averages. Information systems students maintain their strength in quality of interactions (+1.5 points) throughout college, suggesting sustained interpersonal competencies. CS students only show above-average performance in collaborative learning (+0.6 points), though this represents a notable shift from IS students' first-year strength in this area. Both majors perform near average in quantitative reasoning, though CS students drop below average (-1.7 points) while IS students maintain near-parity (-0.1 points). NSSE scores show a drop from six areas of relative strength in the first year to only three by senior year. This pattern further suggests that the NSSE survey may be missing key ways computing students engage as they progress through their degree programs.

To support our argument, we also collected ABET's CAC Student Outcomes (see the Appendix) and correlated them with NSSE's learning-related items, i.e., collaborative learning (CL), higher-order learning (HO), learning strategies (LS), and reflective and integrative learning (RI). ABET's CAC Student Outcomes (see Section 9, the Appendix) are required for any ABET-accredited computing program. We conducted an exploratory stepwise linear regression to determine which NSSE learning engagement indicators best predict ABET's CAC Student Outcomes. While our sample sizes are small (number of students (n)=46), Table 6 reveals that, for CS students, LS (β=.570, p<.01) and CL (β=.298, p<.01) are the best predictors for ABET's Student Outcomes (R^2=.52, F=16.52, p<.001). Only LS (β=.68, p<.01) was a strong predictor for ABET's Student Outcomes (R^2=.52, F=10.34, p<.01) for the IS students.

Major	n	INV	β	p	R^2(DV)
CS	33	LS	.570	<.001	.524
		CL	.298	.033	
IS	13	LS	.680	.007	.462

Table 6: NSSE's Predictors (INV) of ABET's Student Outcomes (DV)

The results suggest that IT students are uniquely individualistic because the LS items capture the behaviors that can be accomplished individually. See Section 9, the Appendix. The reason for the significant CL result among CS students could be related to the need for study groups and team efforts on complex coding projects. More data is needed.

5. DISCUSSION

This work explored whether NSSE is a good tool for measuring student engagement in IT programs. More broadly, it asked: *Why do so many accept the claim that IT students are not engaged, despite overwhelming evidence to the contrary? In other words, is NSSE effective for IT students, and to what extent?*

As mentioned earlier, IT students and professionals often think and communicate in distinct ways. They hold technical interests that set them apart, follow social values that differ from the mainstream, and develop work habits that do not match common expectations.

Figure 1 shows that both computer science (CS) and information systems (IS) majors have lower average NSSE scores than other majors in both their first and fourth years. Whereas the average engagement for all majors increased from the first to fourth years, the average engagement for both CS and IS majors decreased over the same period, further widening the disparity. These results are consistent with earlier research (Morgan et al., 2018; Sinclair et al., 2015).

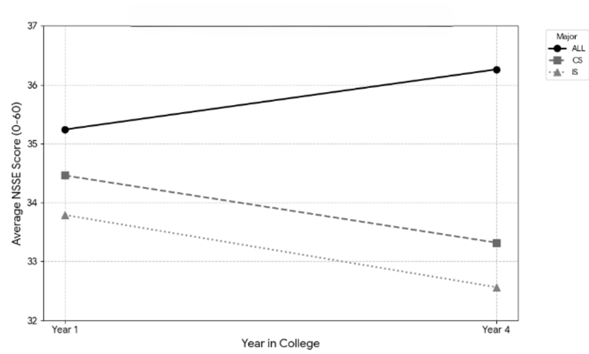

Figure 1: 2023 Overall Average NSSE Scores by Year and Major

This first-year to fourth-year engagement decline suggests that something is amiss with NSSE measures and is perhaps the strongest argument against NSSE's accuracy. NSSE data suggest that fourth-year IT students, who have already passed the notoriously difficult introductory courses and are the nearest to successful degree completion, report lower NSSE scores than first-year computing majors (Morgan et al., 2018; Sinclair et al., 2015). Obviously, given the gaps in understanding, more work is needed to determine the exact cause of the first-year to fourth-year decline in NSSE scores. Nonetheless, Table 6 shows that one of the NSSE measurements, i.e., Learning Strategies, correlates with ABET outcomes. The finding indicates that IT students are engaging in both rote and analytical learning, i.e., reading assignments, reviewing class notes, and summarizing course materials, to build advanced IT skills aligned with ABET's student learning outcomes. But these learning strategies decline over time as IT students approach graduation. Refer to Tables 2 and 3. We can attribute this decline to two factors: 1) the changes in the IT discipline that focus on hands-on practice and the focus of building IT artifacts, which often requires a high level of cognitive effort (Mahatanankoon and Wolf, 2025), and 2) NSSE's Higher-Order Learning does not capture IT's "higher-order" student learning activities or ABET's Student Outcomes. The second reason deserves further investigation.

We observe that NSSE's Collaborative Learning score for IS freshmen is 9.6 points below the NSSE average. Refer to Table 2. But Table 3 shows higher levels of NSSE's Collaborative Learning among senior IT students (+15% for IS; +3% for CS) than among freshmen. It is considered a positive finding as Collaborative Learning is the foundational soft skill for information systems development. While it is difficult for us to increase Collaborative Learning among IS freshmen due to general education requirements and foundational programming classes, we can design assignments that emphasize collaboration in their sophomore and junior years. The positive changes in NSSE observed among senior IS students suggest we are moving in the right direction.

The decreased levels of NSSE's Quality of Interactions within the campus environment among IT seniors are discouraging, but understandable from an IT standpoint. As students approach their graduation, they focus more on job interviews and less on campus activities.

The preliminary investigation substantiates our original premise that the existing NSSE constructs do not capture the essence of IT student engagement and the student learning outcomes demanded by IT curricula. To some extent, all NSSE's constructs serve as a guide to what any undergraduate major needs to accomplish, but NSSE may not be effective for IT students.

NSSE is invaluable and has been well-established. Higher education and its administrators will continue to use NSSE, but IT educators should modify NSSE's constructs or perform item-level analyses to fit their IT curricula, including adopting some of its measurement items to support their students' learning needs and accreditation process.

Regardless, we caution IT faculty and administrators against gaming the system by "teaching to the survey." To improve NSSE scores, IT faculty might cynically engage in assessment-driven instruction by incorporating more research papers and presentations into the curriculum. However, these changes may improve NSSE scores while having little positive impact on IT student engagement or learning.

6. IMPLICATIONS

Changing the curriculum to "game the NSSE survey" could lead to an engagement paradox, which describes situations in which efforts to increase engagement lead to unintended or contradictory outcomes, such as disengagement, overload, or diminished returns (Elamer & Kato, 2025; Huang & Zhang, 2019; Ludike, 2018; Perrmann-Graham et al., 2025; Shernoff & Schmidt, 2008). In information systems and management research, this paradox is particularly relevant in areas such as digital platforms, employee experience management, performance systems, and user interactions with social media (Elamer & Kato, 2025; Huang & Zhang, 2019; Hou et al., 2025; Ludike, 2018).

Other possible unintended consequences of gaming the NSSE survey stem from Campbell's Law and its close cousin, Goodhart's Law. Goodhart's Law states that "when a measure becomes a target, it ceases to be a good measure" (Goodhart, 1984). In other words, when a metric is transformed into a goal, measured entities may strategically alter their behavior specifically to achieve the target metric (Burton-Jones, 2023; Fire & Guestrin, 2019; Treem et al., 2023). The original purpose and validity of the measure are corrupted by this strategic behavior. Strategic behavior is also captured by Campbell's Law, which states that "*The more any quantitative social indicator is used for social decision-making, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the social processes it is intended to monitor.*" (Campbell, 1979).

Several studies within the IT literature show that fixation on decision-making metrics creates incentives for strategic behavior. For example, reputation systems build user trust and enable online transactions among distant strangers, but these systems are also susceptible to gaming (Dellarocas, 2003, 2005; Friedman & Resnick, 2001). Similarly, He et al. (2022) found that tying monetary rewards to metrics for user-generated content leads to unintended behavioral distortions. Likewise, work in finance (Franco-Santos & Otley, 2018; Jensen, 2003) and health care (Agarwal et al., 2010; Edwards, 2019; Muller, 2018; Rabiei & Almasi, 2022) has demonstrated that basing rewards or penalties on performance metrics inevitably leads to system gaming and information manipulation.

When "test scores become the goal of the teaching process, they both lose their value as indicators of educational status and distort the educational process in undesirable ways" (Fire & Guestrin, 2019). Similarly, if IT faculty adopt strategies to boost NSSE results, effectively teaching to the survey, NSSE scores may go up, but the actual level of engagement or quality of the educational experience may suffer.

A better strategy—and one we endorse—is for IT faculty to develop more accurate discipline-specific measures of *learning performance* and *student engagement*. IT educators desperately need empirically grounded tools and strategies to expand the field's appeal, especially among women and underrepresented groups, while sustaining the curiosity and commitment of students and faculty intrinsically interested in computing and technology. Mahatanankoon and Wolf (2025) propose that there are different levels of cognitive engagement in computer programming activities and argue for the use of multi-level learning strategies equivalent to those in Bloom's taxonomy. If the educational objectives of CS and IS are to focus on "experiential learning," thereby creating practical IT artifacts during students' senior years, then it would be advantageous to retrofit NSSE's measures or create new ones that can measure IT-based student engagement as students progress through their degree programs.

In the meantime, accredited IT programs can insert additional "performance indicators" and "student outcomes" that go beyond accreditation criteria. These additions may strengthen the dimensions measured by NSSE. In addition, different types of student engagement instruments, i.e., cognitive, behavioral, and emotional, may also be used to indirectly assess student learning outcomes. For example, these engagement measures may ask about assignments that encourage deep learning (cognitive engagement), actively mentoring junior peers (behavioral engagement), or having an affinity toward IT (emotional engagement). Not all degree programs have accreditation. However, those that do can add their own student learning outcomes in addition to the mandatory ones set by the accrediting body (Leidig, 2022).

7. CONCLUSION

The nature of the IT discipline is unique in terms of its skillset, the diversity of its students and professionals, and the nature of its work and careers. The mixed NSSE scores among IT students compared to other majors should motivate us to explore new or enhanced engagement measures. Future measures may include attributes distinctive to IT students, including motivation, IT work culture, skills, gender, personality traits, and neurodiversity. It is our hope that this paper will inspire IT educators and researchers to explore innovative engagement measures in the context of the IT discipline.

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9. APPENDIX

NSSE Measurements

Higher-Order Learning

- Applying facts, theories or methods to practical problems or new situations
- Analyzing an idea, experience, or line of reasoning in depth by examining its parts
- Evaluating a point of view, decision, or information source
- Forming a new idea or understanding from various pieces of information

Reflective & Integrative Learning

- Combining ideas from different courses when completing assignments
- Connecting your learning to societal problems or issues
- Including diverse perspectives (political, religious, racial/ethnic, gender, etc.) in course discussions or assignments
- Examining the strengths and weaknesses of your own views on a topic or issue
- Trying to better understand someone else's views by imagining how an issue looks from his or her perspective
- Learning something that changed the way you understand an issue or concept
- Connecting ideas from your courses to your prior experiences and knowledge

Learning Strategies

- Identifying key information from reading assignments
- Reviewing your notes after class
- Summarizing what you learned in class or from course materials

Collaborative Learning

- Asking other students to help you understand course material
- Explaining course material to one or more students
- Preparing for exams by discussing or working through course material with other students.
- Working with other students on projects or assignments

ABET's Computer Accreditation Commission (CAC) Student Outcomes Measures

- Analyzing complex computing problems to identify solutions
- Applying principles of computing to identify solutions
- Designing a computer-based solution to meet a given set of computing requirements
- Implementing a computer-based solution to meet a given set of computing requirements
- Evaluating a computer-based solution to meet a given set of computing requirements
- Communicating effectively in a variety of professional contexts
- Recognizing professional responsibilities and making informed judgments in computing practice based on legal and ethical principles
- Functioning effectively as a member or leader of a team engaged in activities

Human - AI Collaboration in Knowledge Transfer: A Research Agenda Integrating Knowledge Management

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Abstract

The rapid diffusion of generative artificial intelligence (AI) has intensified the need for theory-driven frameworks that explain how human actors and AI systems collaborate in knowledge transfer and knowledge work. Addressing this need, this paper synthesizes prior research across knowledge management, learning theory, and information systems ethics to clarify the problem space of human–AI collaboration. Through a comprehensive literature review, the study identifies key theoretical and practical gaps, particularly in understanding how AI reshapes knowledge creation, interpretation, and governance in practice. Building on this synthesis, the paper develops an integrated conceptual model grounded in the Socialization, Externalization, Combination, and Internalization (SECI) model, Self-Determination Theory, and Value-Sensitive Design, which organizes the domain into three interrelated dimensions: knowledge transfer processes, human cognitive and social dynamics, and ethical governance in AI-mediated knowledge work. To move beyond conceptual framing, the paper operationalizes these dimensions into three complementary research streams, providing structured and comparable study designs that enable systematic empirical investigation. These streams examine (1) configurations of human and AI involvement in knowledge transfer, (2) the cognitive and motivational dynamics of AI-mediated knowledge work overtime, and (3) ethical governance structures shaping accountability, fairness, and autonomy. To demonstrate feasibility, a small-scale exploratory exercise is conducted to refine key elements of the experimental design and research protocol. Together, this work provides both a conceptual foundation and a structured research agenda, enabling cumulative and theory-driven investigation of human–AI collaboration while positioning AI as a complementary knowledge resource that reshapes, rather than replaces, human expertise in knowledge-intensive contexts.

Keywords: Knowledge Transfer; Human-AI Collaboration; Ethical AI; Knowledge Management; AI Governance

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Human - AI Collaboration in Knowledge Transfer: A Research Agenda integrating Knowledge Management

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1. INTRODUCTION

The integration of Artificial Intelligence (AI) into knowledge-intensive work has introduced a fundamental shift in how knowledge is created, transferred, and interpreted within organizational settings (Abdel-Karim et al., 2023; Benbya et al., 2024). Generative AI systems such as ChatGPT and Google's Gemini increasingly act as intermediaries between knowledge sources and human users, reshaping how individuals access explanations, synthesize information, and apply expertise in practice (Alsafari et al., 2024; Sturm et al., 2021; Leonardi., 2023). Educational environments offer a particularly visible and bounded context in which these shifts can be observed, as instructors and learners confront questions surrounding authorship, interpretation, and the appropriate division of cognitive labor between humans and AI systems (Chu., 2023). Institutional responses have ranged from outright prohibition to structured integration, reflecting broader organizational challenges in governing AI-mediated knowledge work rather than resistance to technology per se (Yang & Subramanyam., 2022). As AI tools become embedded in everyday knowledge tasks such as research, explanation, and problem solving, the boundaries between human expertise, algorithmic assistance, and independent knowledge construction become increasingly difficult to define (Chu., 2023).

At the same time, the dynamics of knowledge transfer in AI-mediated environments are becoming increasingly multidirectional. Traditional linear flows of knowledge from expert to recipient are being replaced by complex exchanges among human actors, AI systems, and distributed peer networks (Faraj et al., 2018; Jarrahi., 2018; Raisch & Krakowski., 2021). This shift introduces challenges related to knowledge quality, interpretive alignment, and collaborative sensemaking (Al-Emran et al., 2024). Human actors increasingly play a critical role in identifying, interpreting, and applying knowledge within digitally transformed environments, requiring stronger capabilities in managing complex information flows and aligning knowledge with organizational contexts (Thomas., 2024). Despite growing interest, gaps remain in understanding effective models of human–AI collaboration, the implications for autonomy and decision-making in AI-supported knowledge work, and the evolving distribution of cognitive responsibility between humans and systems (Hase & Kuhl., 2024).

These emerging complexities extend beyond isolated interaction patterns and point to a broader lack of clarity in how human–AI collaboration should be conceptualized across knowledge-intensive contexts. As AI technologies become increasingly sophisticated and embedded within knowledge-intensive settings, there is a growing need to better understand how human actors and AI systems interact within knowledge creation, transfer, and use, along with the associated cognitive, social, and ethical implications (García Lozano et al., 2020; Xue et al., 2022; Abdel-Karim et al., 2023). This need is amplified by the rapid pace of AI advancement and its expanding deployment across organizational and institutional settings (Kwon & Lee., 2024; Lin et al., 2023), where governance structures, knowledge management practices, and normative guidelines for human–AI collaboration remain underdeveloped (Fink et al., 2024; Maita et al., 2024). As a result, fundamental questions remain unresolved regarding how AI systems influence knowledge interpretation and judgment; how reliance on AI affects human motivation, autonomy, and self-efficacy; and how responsibility and cognitive effort should be distributed between human actors and intelligent systems (Breitwieser & Brod., 2022; Falebita & Kok., 2024; Wang et al., 2023). These challenges are further compounded by persistent ethical concerns related to privacy, bias, accountability, and autonomy in AI-mediated knowledge environments (Chowdhury & Oredo., 2022; Schwartz & Te'eni., 2024). Taken together, these gaps point to the absence of a coherent, theory-driven understanding of human–AI collaboration in knowledge transfer, underscoring the need to systematically clarify and structure this problem space before it can be meaningfully investigated (Gupta et al., 2024).

This paper advances a research agenda with two primary objectives. The first is to clarify the problem space of human–AI collaboration in knowledge transfer and knowledge work by identifying key theoretical, cognitive, and ethical issues that remain insufficiently understood. The second is to establish a structured foundation for empirical investigation by outlining how these issues can be systematically examined. To address the first objective, the paper conducts a comprehensive literature review synthesizing research across knowledge management, learning theory, and information systems ethics to surface critical gaps and unresolved tensions. To address the second, the paper identifies relevant theoretical foundations, develops an integrated conceptual model, and proposes coordinated study designs that enable systematic investigation.

The paper makes three primary contributions. First, it provides a structured synthesis of prior research that clarifies key gaps and tensions in understanding human–AI collaboration. Second, it develops an integrated conceptual model that connects knowledge processes, cognitive and motivational dynamics, and ethical governance within a unified framework. Third, it operationalizes this framework through three complementary research streams examining (1) knowledge transfer mechanisms, (2) human cognitive and motivational dynamics, and (3) ethical governance in AI-mediated knowledge work. Together, these contributions establish a coherent and theory-driven foundation for systematically investigating how AI reshapes knowledge transfer while preserving the central role of human expertise, judgment, and accountability.

2. LITERATURE REVIEW

The integration of AI into knowledge-intensive contexts is reshaping how knowledge is generated, managed, and applied across organizational settings, as human and machine capabilities become increasingly intertwined in decision-making and work processes (Benbya et al., 2021). This shift disrupts traditional human-to-human knowledge transfer models, giving rise to complex human–AI–human knowledge flows that challenge existing assumptions about sensemaking, authority, and expertise (Faraj et al., 2018; Raisch & Krakowski., 2021; Berente et al., 2021). As a result, foundational questions emerge regarding how knowledge is constructed, shared, and evaluated when AI systems participate directly in knowledge processes.

To examine these issues, we conducted a comprehensive literature review spanning research in information systems, knowledge management, learning theory, and AI ethics. The review search used keywords related to artificial intelligence, knowledge transfer, large language models, and hybrid human–AI knowledge processes, including terms such as "SECI model," "learning outcomes," "computer-assisted instruction," and "hybrid learning." Searches were conducted across EBSCO, JSTOR, Scopus, Web of Science, and ERIC to capture a broad and interdisciplinary body of work relevant to AI-mediated knowledge transfer.

2.1. Human Roles in AI-Mediated Knowledge Transfer

Literature consistently indicates that human roles in AI-mediated knowledge environments are shifting away from direct knowledge transmission toward interpretation, curation, and sensemaking of AI-generated outputs (Jo., 2024; Kong & Yang., 2024; Popenici., 2023). Rather than functioning solely as primary sources of information, human actors increasingly serve as intermediaries who contextualize AI outputs, validate relevance, and support meaning construction. Hybrid and recommender-based AI systems exemplify this transition by positioning humans as moderators of AI-generated knowledge, ensuring alignment with domain context and interpretive goals (Ujjwal & Samit., 2024; Fügener et al., 2021; Lebovitz et al., 2021; Lijie et al., 2024). Across knowledge-intensive settings, this shift reflects a broader movement toward distributed knowledge work in which AI systems participate directly in explanation, analysis, and synthesis.

Research shows that an effective human–AI collaboration depends on the development of AI literacy and interpretive competencies that enable human actors to critically evaluate and refine AI-generated knowledge (Cradduck et al., 2022; Li et al., 2020). As AI systems increasingly automate routine knowledge-processing activities, human expertise becomes more concentrated in higher-order functions such as judgment, contextual framing, and collaborative sensemaking (Manuel et al., 2019). Studies also highlight the importance of professional development and organizational learning mechanisms in supporting these evolving roles, particularly as individuals are expected to balance domain expertise with the ability to work effectively alongside intelligent systems (Wilson & Daugherty., 2024; Jarahi., 2018; Jennex et al., 2026). Collectively, this body of work suggests that AI does not eliminate the need for human expertise but rather reshapes how and where that expertise is applied within knowledge transfer processes.

Similarly, AI systems are often positioned to support the articulation and dissemination of explicit knowledge, while human expertise remains central to meaning-making and contextual alignment (Jennex et al., 2026). However, there is limited clarity on how different configurations of human and AI involvement influence knowledge transfer outcomes in practice. It remains unclear how interpretive depth, contextual understanding, and application vary across human-led, AI-led, and hybrid arrangements, and how cognitive responsibility and authority should be distributed between human actors and AI systems (Liu et al., 2026).

Despite these insights, gaps remain in understanding how different configurations of human and AI involvement influence knowledge transfer outcomes. Existing research largely assumes the value of human oversight without systematically examining how knowledge interpretation, contextual understanding, and concept application vary across human-led, AI-led, and hybrid arrangements (Jo., 2024; Maita et al., 2024). There is inadequate guidance on how cognitive responsibility and interpretive authority should be distributed between human actors and AI systems when tacit knowledge and judgment are central to knowledge work (Sturm et al., 2021). Moreover, while AI literacy and professional development are frequently identified as important, their relationship to measurable differences in knowledge transfer effectiveness remains underexplored. Addressing these gaps, the first stream of the proposed research agenda examines how varying degrees of human and AI involvement shape knowledge creation, interpretation, and application using theoretically grounded assessment frameworks such as the SECI model and Bloom's Taxonomy (Fink et al., 2024).

2.2. Cognitive and Social Dynamics of AI-Mediated Knowledge Work

Research highlights that AI integration significantly shapes the cognitive experiences associated with knowledge work, particularly through personalization, adaptive feedback, and on-demand explanation (Cradduck et al., 2022; Jo., 2024). AI-driven systems have been shown to support individualized knowledge acquisition by adjusting content and pacing to user needs, potentially improving comprehension and efficiency in knowledge-intensive tasks (Manuel et al., 2019). However, scholars caution that sustained reliance on AI systems may alter how individuals engage in reasoning, creativity, and critical evaluation, particularly when AI systems assume an increasingly active role in explanation and problem solving (Chandra et al., 2022). Research also suggests that while AI can assist with skill development, it lacks the empathetic and relational capacities that often support deeper sensemaking and reflective judgment in human knowledge processes (Jo., 2024; Jennex et al., 2026).

Prior research explained a complex social implication arising from AI-mediated knowledge environments. AI-supported platforms can enhance connectivity and participation by lowering barriers to engagement and providing alternative channels for contribution, particularly for individuals who may be hesitant in traditional group settings (Chandra et al., 2022; Wong et al., 2022). However, studies report tensions between increased connectivity and potential social fragmentation, as AI-mediated interactions may reduce opportunities for direct human collaboration or shared sensemaking (Mario & Roberto., 2023; Jo., 2024). The ability to engage productively in AI-supported knowledge spaces appears to be strongly influenced by AI competence and digital literacy, with disparities in access and skill shaping participation and influence within these environments (Hidayat-ur-Rehman., 2024; Kim et al., 2024). As a result, AI integration may simultaneously democratize and stratify knowledge work, depending on how social and technical conditions are configured (Gligorea et al., 2023; Sanusi et al., 2023). Research also show that AI integration can enhance knowledge work through personalization, adaptive feedback, and increased opportunities for participation, while also reshaping how individuals engage in reasoning, collaboration, and sensemaking (Chu., 2023). AI systems can improve efficiency and access to information but may also alter cognitive engagement and reduce opportunities for relational and reflective learning (Hidayat-ur-Rehman., 2024).

However, there is limited understanding of how sustained interaction with AI systems influences deeper psychological constructs such as motivation, autonomy, self-efficacy, and identity, particularly over time and across varying levels of AI involvement. Existing studies do address surface-level outcomes like engagement but offers does not clarity on how AI systems reshape individuals' perceptions of competence, responsibility, and ownership in knowledge creation and problem solving (Falebita & Kok., 2024; Wang et al., 2023). But there is a lack of longitudinal and comparative research examining how varying levels of AI involvement influence cognitive effort, confidence, and social sensemaking within shared knowledge environments. Addressing these gaps, the second stream of the proposed research agenda, focuses on examining the psychological and social dynamics of AI-mediated knowledge work using theoretically grounded constructs drawn from Self-Determination Theory and Social Cognitive Theory.

2.3. Ethical Governance and Accountability in AI-Mediated Knowledge Transfer

Ethical considerations are central to discussions of AI integration in knowledge-intensive contexts, particularly as AI systems increasingly mediate access to information, influence interpretation, and shape decision-making processes (Wilson & Daugherty., 2024). Prior work identifies persistent ethical challenges related to data privacy, algorithmic bias, transparency, and the preservation of human autonomy when AI systems are embedded in knowledge workflows (Abby Sen et al., 2025; Rudolph et al., 2024; Curzon et al., 2021). AI-driven recommendation and explanation systems, while capable of improving efficiency and personalization, may also reinforce existing inequities by privileging certain data sources, user profiles, or interaction patterns (Abby Sen et al., 2025; Cuthbert & Dörfler., 2024). These concerns highlight the need for governance approaches that address not only technical performance, but also fairness, accountability, and the protection of human agency in AI-mediated knowledge environments.

Literature emphasizes that ethical risks extend beyond system design to include how AI technologies are implemented, governed, and normalized within organizations (Chowdary & Oredo.,2022). Studies examining AI adoption document widespread concern among human users regarding data collection, long-term data retention, and the secondary use of interaction data generated through AI-supported knowledge work (Jo., 2024). Perceptions of opacity in AI decision logic and uncertainty about accountability for AI-generated outputs can undermine trust and complicate responsibility attribution. As AI systems increasingly participate in evaluative, advisory, or sensemaking functions, questions emerge regarding who is accountable for errors, bias, or downstream consequences, particularly when human judgment and AI recommendations are tightly coupled (Berente., 2021).

Research highlight that ethical concerns are central to AI-mediated knowledge transfer, with well-documented risks related to privacy, bias, transparency, and the preservation of human autonomy (Curzon et al., 2021; Sen et al., 2026). It also recognizes the challenges to extend beyond system design to encompass implementation practices, organizational governance, and the distribution of responsibility between human actors and AI systems.

Much of the literature articulates normative principles, such as transparency or fairness, without systematically examining how these principles are operationalized in practice or how stakeholders experience their effects (Stevens & Elen., 2023). There remains a lack of comparative research evaluating alternative governance frameworks and their implications for privacy protection, perceived fairness, and human autonomy in AI-supported knowledge work (Sen et al., 2025). Addressing these gaps motivates the third stream of the proposed research agenda, which focuses on examining ethical governance structures for AI-mediated knowledge transfer through multi-stakeholder perspectives and value-sensitive design principles.

2.4. Literature Review Synthesis

The reviewed literature reveals three interrelated areas where current research remains underdeveloped in the context of AI-mediated knowledge work. First, while studies recognize the evolving role of human expertise in relation to AI systems (Li et al., 2020; Manuel et al., 2019), there is little systematic understanding of how different configurations of human and AI involvement shape knowledge interpretation, contextualization, and application in practice. Second, although the cognitive and social implications of AI integration are widely discussed, existing work offers only partial insight into how sustained engagement with AI systems influences motivation, autonomy, self-efficacy, and collaborative sensemaking over time. Third, despite extensive articulation of ethical principles such as fairness, transparency, and accountability, there is insufficient clarity on how these principles are operationalized through governance structures or how they are experienced by stakeholders in AI-mediated knowledge environments. Collectively, these gaps do not simply reflect a lack of findings, but a lack of structured approaches for examining human–AI collaboration across these dimensions in a coherent and comparable manner. Addressing this requires moving beyond isolated analyses toward coordinated research designs that can systematically examine variation in human and AI involvement, capture longitudinal cognitive and social dynamics, and evaluate alternative governance configurations.

3. THEORETICAL BACKGROUNDS & CONCEPTUAL MODEL

Building on the gaps identified in the literature review, the objective is not to apply a single theoretical lens, but to integrate complementary perspectives that collectively address the multifaceted nature of human–AI collaboration in knowledge transfer. Specifically, the selected frameworks provide coverage across three interrelated dimensions: knowledge processes, human cognitive and motivational dynamics, and ethical governance. Each theory is chosen for its ability to illuminate a distinct aspect of the problem space, while also contributing to a broader conceptual structure that supports systematic investigation. To synthesize these perspectives, we present a conceptual model that integrates the selected theories and illustrates how they jointly frame the relationships examined in the proposed studies.

3.1. Socialization, Externalization, Combination & Internalization (SECI)

The SECI model (Nonaka., 1994) provides a foundational framework for understanding how knowledge is created and transferred through the dynamic interaction between tacit and explicit forms of knowledge. The model conceptualizes knowledge creation as a continuous cycle involving four modes: socialization (tacit to tacit), externalization (tacit to explicit), combination (explicit to explicit), and internalization (explicit to tacit). This process emphasizes that knowledge is not merely transmitted, but actively transformed through interaction, interpretation, and contextualization.

The SECI model is well suited to the present study as it offers a structured lens for examining how knowledge evolves across different configurations of human and AI involvement. As AI systems increasingly participate in explanation, synthesis, and information retrieval, they primarily operate within the explicit knowledge domain, while human actors remain central to tacit interpretation and contextual meaning-making. This distinction aligns closely with the gap identified in the literature regarding how knowledge interpretation and application vary across human-led, AI-led, and hybrid arrangements. By grounding the analysis in SECI, the study enables systematic examination of how these configurations influence knowledge conversion processes and interpretive depth in AI-mediated environments.

3.2. Self-Determination Theory (SDT)

Self-Determination Theory (SDT) provides a well-established framework for understanding human motivation and psychological functioning in goal-directed activities (Deci & Ryan., 2012). The theory posits that individuals' motivation and engagement are shaped by the satisfaction of three basic psychological needs: autonomy, competence, and relatedness. Autonomy refers to the perception of control over one's actions, competence reflects a sense of effectiveness and mastery, and relatedness captures the need for social connection and belonging. Together, these dimensions influence how individuals approach learning, problem solving, and participation in knowledge-intensive tasks.

SDT is relevant in the context of AI-mediated knowledge work, where the integration of intelligent systems has the potential to both support and undermine these psychological needs. AI systems can enhance perceived competence by providing immediate feedback and guidance, while also affecting autonomy depending on the degree of reliance or delegation involved. At the same time, increased interaction with AI may alter traditional forms of social engagement, raising questions about relatedness and collaborative sensemaking. This aligns with the gap identified in the literature regarding how sustained engagement with AI systems influences motivation, autonomy, and self-efficacy over time. By grounding the analysis in SDT, the study enables systematic examination of how varying levels of AI integration shape motivational dynamics and human agency in knowledge work.

3.3 Social Cognitive Theory (SCT)

Social Cognitive Theory (SCT) offers a complementary perspective on human behavior by emphasizing the dynamic interplay between personal factors, behavior, and environmental influences (Bandura., 1999). Central to SCT is the concept of self-efficacy, or an individual's belief in their ability to successfully perform tasks and achieve desired outcomes. The theory also highlights the role of observational learning, where individuals acquire knowledge and skills by observing others, as well as the importance of reciprocal determinism, which captures how individuals both shape and are shaped by their environment.

SCT is appropriate in AI-mediated knowledge work, where AI systems increasingly function as interactive agents that influence learning processes, decision-making, and problem-solving strategies. Through exposure to AI-generated explanations, examples, and feedback, individuals may engage in forms of observational learning that shape their reasoning patterns and task approaches. At the same time, repeated interaction with AI systems may influence self-efficacy by either reinforcing confidence or encouraging cognitive offloading. This perspective aligns with the identified gap concerning how AI integration affects cognitive effort, confidence, and social sensemaking in knowledge work. By drawing on SCT, the study enables examination of how human behavior and learning processes evolve through ongoing interaction with AI systems within structured and comparative settings.

3.4 Theory of Perceived Benefits (TPB)

The Theory of Perceived Benefits (TPB) provides a lens for understanding how individuals evaluate and adopt technologies based on their anticipated value and utility (Pirham et al., 2025; Thompson et al., 1991). The theory suggests that individuals are more likely to engage with and rely on a system when they perceive clear benefits, such as improved efficiency, enhanced performance, or reduced cognitive effort. In knowledge-intensive contexts, perceived benefits often relate to the ability of a system to support information access, problem solving, and task completion in a timely and effective manner.

TPB is a relevant and appropriate framework in AI-mediated knowledge work, where both the adoption and continued use of AI systems are shaped by users' perceptions of their usefulness in supporting knowledge-related tasks. AI tools that offer rapid explanations, personalized feedback, or structured guidance can enhance perceived benefits, encouraging greater reliance and integration into everyday workflows. At the same time, increased reliance on such systems may influence how individuals allocate cognitive effort and participate in knowledge construction. This perspective aligns with the identified gap concerning how varying levels of AI involvement shape user behavior, engagement, and reliance over time. Incorporating TPB allows for examination of how perceived value influences interactions with AI systems and contributes to broader cognitive and motivational dynamics in knowledge work.

3.5 Value-Sensitive Design (VSD)

Value-Sensitive Design (VSD) provides a principled framework for integrating human values into the design and implementation of technological systems (Friedman et al., 2006). VSD emphasizes the proactive identification and incorporation of values such as fairness, accountability, transparency, and autonomy throughout the design process. The approach adopts a tripartite methodology that considers conceptual, empirical, and technical investigations, enabling systematic examination of how stakeholder values are embedded, negotiated, and realized within sociotechnical systems.

VSD is appropriate in the context of AI-mediated knowledge work, where AI systems increasingly influence access to information, shape interpretation, and support decision-making processes. As these systems become more integrated into knowledge workflows, ethical concerns extend beyond technical performance to include how values are operationalized through governance structures and experienced by users. This aligns with the identified gap regarding the lack of clarity on how ethical principles are enacted in practice and how different governance approaches shape perceptions of fairness, accountability, and autonomy. By drawing on VSD, the study provides a structured lens for examining how ethical considerations can be systematically embedded and evaluated within AI-supported knowledge environments.

3.6 Conceptual Model

The conceptual model (Fig 1) underpins the proposed research agenda and integrates the theoretical perspectives introduced earlier. The model is intended to provide a structured representation of the key dimensions of human–AI collaboration in knowledge transfer. Drawing on established theories from knowledge management, learning, and information systems ethics, the model organizes the problem space into a coherent structure that connects knowledge processes, human cognitive and behavioral dynamics, and ethical governance. In doing so, it offers a foundation for systematically examining how AI systems and human actors interact within knowledge-intensive environments.

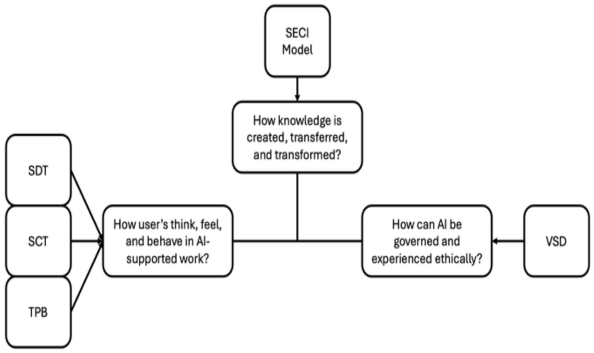

Figure 1: Conceptual Model

The conceptual model aligns the identified gaps in the literature with the research objectives and proposed studies by organizing them into three interrelated areas of inquiry. The first dimension focuses on knowledge processes and is grounded in the SECI model, addressing the gap related to how knowledge is created, transferred, and transformed across different configurations of human and AI involvement. The second-dimension centers on human cognitive and behavioral dynamics, drawing on Self-Determination Theory, Social Cognitive Theory, and the Theory of Perceived Benefits. This dimension addresses the need to better understand how individuals think, feel, and behave in AI-supported knowledge work, particularly in terms of motivation, autonomy, self-efficacy, and reliance over time. The third dimension focuses on ethical governance and is informed by Value-Sensitive Design, addressing the lack of clarity on how ethical principles are operationalized and experienced in AI-mediated environments. Together, these dimensions directly correspond to the two objectives of this paper: clarifying the problem space and outlining structured approaches for future empirical investigation. By linking each dimension to a corresponding study, the model provides a coherent bridge between theoretical foundations, identified gaps, and the design of research that can systematically examine human–AI collaboration in knowledge transfer.

4. EXPERIMENT DESIGNS

The purpose of these research designs is to illustrate how the core issues identified earlier can be studied systematically and comparatively. Each proposed study focuses on a distinct yet interrelated dimension of human–AI collaboration in knowledge transfer: knowledge creation and interpretation, cognitive and social dynamics, and ethical governance. Together, the three designs form a coordinated program of inquiry that enables cumulative investigation of how varying configurations of human and AI involvement shape knowledge work. The studies are presented at the level of design logic, theoretical grounding, and methodological considerations, providing a foundation for future empirical implementation.

Study 1

The first study aims to examine how different configurations of human and AI involvement influence knowledge creation, transfer, and interpretation in knowledge-intensive settings. Grounded in the SECI model (Nonaka., 1994), the study conceptualizes knowledge transfer as a dynamic process involving the interaction between tacit and explicit knowledge through socialization, externalization, combination, and internalization. The objective is to systematically compare how these processes unfold across three instructional configurations: (1) human-led, (2) AI-led, and (3) hybrid human–AI knowledge transfer.

The SECI model provides a guiding structure for how learning activities and interactions are designed within the study, ensuring that each instructional condition meaningfully engages different modes of knowledge conversion. Socialization (S) is reflected in opportunities for shared experience and tacit knowledge exchange, such as discussion, peer interaction, or guided dialogue, which are emphasized in the human-led and hybrid conditions. Externalization (E) is incorporated through tasks that require participants to articulate understanding, such as explaining concepts, constructing examples, or translating implicit insights into explicit representations. Combination (C) is operationalized through activities that involve organizing, integrating, and applying structured information, particularly in AI-supported environments where participants engage with synthesized content. Internalization (I) is addressed through application-based assignments that require learners to apply knowledge in new contexts, reinforcing learning through practice. Designing tasks to explicitly engage each of these processes ensures that the study does not merely compare instructional modes but systematically examines how different configurations of human and AI involvement shape the full cycle of knowledge creation and transformation.

The study adopts a controlled experimental design in which participants are randomly assigned to one of the three configurations. In the human-led condition, a domain expert delivers content through direct instruction, discussion, and contextual examples, emphasizing tacit knowledge exchange and interpretive guidance. In the AI-led condition, participants interact exclusively with a domain-constrained AI system trained on the same instructional material, allowing for self-directed learning through AI-generated explanations and examples. In the hybrid condition, participants engage with both the human expert and the AI system, enabling examination of how human and AI contributions interact in supporting knowledge transfer.

To ensure comparability across conditions, the study should control for content scope, instructional time, and learning objectives. All instructional materials are standardized, and both the human expert and AI system are aligned to the same domain-specific corpus. The AI system is pre-trained on curated materials to ensure consistency and to prevent introduction of external or uncontrolled information. Human instructors are selected based on demonstrated subject-matter expertise and teaching experience to ensure quality and consistency of instruction.

Assessment is designed to capture multiple dimensions of knowledge transfer aligned with the SECI framework. Individual assessments evaluate participants' ability to interpret and apply concepts, reflecting internalization and externalization processes. Group-based assessments are incorporated to examine collaborative knowledge creation and socialization, particularly in the human-led and hybrid conditions. In addition, responses are analyzed for evidence of conceptual integration, contextual understanding, and transfer of knowledge to novel scenarios. Bloom's Taxonomy is used to structure assessment tasks across increasing levels of cognitive complexity, from basic comprehension to higher-order application and analysis.

The study incorporates multiple checks and controls to maintain internal validity. Participants are matched or stratified based on prior knowledge and familiarity with the subject domain. Interaction logs are collected in the AI-led and hybrid conditions to capture engagement patterns, query behavior, and reliance on AI-generated outputs. In the human-led condition, instructional sessions are recorded and standardized to minimize variability in delivery. Independent evaluators assess participant outputs using predefined rubrics to reduce grading bias.

In order to access the practicality of the proposed design, a small-scale feasibility exercise was conducted focusing on core elements of the Study 1 configuration. The exercise confirmed that contrasting human-led and AI-led knowledge transfer conditions can be implemented under controlled settings, that a domain-constrained AI system can reliably support instructional tasks, and that case-based assessments can surface meaningful differences in knowledge interpretation and application. Observations from the exercise also highlighted differences in interaction patterns, levels of autonomy, and the role of interpretive guidance across conditions, while identifying practical considerations such as pacing and cognitive load in AI-mediated environments. Importantly, the feasibility exercise serves as methodological validation supporting the operational viability of the proposed design. Additional details regarding the feasibility setup, procedures, and observations are provided in Appendix A.

Study 2

The second study proposes examining how varying levels of AI integration influence cognitive, motivational, and social dynamics in knowledge-intensive environments over time. Building on Self-Determination Theory (SDT) (Deci & Ryan., 2012), Social Cognitive Theory (SCT) (Bandura., 1999), and the Theory of Perceived Benefits (TPB), the study conceptualizes human–AI interaction as a process that shapes autonomy, competence, self-efficacy, and patterns of engagement. The objective is to understand how sustained exposure to AI systems affects how individuals think, feel, and behave in knowledge work, particularly in relation to motivation, cognitive effort, and social sensemaking.

The integration of SDT, SCT, and TPB provides a structured lens for designing both the intervention and the measurement strategy in this study. Self-Determination Theory (SDT) informs how learning environments are configured to support or constrain autonomy, competence, and relatedness, guiding the design of tasks, feedback mechanisms, and degrees of AI assistance across conditions. Social Cognitive Theory (SCT) complements this by emphasizing self-efficacy, observational learning, and reciprocal interaction between individuals, technology, and environment, which shapes how participants engage with AI tools and develop confidence in their capabilities over time. The Theory of Perceived Benefits (TPB) captures how individuals evaluate the usefulness and value of AI systems, influencing their willingness to rely on, adapt to, or resist AI support. Together, these frameworks ensure that the study does not simply track outcomes but systematically examines how variations in AI integration affect motivation, perceived value, behavioral engagement, and social interaction patterns, enabling a more comprehensive understanding of how human–AI collaboration evolves over time.

The study adopts a longitudinal mixed-methods design conducted over an extended period, such as an academic term or year. Participants are assigned to one of three conditions representing different levels of AI integration: (1) low integration, where AI tools are limited to administrative or peripheral support; (2) moderate integration, where AI assists with specific learning tasks such as explanation, feedback, or problem solving; and (3) high integration, where AI systems are embedded across a wide range of knowledge activities, including content generation, iterative reasoning, and task support. These conditions enable systematic comparison of how increasing AI involvement shapes human engagement with knowledge processes.

The study controls for curriculum content, instructional objectives, and exposure time across all groups to ensure comparability. Participants are matched based on prior academic performance, familiarity with digital tools, and demographic characteristics. Instructional environments are standardized to maintain consistency in classroom size, resources, and teacher preparation. Implementation fidelity is monitored throughout the study to ensure that each condition reflects its intended level of AI integration.

Measurement focuses on multiple dimensions aligned with the theoretical framework. Quantitative instruments assess motivation and psychological needs based on SDT (autonomy, competence, relatedness), as well as self-efficacy and learning behaviors informed by SCT. Perceived benefits of AI use are measured to capture how users evaluate and rely on AI systems over time. Cognitive outcomes are assessed through tasks measuring problem-solving ability, critical thinking, and creative application. In parallel, qualitative data are collected through periodic interviews, reflective journals, and classroom observations to capture changes in sensemaking, collaboration, and perceived responsibility.

Behavioral data are incorporated through analysis of AI interaction logs, including frequency of use, types of queries, and patterns of reliance or delegation. This enables examination of how perceived benefits translate into actual usage behavior and how these patterns evolve over time. To strengthen validity, validated psychological instruments are used, observers are trained, and inter-rater reliability checks are conducted for qualitative assessments.

This study emphasizes how engagement with AI systems reshapes underlying cognitive and motivational processes. The main focus is given to examine how autonomy is maintained or diminished, how self-efficacy develops in relation to AI-supported tasks, and how social interaction patterns shift in environments with varying levels of AI integration. By examining these dynamics longitudinally, the study provides a structured approach for understanding how AI systems influence human development and participation in knowledge work overtime. To support the practical implementation of this design, a small-scale feasibility exercise is proposed to evaluate the operability of the integration conditions, measurement instruments, and data collection approach. Details of this feasibility exercise are provided in Appendix A.

Study 3

The third study examines how different ethical governance configurations shape user experiences, perceived fairness, and accountability in AI-mediated knowledge environments. Grounded in Value-Sensitive Design (VSD) (Friedman et al., 2006), the study conceptualizes AI systems as socio-technical artifacts that embed and reflect human values. The objective is to investigate how variations in governance design influence ethical outcomes, particularly in relation to privacy, fairness, and accountability, within a controlled educational setting.

VSD provides a structured foundation for conceptualizing and evaluating governance mechanisms. In this study, core values such as privacy, fairness, accountability, and transparency are translated into distinct governance conditions that can be implemented within a single course or across multiple sections of the same course. The conceptual component guides the definition of these values, the empirical component captures how they are experienced by users, and the technical component reflects how governance features are embedded into AI-supported learning activities.

The study adopts a within-institution,

comparative design conducted across multiple course sections or cohorts. Participants are assigned to one of three governance conditions:

(1) minimal governance, consisting of basic usage guidelines and standard data protections; (2) moderate governance, incorporating additional transparency statements, bias awareness prompts, and structured guidance on appropriate AI use; and (3) enhanced governance, introducing clearer accountability structures, usage expectations, and reflective prompts that make responsibility and decision-making more explicit. These conditions allow for systematic comparison while remaining feasible within a typical teaching environment.

To ensure comparability, all participants engage with the same course content, learning objectives, and AI-supported tools. Variation is introduced only through governance features embedded in instructions, prompts, and course policies. Data collection focuses on students and instructors within the course context. Student's complete surveys and short reflections assessing perceived fairness, trust in AI, clarity of responsibility, and privacy concerns. Instructors document observed challenges and ethical tensions through structured logs and brief reflections. Where feasible, optional interviews or focus groups may be conducted to provide deeper insight into how governance features influence user experience.

Measurement includes both quantitative and qualitative indicators. Survey instruments assess perceptions of fairness, trust, and accountability, while qualitative responses capture how participants interpret and respond to ethical tensions in practice. Interaction artifacts, such as AI prompts or usage patterns, may also be analyzed to examine how governance influences behavior.

To strengthen rigor, the study employs validated survey instruments, standardized reflection prompts, and systematic coding procedures for qualitative data. Comparative analysis is used to identify patterns across governance conditions, focusing on how different configurations influence perceptions of fairness, trust, and responsibility in AI-supported knowledge work. By comparing lightweight, implementable governance approaches, the study provides a practical pathway for understanding how ethical design choices shape AI-mediated knowledge work. The findings can inform course-level practices and serve as a foundation for future, larger-scale investigations of AI governance in educational contexts.

5. Commentary: Clarifying the Problem Space of Human–AI Knowledge Transfer

The central objective of this paper is to clarify the problem space surrounding human–AI collaboration in knowledge transfer and knowledge work. As AI systems increasingly participate in explanation, synthesis, and sensemaking, existing research has tended to focus on isolated tools, outcomes, or use cases, often without a shared conceptual foundation. This fragmentation has made it difficult to compare findings, accumulate knowledge, or design studies that meaningfully advance theory. This paper contributes by articulating the underlying issues in greater detail, identifying points of tension, and organizing them into a coherent research agenda that can support systematic inquiry.

By synthesizing prior work (Table 1) across knowledge management, cognitive and motivational theory, and information systems ethics, the paper surfaces three interdependent dimensions that shape AI-mediated knowledge transfer: the evolving role of human expertise, the cognitive and social dynamics of AI-supported knowledge work, and the governance structures that shape ethical responsibility and accountability. Clarifying these dimensions helps distinguish between problems of information access and problems of interpretation, between automation and delegation of judgment, and between ethical principles and operational governance. This conceptual clarification is a necessary precursor to meaningful empirical investigation, as it defines what should be measured, compared, and explained.

To support this effort, the paper includes three small-scale feasibility exercise reported in Appendix A. The exercise demonstrated that contrasting human-led and AI-led knowledge transfer configurations can be implemented under controlled conditions, that a domain-constrained AI system can reliably support explanation, and that assessment artifacts can reveal differences in interpretive approach. These observations informed refinements to the proposed study designs, such as the need for pacing controls and interpretive scaffolding in AI-mediated conditions. Readers seeking methodological detail or early design insights are directed to the appendix.

For researchers, this clarification suggests the importance of designing studies that vary configurations of human–AI collaboration, attend

Study Focus	Theoretical Implications	Practical Implications
Study 1: AI-Mediated Knowledge Transfer and the SECI Model	Extends Nonaka & Takeuchi's SECI model to account for AI-mediated knowledge conversion processes and hybrid human–AI knowledge flows (Nonaka., 1994). Advances understanding of tacit and explicit knowledge interaction when AI systems participate in explanation and interpretation (Sarker et al., 2024).	Guides the design of AI integration strategies aligned with different modes of knowledge conversion and sensemaking (Fischer et al., 2020). Informs the appropriate distribution of interpretive responsibility between human actors and AI systems in knowledge-intensive work (Schwartz & Te'eni., 2024). Provides design principles for structuring hybrid human–AI knowledge environments (Hase & Kahl., 2024).
Study 2: Cognitive and Social Dynamics of AI-Mediated Knowledge Work	Applies Theory of Perceived Benefits and Self-Determination Theory with Social Cognitive Theory to explain motivation, autonomy, and self-efficacy in AI-supported knowledge work (Legault et al., 2007). Advances theory on social sensemaking and collaboration in technology-mediated knowledge environments (Kankanhalli., 2024; Gligorea et al., 2023).	Informs organizational protocols for AI tool use that support human agency, motivation, and well-being in knowledge-intensive roles (Xue et al., 2022). Provides guidance on balancing AI-supported and human-led knowledge activities to avoid over-automation (Fügener et al., 2021). Guides the design of support mechanisms that help individuals adapt to AI-mediated knowledge work (Breitwieser & Brod., 2022).
Study 3: Ethical G overnance of AI-Mediated Knowledge Transfer	Extends Value-Sensitive Design theory to AI governance in knowledge-intensive contexts (Asghar., 2022). Advances understanding of power, accountability, and institutional structures shaping AI-mediated knowledge work (Benbya., 2024).	Provides actionable frameworks for responsible AI governance in organizations (Kong & Yang., 2024) Offers models for multi-stakeholder engagement, communication, and oversight in AI governance (Cradduck et al., 2022). Guides the development of privacy protection, fairness mechanisms, and ethical monitoring systems for AI-enabled knowledge environments (Curzon et al., 2021; Fu-Yun & Chun-Ping., 2016).

Table 1: Cross-Analysis of Theoretical Contributions and Practical Implications

to cognitive and motivational dynamics, and treat ethics as an operational governance challenge rather than a purely normative concern. For organizations and designers, it highlights the need to introduce AI as an interpretive support instead of an authoritative replacement, for managing pace and cognitive load, and to establish governance mechanisms that make accountability and oversight explicit. In this way, the paper lays conceptual groundwork that enables future empirical research to proceed with greater precision, coherence, and cumulative value.

6. LIMITATIONS AND EXTENSIONS

This paper has several limitations that also define directions for future research. First, the primary objective was to clarify and structure the problem space surrounding human–AI collaboration in knowledge transfer, therefore, the proposed studies are conceptual and design-oriented, and empirical analysis is intentionally deferred to future work. Second, while the feasibility exercise provided methodological insight, its small scale and exploratory nature preclude generalization and should be interpreted solely as design scaffolding. Third, the agenda focuses on knowledge-intensive contexts and does not explicitly address domain-specific variations, organizational scale, or cultural differences that may shape AI-mediated knowledge work. Future research should implement the proposed studies at scale, examine longitudinal effects across diverse settings, and refine measurement instruments that capture interpretation, autonomy, and governance dynamics. Such efforts will be essential for translating this clarified problem space into cumulative empirical knowledge.

7. CONCLUSIONS

This paper advances a structured research agenda for understanding human–AI collaboration in knowledge-intensive contexts, with a particular focus on how generative AI reshapes knowledge transfer, human cognition, and governance. This agenda integrates the above through a coherent theoretical and empirical framework grounded in knowledge management, behavioral theory, and ethical design. By linking SECI-based knowledge processes, motivational and cognitive dynamics, and value-sensitive governance, the paper provides a unified lens for examining how AI systems participate in and transform knowledge work.

The primary contribution of this agenda lies in its ability to move the field beyond descriptive accounts of AI adoption toward systematic, theory-driven investigation. It enables researchers to operationalize human–AI collaboration through clearly defined configurations, measurable constructs, and comparative designs. In doing so, it provides a pathway for disentangling how varying levels of AI involvement influence not only performance outcomes, but also interpretation, agency, and responsibility in knowledge processes.

Importantly, this agenda also establishes a foundation for evaluating trade-offs between efficiency, interpretability, and ethical integrity in AI-mediated environments. By explicitly incorporating governance structures and stakeholder perspectives, it enables examination of how ethical principles are enacted in practice. The proposed research program offers a practical and theoretically grounded roadmap for future empirical work. It enables cumulative knowledge development by aligning conceptual clarity with implementable study designs, positioning human–AI collaboration as a central and tractable domain of inquiry in the evolving landscape of knowledge work.

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APPENDIX A

Feasibility Experiment: Study 1

To assess the practical feasibility of the first proposed research stream, the paper includes a small-scale feasibility exercise designed to test core elements of the Study 1 design. The objective of this exercise was to explore whether contrasting configurations of human-led and AI-led knowledge transfer could be implemented under controlled conditions, whether a custom AI tool could reliably support domain-specific explanation, and whether the proposed assessment approach could surface meaningful differences in knowledge interpretation and application. Given this purpose, the exercise was explicitly exploratory and intentionally limited in scale.

The feasibility exercise employed a custom-built AI tool developed through an API comparable in function to large language models such as ChatGPT. The system was trained exclusively on instructor-provided materials drawn from a Knowledge and Project Management course, including lecture notes, slides, and assignment explanations. The AI was instructed to remain aligned with stated learning objectives while retaining flexibility to generate contextual examples when prompted, mirroring how a human expert might tailor explanations to individual interests while maintaining conceptual fidelity. This design allowed examination of AI-mediated knowledge transfer without reliance on external content or uncontrolled sources.

Four undergraduate participants volunteered and completed the full exercise, each contributing approximately two and a half hours. Participants were assigned to one of two conditions: a human-led knowledge transfer condition or an AI-led knowledge transfer condition. Both conditions were allocated equal time. In the human-led condition, participants engaged in a ninety-minute session with a senior domain expert who delivered explanations, examples, and discussion aligned with the course material. In the AI-led condition, participants were provided with the syllabus, learning objectives, and unrestricted access to the AI tool for the same duration. They were instructed to self-direct their engagement with the system in whatever manner they found most effective, reflecting a knowledge transfer configuration in which AI functions as the primary explanatory resource.

Following the instructional phase, all participants completed the same case-based assessment under controlled conditions without access to the AI tool or external materials. The case required application of conceptual knowledge to an unfamiliar organizational scenario, emphasizing interpretation and reasoning rather than recall. Responses were anonymized and independently evaluated by multiple graders to reduce individual bias. In addition, short post-task interviews were conducted, and interaction logs from the AI tool were retained to capture engagement patterns and user strategies.

Although the feasibility exercise was not designed to support inference, several consistent observations emerged that are relevant to refining the proposed research agenda. Participants in the human-led condition engaged in dialogic interaction, benefited from narrative examples, and appeared to rely on instructor cues to prioritize and contextualize information. Participants in the AI-led condition demonstrated high autonomy and sustained engagement, frequently requesting clarification or simplified explanations, but also encountered moments of cognitive overload due to the density and pace of AI-generated responses. Across data sources, the exercise highlighted differences in how meaning was constructed, with less variation in whether information was acquired.

Importantly, the feasibility exercise confirmed that the proposed Study 1 design elements are workable in practice. The AI system reliably remained within domain boundaries, participants adhered to assigned conditions, the case-based assessment surfaced differences in interpretive approach, and the combination of artifacts, observations, and reflections produced analyzable data despite the small scale. These outcomes support the viability of the broader experimental design while also revealing design considerations, such as the need for pacing controls and interpretive scaffolding in AI-mediated conditions, that can be incorporated into future implementations.

Proposed Feasibility Experiment: Study 2

To assess the practical feasibility of the second proposed research stream, a small-scale pilot exercise may be conducted to test core elements of the Study 2 design, without evaluating long-term outcomes. The purpose of this exercise would be to determine whether varying levels of AI integration can be implemented in a controlled educational setting, whether the proposed instruments can capture early differences in motivation, self-efficacy, and perceived usefulness, and whether mixed-methods data collection can generate meaningful insight into participants' cognitive and social experiences. Given this purpose, the exercise would be explicitly exploratory and limited in duration.

The feasibility exercise could be conducted over a short instructional period, such as two to four weeks, within a bounded course module. Participants would be assigned to one of three conditions representing low, moderate, and high AI integration. In the low-integration condition, AI tools would be restricted to peripheral or administrative support, such as scheduling, reminders, or access to static resources. In the moderate-integration condition, participants would use AI to support selected learning tasks, such as clarification, feedback, or guided explanation. In the high-integration condition, AI would be embedded more extensively into knowledge activities, including brainstorming, drafting, explanation, and iterative problem solving. All groups would work with the same course content, learning objectives, and assessment tasks.

Data collection would combine short, validated survey instruments with qualitative reflections and behavioral records. Surveys administered at the beginning and end of the pilot would assess autonomy, competence, relatedness, self-efficacy, and perceived usefulness of AI support. Participants would also complete brief reflection logs describing how AI affected their engagement, confidence, and sense of responsibility for the work. In the moderate and high AI conditions, interaction logs would be collected to examine usage frequency, types of requests, and reliance patterns. Classroom observations or facilitator notes could be used to document differences in collaboration, participation, and help-seeking behavior across conditions.

Although the exercise would not be designed to support inferential claims, it would provide useful early evidence regarding the viability of the broader Study 2 design. It could reveal whether the three AI integration conditions are meaningfully distinguishable in practice, whether participants interpret and respond to the survey items as intended, and whether the qualitative and behavioral data sources produce analyzable indicators of motivational and social change. It may also surface practical design considerations, such as the need to refine condition boundaries, adjust instrument timing, or better distinguish between productive AI support and excessive cognitive offloading.

Proposed Feasibility Experiment: Study 3

To assess the practical feasibility of the third proposed research stream, a small-scale pilot exercise may be conducted to evaluate whether the governance configurations outlined in Study 3 can be meaningfully implemented and distinguished within a course-level setting. The purpose of this exercise is not to assess ethical outcomes, but to examine whether participants recognize and respond to differences in governance design, and whether these differences produce observable variation in perception and behavior.

The feasibility exercise can be conducted within a single course or across multiple sections over a short period, such as two to four weeks. Rather than introducing new structures, the study implements the governance variations described in Study 3 through instructional design elements such as usage guidelines, prompts, and expectations, while holding the underlying AI tool and course content constant.

Data collection focuses on capturing whether governance distinctions are perceptible and consequential in practice. Students complete short surveys and reflection prompts assessing perceived fairness, trust, clarity of responsibility, and privacy concerns, while the instructor documents instances of misunderstanding, disengagement, or selective adherence to governance guidance. Attention is given to whether participants actively engage with governance features or treat them as peripheral instructions.

Although the exercise is not intended to produce generalizable findings, it provides insight into key design assumptions underlying Study 3. Specifically, it allows examination of whether governance conditions are sufficiently distinct, whether participants meaningfully interpret ethical guidance, and whether the proposed measures capture variation in perception and behavior. It may also surface practical challenges, such as participants ignoring governance cues, misinterpreting expectations, or experiencing governance as either supportive or restrictive.

Digital Twins as Integrative Learning Artifacts in Systems Education

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Abstract

Digital twins (DTs)—dynamic digital representations of physical systems—are increasingly used in organizational contexts to support monitoring, simulation, and data-driven decision-making. Despite their growing relevance, digital twin concepts remain underrepresented in undergraduate Information Systems (IS) curricula, limiting students' opportunities to develop integrated competencies in systems thinking, data integration, digital infrastructure, and governance. This paper proposes a structured instructional framework for integrating digital twin education into undergraduate IS programs, grounded in both the IS 2010 Curriculum Guidelines and the IS 2020 Competency Model. The framework emphasizes (1) clearly defined student learning outcomes aligned with IS competencies, (2) foundational instruction in digital twin architecture and system integration, and (3) experiential learning through hands-on laboratories and project-based activities supported by affordable and scalable learning kits. A comparative taxonomy of commonly used digital twin platforms is presented to assist educators in selecting instructional tools aligned with curricular goals and resource constraints. An illustrative classroom implementation demonstrates how digital twin learning artifacts can support experiential learning while reinforcing core IS competencies in data management, systems integration, human-centered decision-making, and governance. The paper concludes by discussing educational implications and future directions for integrating digital twins into undergraduate IS education.

Keywords: Digital Twin, Curriculum integration, Educational Technology, Project-based Learning, Learning Kits, Hands-on Learning

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Digital Twins as Integrative Learning Artifacts in Systems Education

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1. INTRODUCTION

Digital transformation has reshaped how organizations design, operate, and optimize complex systems, particularly through the integration of cyber-physical assets, real-time data streams, and advanced analytics. Among the technologies driving this transformation, digital twins (DTs) have emerged as a critical enabler of monitoring, simulation, and continuous improvement of physical systems. A digital twin is commonly described as a dynamic digital representation of a physical entity that is continuously updated through bidirectional data exchange between the physical and digital environments (Grieves, 2014). Advances in the Internet of Things (IoT), cloud computing, and data analytics have significantly accelerated the development and adoption of digital twins across sectors such as smart infrastructure, manufacturing, healthcare, energy management, transportation, and academic settings (Tao et al., 2019; Zhang et al., 2023; National Academies of Sciences, Engineering, and Medicine, 2024; Schalkwyk, 2024).

The digital twin concept was formalized by Grieves (2014), who described it as a system comprising a physical entity, its digital counterpart, and the data connections that enable continuous interaction between them. Since then, the concept has evolved beyond static digital models toward dynamic, data-driven systems capable of reflecting current operational conditions and, in some cases, anticipating future behavior. Tao et al. (2019) characterize digital twins as integrated, multiscale simulations that combine real-time sensor data, historical records, and analytical models to mirror the behavior and lifecycle of a physical system. This evolution positions digital twins not merely as visualization artifacts, but as operational information systems that support diagnostics, optimization, and strategic decision-making within complex organizational environments.

While digital twins have been widely studied in engineering and manufacturing (MIT Open Learning, 2024; Omran et al., 2024; Hazrat et al., 2023), they have received relatively limited attention in other domains. As organizations increasingly adopt digital twin platforms, graduates are expected to understand how physical data sources, digital infrastructures, analytics engines, and governance mechanisms interact within enterprise systems. However, in many undergraduate Information Systems (IS) programs, related topics—such as systems analysis, data management, IoT, and emerging technologies—are introduced independently, without an explicit integrative framework that reflects real-world cyber-physical systems (Liu et al., 2021; Jankovskis et al., 2024). As a result, students may graduate with familiarity across individual technologies but have limited experience designing or reasoning about systems that bridge physical operations and digital decision infrastructures.

Recent updates to undergraduate IS curriculum guidance further underscore this gap. The IS 2020 Competency Model shifts emphasis from prescriptive course structures toward demonstrable competencies that graduates should exhibit upon degree completion, aligning IS education with evolving organizational and societal needs. Core IS 2020 competencies—including systems thinking, data integration, digital infrastructure, security, and organizational alignment—map directly to the capabilities required for effective digital twin design and deployment. From this perspective, digital twins represent a natural extension of contemporary IS education rather than an external or specialized topic confined to engineering-centric domains, because they directly reinforce the systems thinking, data integration, and organizational alignment emphasized in modern IS curriculum guidance (Topi et al., 2020).

Although this work is primarily grounded in the IS 2020 Competency Model, it also acknowledges the continued relevance of the IS 2010 Curriculum Guidelines, which remain in use across many undergraduate IS programs. IS 2010 established foundational competencies in systems analysis, data management, and organizational context that continue to underpin contemporary IS education. The IS 2020 model builds upon this foundation by emphasizing digital transformation, data-driven systems, platform ecosystems, and societal impact. Digital twin education aligns with both models—extending traditional IS competencies articulated in IS 2010 while directly supporting the competency-based, transformation-oriented emphasis of IS 2020. Recognizing this continuity allows digital twins to be integrated into IS curricula without requiring wholesale restructuring, consistent with the evolutionary curriculum perspective articulated in IS 2010 and extended in the IS 2020 competency model (Topi et al., 2010; Topi et al., 2020).

Despite this strong conceptual alignment, educators face significant challenges when attempting to incorporate digital twin instruction into undergraduate IS curricula. Digital twin systems are inherently multidisciplinary, requiring integration of real-time data acquisition, system modeling, platform interoperability, cybersecurity, and visualization. Additional barriers include the diversity and cost of available platforms, limited faculty familiarity with digital twin ecosystems, and uncertainty regarding how to design hands-on learning experiences that are accessible, scalable, and pedagogically coherent (Hadfield, 2020; Jankovskis et al., 2024). Without structured instructional guidance, digital twin concepts risk being addressed superficially or framed as advanced engineering topics beyond the scope of traditional IS programs.

This paper addresses these challenges by proposing a structured instructional framework for integrating digital twin education into undergraduate IS programs grounded in the IS 2020 Competency Model. The framework consists of three interrelated components: (1) student learning outcomes explicitly mapped to IS 2020 competencies; (2) foundational digital twin concepts emphasizing systems architecture and data flow; and (3) hands-on laboratories and project-based learning activities supported by affordable and scalable digital twin learning kits. Rather than positioning digital twins as an advanced specialization, this approach embeds digital twin concepts within core IS domains, reinforcing existing competencies while exposing students to emerging cyber-physical systems.

In addition, this study presents a comparative taxonomy of commonly used digital twin platforms and educational kits, examining their cost, technical requirements, instructional affordances, and alignment with IS competencies. A classroom-based example further illustrates how low-cost digital twin kits can be incorporated into project-based learning activities, enabling students to explore real-time data integration, system interaction, and applied decision-making. These contributions provide a practical and replicable approach for aligning undergraduate IS education with evolving workforce demands shaped by intelligent, connected, and data-driven systems. This study contributes a competency-aligned instructional framework, a dual IS 2010–IS 2020 curriculum mapping, and an experiential digital twin learning model suitable for undergraduate IS programs.

2. DIGITAL TWIN CURRICULUM DESIGN

The growing use of digital twin (DT) technologies in domains such as smart infrastructure, healthcare, and energy systems has created new expectations for Information Systems (IS) graduates. As digital twins increasingly shape how organizations monitor operations, integrate heterogeneous data sources, and support decision-making, IS professionals are expected to understand how physical systems, digital platforms, analytics, and organizational processes interact within enterprise environments. These developments motivate the integration of digital twin concepts into undergraduate IS curricula.

Unlike earlier curricular models that emphasized prescribed course structures, the IS 2020 Competency Model adopts a competency-based approach that prioritizes demonstrable capabilities over specific technologies, reflecting the long-standing IS emphasis on adaptable, transferable skills (Topi et al., 2010; Topi et al., 2020). This orientation provides a suitable foundation for incorporating digital twins into IS education, as DT systems inherently require integrated competencies such as systems thinking, data integration, digital infrastructure, and governance. At the same time, many IS programs continue to draw on the foundational structure articulated in IS 2010, particularly in areas such as systems analysis, data management, and organizational context. Digital twin instruction can therefore function as a connective element between these models, extending foundational IS competencies toward contemporary cyber-physical applications.

Digital twin systems combine physical assets, sensing technologies, digital platforms, data pipelines, analytics, and organizational processes. Prior research suggests that DT-related instruction is often fragmented, with components such as simulation, IoT, or analytics introduced independently and without an explicit integrative framework that reflects operational systems in practice (Liu et al., 2021; Jankovskis et al., 2024; Ahmed & Zaidi, 2025). From an IS 2020 perspective, this fragmentation constrains students' ability to apply systems thinking and to reason about integrated digital solutions in organizational contexts, a concern explicitly raised in prior IS curriculum discussions emphasizing integration across technical and organizational domains (Topi et al., 2010; Topi et al., 2020).

In response, this paper proposes a structured instructional framework for digital twin education in undergraduate IS programs. The framework consists of three interrelated elements: (1) explicitly defined student learning outcomes aligned with IS competencies, (2) instruction in digital twin architecture and system integration, and (3) hands-on laboratories and project-based learning activities supported by accessible and scalable learning kits. Rather than positioning digital twins as a specialized or advanced topic, the framework embeds DT concepts within core IS domains, reinforcing existing competencies while exposing students to cyber-physical systems that are increasingly central to digital transformation.

Student Learning Outcomes (SLOs)

To further operationalize the SLO categories, the following learning objectives provide measurable outcomes for undergraduate IS students:

1. Design a basic DT-enabled data pipeline that integrates data from physical or simulated sources into a digital platform.
2. Analyze system behavior using real-time or simulated data to support operational or managerial decision-making.
3. Develop and interpret visualizations (e.g., dashboards, digital representations) that reflect system state and performance.
4. Evaluate DT-based solutions in terms of data quality, security, interoperability, and organizational impact.
5. Justify system design decisions by considering technical constraints, governance requirements, and user needs.

These objectives translate high-level competencies into actionable outcomes that can guide instructional design and assessment.

Effective digital twin curriculum design should be grounded in clearly articulated student learning outcomes (SLOs) that align with the IS 2020 competency framework, which emphasizes competency demonstration, integration, and organizational relevance as defining characteristics of undergraduate IS education (Topi et al., 2020).

Drawing on the IS 2020 Competency Model and prior work on digital twin education (Liu et al., 2021), this study identifies three learning outcome categories that support DT instruction in undergraduate IS programs.

SLO1: Data Integration and Management

- Collecting, cleaning, and synchronizing data across physical and digital platforms.
- Managing and synchronizing real-time IoT data streams while ensuring data quality and consistency.
- Applying knowledge of IoT architectures and sensor networks to support integrated information systems.

SLO2: System Modeling, Simulation, and Digital Infrastructure

- Developing conceptual and data-driven representations of physical assets, processes, or systems using appropriate IS-oriented tools and techniques.
- Analyzing system behavior and performance through scenario-based reasoning, dashboards, and data-driven feedback mechanisms.
- Utilizing accessible tools such as spreadsheet-based models, Python-based data analysis, low-code platforms, or cloud-based DT services to support system understanding and decision-making.
- Interpreting system dynamics and analytics outputs to evaluate alternative operational or design scenarios.

SLO3: Cybersecurity and System Interoperability

- Applying secure data exchange practices to protect digital twin systems and associated data assets.
- Identifying interoperability challenges when integrating digital twin platforms across heterogeneous systems and environments.
- Demonstrating awareness of organizational, ethical, and risk considerations in digital twin development (e.g., OPC UA, BIM, ISO 23247).
- Integrating DT solutions across platforms and organizational boundaries while considering governance and security constraints.

The classroom digital twin implementation further illustrates the competency mappings summarized in Table 2.1. At the introductory level, students focused on real-time data ingestion, validation, and visualization, directly reinforcing SLO1 (Data Integration and Management). Intermediate activities required students to reason about system behavior, spatial context, and feedback loops between physical and digital components, supporting SLO2 (System Modeling, Simulation, and Digital Infrastructure). Advanced tasks emphasized secure data exchange, cross-platform integration, and the design of transparent operational policies, aligning with SLO3 (Cybersecurity, Interoperability, and Governance). This progression demonstrates how a single digital twin learning artifact can support multiple IS 2020 competencies through scaffolded experiential learning.

Fundamentals of Digital Twin Architecture and System Integration

To support the identified learning outcomes, instruction in digital twin fundamentals introduces students to the core architectural elements of DT systems, including physical assets, sensing and data acquisition layers, digital representations, analytics and simulation components, and visualization or interaction interfaces. Building on Grieves' (2014) conceptual model and subsequent refinements (Tao et al., 2019), students examine how data flows between physical and digital domains and how insights generated by the digital twin inform operational and managerial decision-making.

A central instructional consideration involves determining which competencies to emphasize within limited curricular space. The IS 2020 model encourages programs to prioritize transferable capabilities—such as systems thinking, integration, and organizational alignment—over tool-specific training (Topi et al., 2020). Consistent with this guidance, the

Category	DT Competency Area	Description	IS 2010 Alignment	IS 2020 Core Area Alignment
Student Learning Outcomes (SLOs)	SLO1: Data Integration & Management	Collecting, cleaning, and synchronizing IoT and operational data; ensuring data quality and real-time access	Data and Information Management; Systems Analysis & Design	Data Integration; Data-Driven Decision Making
	SLO2: System Modeling, Simulation, and Digital Infrastructure	Creating and maintaining digital representations of physical systems; basic simulation and predictive reasoning	Systems Analysis & Design; IT Infrastructure	Solution Development; Digital Infrastructure; Systems Thinking
	SLO3: Cybersecurity & Interoperability	Secure data exchange, cross-platform integration, governance, and risk mitigation.	IS Risk Management; IT Infrastructure	Risk Management; Ethics & Professional Responsibilities; Enterprise Integration
Digital Twin Architectural Concepts	Fundamentals: System Architecture & Connectivity	Designing cyber-physical architecture; sensor integration; data pipelines	IT Infrastructure; Systems Analysis & Design	Digital Infrastructure; Systems Thinking
	Fundamentals: Visualization & Interaction	Dashboards, 3D models, and interactive interfaces supporting decision-making	Data and Information Management	Human-Centered Design; Solution Development
	Cybersecurity & Ethical Considerations	Ensuring secure, interoperable, and responsible DT deployments	Data and Information Management	IS Risk Management & Security; IT Strategy, Management & Acquisition
	Fundamentals: Diagnostics & Analytics	Monitoring, anomaly detection, predictive insights, and decision support	Systems Analysis & Design	Analytics; Data-Driven Decision Making

Table 2.1 Mapping of DT Learning Outcomes and Architectural Concepts to IS 2020 Curriculum Areas

proposed framework emphasizes architectural reasoning, data flow, interoperability, and governance rather than mastery of any single digital twin platform. This approach supports conceptual understanding that is applicable across industries and remains resilient to changes in specific tools or technologies.

By grounding digital twin learning outcomes and architectural concepts in established IS curriculum models, digital twin education can be positioned squarely within the IS discipline rather than framed as an external or engineering-centric topic. This alignment reinforces the role of IS programs in preparing graduates to design, manage, and govern complex digital systems that connect physical operations with organizational decision-making.

Mapping DT Fundamentals to IS Curriculum Models (IS 2010 and IS 2020)

While this instructional framework is primarily aligned with the IS 2020 Competency Model, explicit mapping to the IS 2010 curriculum structure remains important for programs that continue to use IS 2010 as a foundational reference. Accordingly, the competencies emphasized in DT instruction can be mapped to both IS curriculum models, demonstrating continuity rather than replacement. Under IS 2010, DT learning outcomes align with core areas such as Data and Information Management, Systems Analysis and Design, IT Infrastructure, and IS Risk Management (Topi et al., 2010). These same outcomes map naturally to IS 2020 competencies related to systems thinking, data integration, digital infrastructure, and organizational alignment (Topi et al., 2020). This dual alignment illustrates how digital twin education can be adopted incrementally, supporting contemporary competency development while remaining compatible with existing IS program structures. Table 2.1 summarizes this dual alignment by mapping digital twin learning outcomes and foundational competencies to IS 2010 core curriculum areas and their corresponding IS 2020 competency domains, illustrating how digital twin concepts can be integrated incrementally within existing IS programs.

Instructional Context and Prerequisites

The proposed framework is designed for upper-level undergraduate Information Systems courses, including Systems Analysis and Design, Data Management, Emerging Technologies, or Capstone experiences. Students are expected to have foundational knowledge in introductory programming, basic data management, and core IS concepts such as systems thinking and information flow. This positioning allows digital twin concepts to function as an integrative layer that connects prior learning across technical and organizational domains.

3. EXPERIENTIAL LEARNING AND DIGITAL TWIN INSTRUCTION

Experiential learning is a central element of the IS 2020 competency model, which emphasizes applied problem-solving, systems thinking, and the ability to integrate digital solutions within organizational contexts. Within this framework, hands-on laboratories and project-based learning function as primary instructional mechanisms through which students develop and demonstrate Information Systems competencies, rather than supplementary activities. DT learning kits offer a practical way to support this approach by enabling students to engage directly with cyber-physical systems that integrate data, infrastructure, analytics, and decision processes.

Figure 3.1 illustrates a conceptual digital twin learning architecture that supports experiential learning and human-centered decision-making in undergraduate IS education. The figure illustrates the integration of a physical environment, data integration layer, digital twin representation, and human-centered decision and governance processes. The architecture emphasizes systems thinking, real-time data flow, and human oversight rather than tool-specific implementation details, aligning digital twin instruction with IS 2020 competency development.

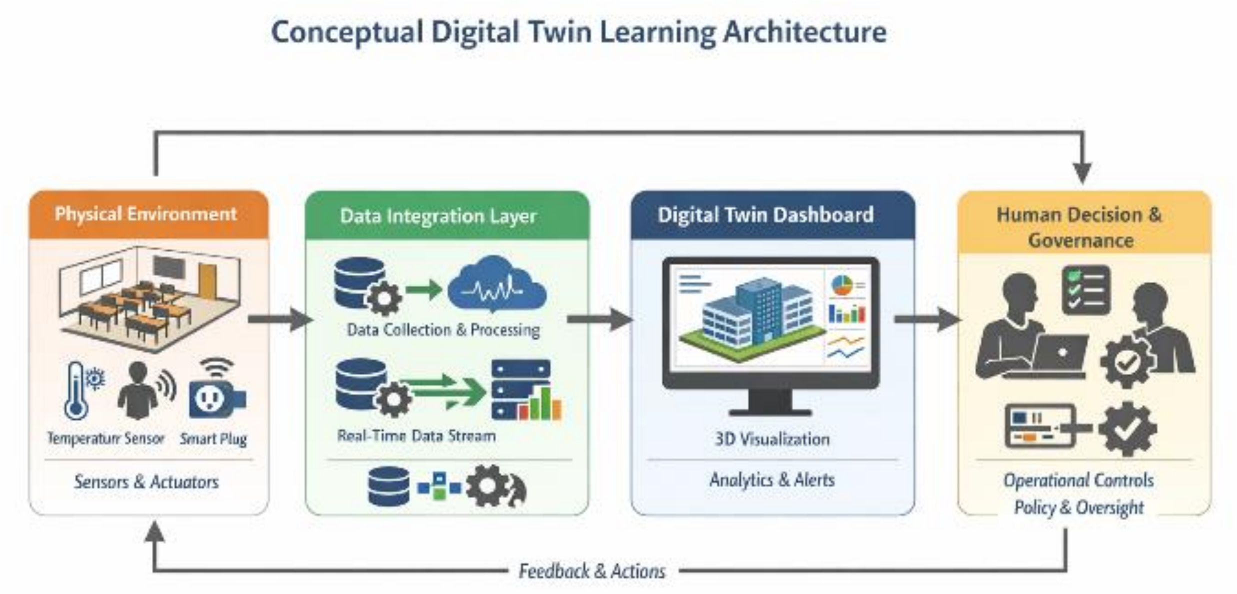

Figure 3.1 Conceptual Digital Twin Learning Architecture.

DT learning kits serve as accessible entry points for experiential learning by enabling students to design, observe, and interact with digital representations of physical systems. When incorporated deliberately into course design, these kits can support multiple IS 2020 competencies, including data integration, digital infrastructure, solution development, and organizational alignment. In contrast to purely simulated environments, DT kits expose students to real-time data flows, system constraints, and integration challenges that more closely resemble those encountered in organizational settings. This exposure helps students move beyond abstract conceptualization toward applied systems reasoning.

From an instructional standpoint, the pedagogical value of DT learning kits lies less in the sophistication of the underlying hardware and more in their capacity to support learning progression. Introductory activities may focus on foundational tasks such as data acquisition, basic integration, and visualization, aligning with learning outcomes related to data and information management (SLO1). More advanced projects can then introduce system modeling, analytics, security considerations, and cross-platform integration, supporting learning outcomes associated with systems thinking and risk management (SLO2 and SLO3). This staged approach is consistent with IS 2020's emphasis on competency development over tool-specific training and encourages the development of transferable skills applicable across technologies and organizational contexts.

DT learning kits provide affordable and scalable entry points for experiential learning, enabling students to design, monitor, and control virtual replicas of physical systems. Platforms such as Arduino, Raspberry Pi, Unity, MATLAB/Simulink, and Microsoft Azure Digital Twins directly support IS 2010's emphasis on experiential and systems integration learning. By lowering barriers to engagement, these kits make abstract IS concepts tangible and foster project-based learning across disciplines.

Strategies for Incorporating Digital Twins into IS curricula

Aligned with the flexible, competency-based approach of IS 2020, digital twin concepts can be incorporated into undergraduate IS programs through several complementary instructional strategies.

a) **Integrating Digital Twin Topics into Existing Curricula:**
Digital Twin concepts can be embedded within established IS courses such as systems analysis and design, data management, enterprise systems, emerging technologies, or IT infrastructure. For instance, a DT-based laboratory might have students trace data flows between physical sensors and cloud platforms, reinforcing systems thinking and data integration competencies without requiring a standalone course.

b) **Incorporating Dedicated Digital Twin or**

Cyber-Physical System Courses:
Programs with sufficient curricular flexibility may offer elective or capstone courses focused specifically on digital twins or cyber-physical systems. These courses allow for more in-depth study of architecture, analytics, interoperability, and governance, while remaining aligned with IS 2020 competencies such as solution development, risk management, and organizational alignment.

c) **Offering Project-Based and Capstone Experiences:**
Capstone projects offer an ideal setting for DT-based learning, enabling students to design end-to-end solutions for realistic organizational problems. Examples include smart building monitoring, energy optimization, or predictive maintenance scenarios. These projects emphasize system integration, stakeholder considerations, and applied decision-making, supporting the achievement of SLO1–SLO3 in authentic, practice-oriented contexts.

Role of Digital Twin Learning Kits
Digital twin learning kits typically include low-cost hardware components (e.g., microcontrollers, sensors, actuators), software platforms, communication protocols, and visualization tools that together model key aspects of real-world systems. These kits allow students to build small-scale DT implementations that capture essential features of enterprise information systems, such as real-time data collection, digital representation, and feedback control.

These kits are designed to be accessible to students with varying technical backgrounds. Many platforms provide rapid-prototyping capabilities and visual or high-level programming environments, enabling students to focus on system behavior, integration, and decision logic rather than low-level hardware issues. As projects grow in complexity, students can incorporate analytics, security mechanisms, or cloud-based services, supporting higher-level IS competencies such as governance, scalability, and interoperability.

Within an IS curriculum, DT learning kits serve as boundary objects that bridge technical implementation and organizational analysis. Students are expected not only to construct functional systems but also to justify design choices, assess risks, and explain how DT solutions create value within enterprise environments. This combination of technical and organizational reasoning aligns closely with the goals of IS education and demonstrates the instructional potential of digital twins in undergraduate programs.

Comparative Taxonomy of Digital Twin Platforms
Digital twin platforms differ widely in cost, technical requirements, instructional affordances, and alignment with IS competencies. Understanding these differences is essential for selecting platforms that support meaningful experiential learning in undergraduate IS programs. This study organizes commonly used DT platforms into a comparative taxonomy along four dimensions:

a) Cost and Accessibility
Platforms range from low-cost, entry-level kits suitable for classroom use to more sophisticated commercial solutions. Low-cost kits enable hands-on experimentation without significant resource investment, making them accessible to programs with limited budgets. Higher-end platforms provide expanded capabilities for analytics, cloud integration, or large-scale system modeling but may require additional technical support.

b) Technical Requirements
Platforms differ in hardware and software complexity. Some kits rely on microcontrollers and modular sensors, supporting visual or high-level programming environments. Others require advanced coding, database management, or cloud configuration. Instructors should balance technical depth with student preparedness and course objectives when selecting a platform.

c) Instructional Affordances
Platforms vary in the pedagogical experiences they support. Some focus on foundational system behavior, data acquisition, and visualization, while others allow advanced exercises in system modeling, predictive analytics, or multi-platform integration. Platforms that provide modularity and scalable complexity enable instructors to design progressive learning experiences aligned with multiple student learning outcomes (SLO1–SLO3).

d) Alignment with IS Competencies
Effective platforms support both technical and organizational reasoning. Ideal platforms allow students to examine data flows, system

interactions, security considerations, and organizational impact, linking hands-on implementation to broader IS learning objectives. Alignment with IS 2020 competencies—systems thinking, data integration, solution development, and enterprise alignment—ensures that experiential exercises reinforce skills students are expected to demonstrate in professional practice.

By organizing digital twin platforms along these dimensions, educators can make informed decisions that reflect program resources, student experience, and instructional goals. The taxonomy also provides a basis for evaluating new platforms and adapting curricula as technology and pedagogy evolve.

Illustrative Digital Twin Classroom Implementation

To demonstrate the practical feasibility of the proposed instructional framework, a low-cost, replicable digital twin learning module was implemented in a classroom. The module was designed to function as an integrative learning artifact rather than a technical systems exercise, enabling students to engage with real-time sensing, data integration, visualization, and operational decision-making within a single coherent system. The instructional objective was to help students understand how physical environments, digital infrastructure, analytics, and governance mechanisms interact to support organizational decisions, consistent with the IS 2020 competency model.

The classroom digital twin focused on occupancy, space utilization, and indoor environmental conditions as a familiar and organizationally relevant context. Students worked in teams designing a small-scale cyber-physical system that collected real-time data from the physical space, routed and stored that data through an integration layer, and presented it through a spatially contextualized digital interface. Emphasis was placed on data flow, system integration, and interpretability rather than on low-level hardware configuration. This approach allowed students with diverse technical backgrounds to participate meaningfully while reinforcing IS competencies related to data management, systems thinking, and digital infrastructure.

Importantly, the instructional design emphasizes human-centered governance rather than automation alone. Students implemented transparent, rule-based operational policies that reflected organizational constraints and accountability, such as occupancy-aware resource control and threshold-based alerts. All system actions were observable and reversible, enabling discussion of trust, oversight, and ethical responsibility in digital systems. This implementation illustrates how digital twin learning activities can operationalize IS 2020 competencies in an experiential format without positioning digital twins as an engineering specialization.

By organizing digital twin platforms along these dimensions and providing examples in Table 3.1, educators can make informed decisions that match program resources, student experience, and instructional objectives. This framework also allows instructors to evaluate new platforms as technologies evolve while ensuring alignment with IS 2020 competencies and learning outcomes.

In this implementation, low-cost IoT-based platforms (e.g., microcontroller and sensor-based kits with cloud integration) were used to support real-time data acquisition and visualization. One challenge encountered was accommodating varying levels of student technical experience, particularly in configuring data pipelines and integrating hardware components. To address this, instructional scaffolding and template-based configurations were provided.

What worked particularly well was the use of real-time data streams, which significantly improved student engagement and helped reinforce systems thinking concepts. In future iterations, additional structured guidance and pre-configured modules could further reduce setup time and allow more focus on analytical and decision-making aspects. Informal student feedback indicated that hands-on interaction with live data improved understanding of system integration and increased interest in applied IS topics.

Assessment Considerations

Assessment of DT-based learning activities can be structured around project-based evaluation aligned with the defined learning objectives. Example assessment components include:

- Data integration and system functionality (e.g., correctness and completeness of data pipelines)
- System design and architecture (e.g., clarity of data flow and component interaction)
- Analytical reasoning (e.g., interpretation of system behavior and decision-making)
- Governance and security considerations

Platform / Kit	Approx. Cost	Technical Skills Required	Primary Learning Focus	IS 2020 Competencies Supported
Arduino-based Smart Home / IoT Kits	$50–$120	Basic electronics, C/C++ programming	Sensor integration, basic data acquisition, simple automation	Data & Information Management; Systems Analysis & Design
Raspberry Pi Digital Twin Starter Kits	$80–$150	Python, Linux, IoT networking	Edge computing, Linux-based services, real-time monitoring	Digital Infrastructure; Data Integration; Solution Development
MATLAB/Simulink	Academic license ($50–$100 student; higher institutional)	MATLAB coding, modeling, simulation	System modeling, simulation, predictive analysis	Analytics; Systems Thinking; Data-Driven Decision Making
Unity + IoT Sensor Integration	Free (student), add-ons vary ($0–$50)	Unity (C#), visualization, IoT data streams	Visualization, 3D modeling, interactive DT interfaces	Human-Centered Design; Solution Development
Microsoft Azure Digital Twins	Free tier; scales with usage ($0–$50/month for academic)	Cloud computing, APIs, data pipelines	Cloud-scale DT deployments, enterprise integration, IoT hub	Digital Infrastructure; Enterprise Integration; Data Management
Siemens Mindsphere Academic Tools	Institutional license (varies)	Industrial IoT, advanced analytics	Industrial DT scenarios, predictive maintenance	Enterprise Integration; Risk Management; Analytics
Node-RED + MQTT Prototyping Kits	Free software; hardware <$100	IoT protocols, data routing, event-driven programming	Middleware prototyping, automation flows, plug-and-play DTs	Systems Integration; Digital Infrastructure; Emerging Technologies

Table 3.1. Digital Twin Learning Platforms and Alignment with IS 2020 Curriculum Competencies

Note: Costs are approximate as of 2026 and may vary depending on institutional licensing, availability, and usage.

- (e.g., awareness of risks, controls, and organizational constraints)

Rubrics can be designed to evaluate both technical implementation and the ability to justify design decisions within an organizational context, consistent with IS competency-based learning.

4. EDUCATIONAL IMPLICATIONS AND FUTURE DIRECTIONS

Integrating digital twin (DT) technologies into undergraduate Information Systems curricula represents a significant opportunity to strengthen competency-based learning in the context of increasingly data-driven and cyber-physical organizational environments. By positioning digital twins as integrative learning artifacts rather than specialized engineering tools, this approach enables students to connect foundational IS domains—including data integration, systems analysis, digital infrastructure, and governance—within a unified experiential learning context. This section examines the educational implications of incorporating DT-based learning tools into IS

curricula and highlights emerging directions for advancing digital twin–enabled IS education.
A key advantage of DT learning tools is their accessibility and scalability. A range of kits—from do-it-yourself to ready-to-run solutions—is available at varying cost levels, allowing instructors to adjust activities based on institutional resources and student readiness. These tools lower barriers to complex topics, enabling students from diverse backgrounds to participate meaningfully. DT kits also support scaffolded learning: introductory exercises focus on data acquisition and visualization, while advanced projects address system integration, modeling, analytics, and security.

Digital twin activities encourage interdisciplinary engagement while remaining grounded in IS domains. Although DT systems draw on multiple technical areas, their value in IS education comes from linking technical implementation with organizational analysis, governance, and decision-making. Students are expected not only to build functional systems but also to justify design choices, assess risks, and evaluate how DT solutions deliver enterprise value. This combination reflects real-world IS practice and reinforces the systems thinking emphasized in IS 2020.

Emerging Directions in Digital Twin Education

Recent developments in DT technology offer new opportunities for IS instruction. Greater integration of IoT and sensor networks enhances the realism of DT-based learning by enabling real-time synchronization between physical and digital systems. Cloud-based DT platforms allow exploration of scalability, interoperability, and enterprise integration—central aspects of contemporary IS practice.

Advances in edge computing and analytics extend instructional possibilities by supporting near-real-time decision-making and autonomous system behavior. These capabilities can be incorporated into advanced courses or capstone projects to explore predictive maintenance, resource optimization, and resilient digital infrastructures. Immersive visualization tools, including 3D modeling and augmented or virtual reality, further support experiential and inquiry-based learning by improving system understanding and user interaction.

Importantly, the educational value of these technologies lies not in novelty but in reinforcing competency-based learning. Digital twin platforms provide opportunities to explore cybersecurity, ethical considerations, and governance challenges associated with integrated digital systems, addressing topics that are increasingly critical in IS curricula.

5. CONCLUSIONS

This paper presented a structured instructional framework for integrating digital twin education into undergraduate Information Systems programs, grounded in the IS 2010 Curriculum Guidelines and the IS 2020 Competency Model. By framing digital twins as integrative learning artifacts rather than specialized engineering systems, the proposed approach demonstrates how digital twin concepts can reinforce core IS competencies related to data integration, systems thinking, digital infrastructure, and governance.

The framework emphasizes clearly articulated learning outcomes, foundational architectural reasoning, and experiential learning supported by accessible digital twin learning kits. An illustrative classroom implementation highlights how a single digital twin learning artifact can be used to scaffold competency development across multiple levels, enabling students to engage with real-time data, system integration, and human-centered operational decision-making within an organizational context.

By aligning digital twin instruction with established IS curriculum models, this work offers a practical and transferable approach for IS educators seeking to modernize curricula without wholesale restructuring. As organizations increasingly rely on cyber-physical systems and data-driven operations, thoughtfully integrating digital twin concepts into IS education represents an important opportunity to prepare graduates for emerging professional roles while reinforcing the disciplinary identity of Information Systems education.

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Teaching Case

Operational Analytics in Excel: A Transaction-Level Car Wash Case for Introductory Data Literacy

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Hook

"I know our washes are busy, but are we actually making money? And which location is really pulling its weight?" Matthew Auger, Director of Operations at Soapy Noble Express Car Wash, leaned back from his laptop and stared at a dashboard full of charts he did not fully trust. Since the company rolled out a new point-of-sale system across its eight New England locations, Soapy Noble had more detail than ever, including timestamps, product mix, payment types, and transaction totals for every wash sold.

The problem was turning all of that activity into decisions. Some sites looked consistently strong, while others surged on weekends and then went quiet. The monthly unlimited plan was growing, but Matthew could not tell whether it was boosting revenue or cannibalizing single-wash sales. He also needed to know when demand peaked, whether staffing patterns matched actual traffic, and which levers, such as pricing, promotions, hours, or service mix, were most likely to move results. With transaction data flowing in across eight locations and no shortage of operational questions, Matthew brought in an external consulting team and asked for clear, data-backed recommendations he could act on quickly.

Abstract

This teaching case introduces introductory level students to data literacy through an applied operational analytics project based on a regional express car wash business. Students assume the role of an external consulting team hired by Soapy Noble Express Car Wash, a fast-growing chain operating eight locations in New England, to analyze transaction level point of sale data and develop actionable recommendations for management. Using approximately one year of transaction records at scale, students apply Excel based techniques such as data cleaning, descriptive statistics, pivot tables, and visualization to identify patterns in customer demand, service mix, location performance, and monthly unlimited plan usage. To extend analysis beyond the internal dataset, the case encourages students to locate and integrate relevant external sources, such as weather or demographic data, and to explain how these sources inform interpretation and recommendations. The case is designed for first year courses in data literacy, business analytics, or introductory CIS and includes team-based deliverables appropriate for nontechnical decision makers, including an analysis workbook and a concise executive memo and presentation.

Keywords: Data Literacy, Project Based Learning, Business Analytics, Excel, Operational Analytics

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Operational Analytics in Excel: A Transaction-Level Car Wash Case for Introductory Data Literacy

Kevin Mentzer, Robert Russo, Nathaniel Lawshe, and Elizabeth Mullen

1. INTRODUCTION

As data becomes increasingly central to decision-making in every industry, developing data literacy, including the ability to read, analyze, interpret, and communicate with data, has emerged as a critical competency for the modern workforce (Carlson & Johnston, 2015; Mentzer et al., 2024; Wolff et al., 2016). Employers across sectors consistently identify data competency as essential not only for analysts, but for all professionals responsible for strategic thinking and operational improvement (Miller & Hughes, 2017). This widespread need reflects a shift toward data-informed culture across all organizational levels, requiring graduates to be fluent in both data interpretation and evidence-based reasoning.

Yet, for many undergraduate students, data remains abstract, locked in textbook problems, isolated spreadsheets, or hypothetical scenarios that do not mirror real business complexity. Prior research has noted that learners benefit most when they engage with authentic data and real-world problems, which promote motivation, relevance, and long-term skill retention (Gould, 2010; Kolodner et al., 2003). Project-based learning (PBL), an instructional method that situates students in realistic roles with complex, open-ended challenges, offers a pedagogical bridge between theory and applied practice (Bell, 2010; Blumenfeld et al., 1991).

PBL immerses students in sustained inquiry and collaborative problem-solving, encouraging deeper cognitive engagement and fostering both technical and professional skills. Research has shown that PBL can increase student motivation and improve transfer of learning across contexts (Barron & Darling-Hammond, 2008; Thomas, 2000), benefits that are particularly relevant in data-focused education where students must navigate ambiguity, clean and interpret data, and develop actionable insights.

This teaching case is designed as a project-based learning experience for first-year undergraduate students developing foundational data analysis skills in an introductory Data Literacy context. Students assume the role of an external consulting team hired by a regional car wash chain to analyze operational data and make strategic recommendations to senior management. By integrating real transaction records with optional external datasets such as weather and census information, students are challenged not only to build technical proficiency in Excel and visualization tools, but also to apply data to support meaningful business decisions.

Implemented in a required first-year undergraduate Data Literacy course, this case supports AACSB-relevant assurance-of-learning documentation by generating assessable student artifacts (Excel analysis, memo, and presentation) and by evaluating them with a common scoring rubric. The judges used the rubric (see Appendix C) to score each team and select the winners of the case competition; instructors may also use rubric dimensions as direct evidence of data literacy and analytic communication outcomes for AoL reporting.

Working with real transaction data and optional external sources, students will explore customer behavior, pricing models, and performance across multiple locations. The case challenges students to use Excel as their primary analysis tool, applying descriptive statistics, visualizations, and business reasoning to deliver a professional, data-driven presentation. By engaging students through a hands-on, scenario-based project, this case supports not only the acquisition of data literacy skills, but also the broader development of analytical mindset and professional readiness, key outcomes for twenty-first century learners.

2. MOTIVATION

Instructors in introductory CIS, MIS, and analytics courses often seek datasets that are authentic, engaging, and appropriately scoped for novice learners. Public repositories such as Kaggle and data.gov can be useful starting points, but they frequently present tradeoffs for introductory teaching. Many Kaggle datasets and competitions presume advanced modeling skills beyond the first-year level, while some government datasets can be either too narrow or insufficiently engaging to sustain a multi-week, team-based project.

To better understand the current landscape of published teaching cases in the *Information Systems Education Journal* (ISEDJ), we reviewed teaching cases published over the past six years (2020–2025). We identified 39 cases (Appendix E) and examined two practical considerations for instructors adopting cases: whether the case supplies a dataset, and the intended student level. We also summarized case keywords to visualize the range of skills emphasized in recent publications (Figure 1).

Across the 39 cases, 23% (n = 9) provided data for student use. Regarding intended audience, 25.6% (n = 10) were aimed at introductory courses, 51.3% (n = 20) at upper-level courses, 10.2% (n = 4) at graduate courses, and 12.8% (n = 5) at both upper-level and graduate courses (Figure 2).

Figure 2. ISEDJ Prior Cases Keywords Word Cloud

When focusing specifically on cases that were both (a) introductory level and (b) supplied a dataset, only two cases met both criteria. Neither relied on a novel dataset; instead, both used publicly available data. We also observed multiple cases that referenced external datasets via links that were no longer accessible, suggesting that authors who rely on public sources should consider providing a stable copy of the dataset alongside the case materials.

This case is designed to address these gaps by providing: (1) a novel, real-world dataset; (2) an introductory-level project suitable for first-year students in data literacy or introductory MIS/analytics; (3) data at a scale that is large enough to require meaningful summarization and support the discovery of non-obvious patterns; and (4) a business context that is easily relatable to students.

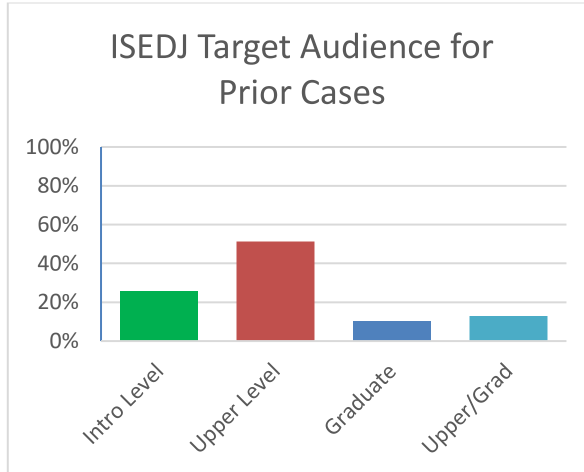

Figure 3. ISEDJ Target Audience for Prior Cases

By completing this case, students will be able to:

- Apply descriptive statistics to identify demand and usage trends.
- Create Excel-based visualizations (for example, pivot charts and time series) to support decision-making.
- Interpret transaction-level data to assess operational performance.
- Compare performance across locations.
- Evaluate the viability of a monthly unlimited plan.
- Incorporate external data sources to add context to analysis.
- Communicate findings and recommendations in a professional format.

3. COMPANY BACKGROUND

Soapy Noble Express Car Wash (http://soapynoble.com) is a regional express car wash chain operating eight locations across New England. The company offers a fast, automated wash experience supported by complimentary amenities such as vacuum stations, air nozzles, and drying towels. Customers may purchase individual washes or enroll in a monthly unlimited plan. Soapy Noble promotes its "Noble Guarantee," which emphasizes consistent service quality and customer satisfaction.

In early 2024, Soapy Noble implemented a new point-of-sale system that captures detailed, transaction-level information, including timestamps, location identifiers, products purchased, payment types, and revenue amounts. With this new visibility into operations and sales, leadership is seeking to use the data to support decisions related to pricing, staffing, marketing, operational improvements, and future growth.

4. PROJECT OVERVIEW

Students are placed in the role of an external consulting team hired to help Soapy Noble interpret and act on its newly available point-of-sale data. Management has asked the team to evaluate:

- Which locations are overperforming or underperforming, and why
- Patterns in demand by time of day and day of week
- Seasonal patterns in usage
- The financial implications of the monthly unlimited plan
- Service mix and pricing effectiveness
- Broader market factors that may influence performance (for example, demographics and weather)

Students receive approximately one year of transaction-level data (about 1 million rows) and are encouraged to enhance their analysis with one or more external datasets (for example, U.S. Census data or NOAA weather data).

Analysis Expectations
In the analysis phase, teams translate raw transaction records into management-ready insights and recommendations. The goal is not to build a perfect model, but to use structured Excel analysis to identify operational patterns, test plausible explanations, and quantify the business implications of those patterns. Successful teams make their work transparent by labeling assumptions, documenting steps, and presenting summaries that a nontechnical stakeholder could follow.

Student teams are expected to:

1. Clean and summarize the data provided in Excel.
2. Use pivot tables and visualizations to identify key trends.
3. Integrate one or more external datasets to add depth.
4. Prepare management-ready findings and recommendations for the memo and presentation.

Optional tools like Tableau may be used for dashboarding, but Excel is required.

Client-Facing Deliverables
Deliverables are intentionally designed to mirror what an external consulting team would provide to an operations leader. Each artifact serves a distinct purpose: the workbook documents the analytical trail, the memo communicates the headline findings concisely, and the slide deck supports a decision-focused presentation. Together, these deliverables emphasize clarity, visual communication, and actionable recommendations rather than technical jargon.

Each team must submit:

- An Excel workbook with labeled analysis and visuals
- A management-facing slide deck
- A one-page executive memo
- A list of 2–3 strategic recommendations backed by data

Case Competition Format
We implemented this case as a competition across five sections of Data Literacy, a required first-year course that builds foundational Excel, Word, and PowerPoint skills. Students self-selected into teams of two to five and had approximately three to four weeks to complete the analysis.

During the first week, instructors distributed the dataset through the LMS, provided time for students to review the data structure, and held a Q&A session to clarify variable definitions and expectations. Instructors were asked to support student-led analysis plans and execution, while avoiding injecting their own conclusions into teamwork.

In the preliminary round, each course section selected a finalist team to represent the section in the final presentation round. Teams typically spent Weeks 1 through 3 on exploration, cleaning, external data integration, figure development, and executive summary preparation, with section presentations occurring during Week 4. Sections used peer feedback, instructor notes, or the shared rubric (Appendix C) to support selection of a section winner.

Before the final event, finalist teams met briefly with instructors to confirm presentation format and timing. Finalists then delivered a 15-minute presentation to Soapy Noble’s management team and other judges, who used the supplied scoring rubric to select the overall winners.

5. INSTRUCTOR AND STUDENT FEEDBACK

Faculty Reaction
Faculty observations were generally positive, with several predictable challenges that are common

in introductory, open-ended analytics work. After the project launch, some students expressed low confidence in the quality of the work they could produce. Others felt overwhelmed by the scale of the dataset (approximately 1 million rows) and the number of variables available, and some teams struggled to determine where to begin. Students were also understandably anxious about presenting their findings to Soapy Noble's management team.

To support students through these early barriers without reducing the authenticity of the task, instructors required each team to create a brief analysis plan before building charts or drafting recommendations. Teams articulated the questions they intended to answer, identified the variables they would use, and wrote down what they expected to find. This planning step increased confidence and helped teams establish a workflow. Instructors implementing this case should monitor student confidence closely and provide structure early, as the assignment is intellectually demanding.

Faculty also reported that the local nature of the client increased student engagement. Several students were familiar with the business, and some had been customers. This strengthened the perceived relevance of the work and helped students connect data analysis to real operational decisions.

Student Feedback

Student feedback was largely positive. Many students described the project as engaging, useful, and more challenging than typical spreadsheet assignments. Several students highlighted the difficulty of translating analysis into a clear narrative and selecting visuals that directly address the business questions. This is a desired outcome of the case, since the ability to explain and defend analytical choices is central to data literacy.

How to AI-Proof this case

While no case can fully prevent the use of AI tools, instructors can design the assignment so that meaningful learning depends on student decision-making, documentation, and communication. Several approaches have worked well with this case:

1. Use constraints that require hands-on analysis. Because transaction-level datasets of this size are difficult to paste directly into typical chat tools, students still need to summarize, clean, and structure the data in Excel before they can ask useful AI-supported questions.
2. Require stakeholder-specific deliverables. Ask teams to tailor their messaging to different audiences (for example, operations leadership versus marketing). Generic, one-size-fits-all responses tend to fail when context and tradeoffs matter.
3. Require external data selection and justification. Do not provide the external datasets. Instead, require teams to find, justify, and cite their own sources (for example, weather, demographics, local events) and explain how the added context changes interpretation.
4. Build in process checkpoints. Include interim submissions such as an analysis plan, draft visuals, and a walkthrough of workbook logic. Use brief in-class progress reviews to surface whether teams understand their own work.
5. Collect the workbook as evidence. Require students to submit the Excel file with formulas, pivot tables, and labeled steps so the analytical trail is transparent.
6. Use live presentations and questioning. Ask teams to defend choices and explain tradeoffs, such as why they selected a specific metric, chart type, filter, or segmentation approach, and what alternative explanations they considered.

6. CONCLUSIONS

This teaching case demonstrates how transaction-level point-of-sale data can be used to build foundational data literacy skills through an applied, decision-focused project. By positioning students as an external consulting team for a regional express car wash chain, the case creates an authentic context in which learners must move beyond mechanical spreadsheet steps and instead translate data into operational insight and actionable recommendations.

The case is intentionally designed for introductory learners and can be completed using Excel as the primary analysis tool. Students practice core competencies such as data cleaning, descriptive statistics, pivot tables, and visualization, while also developing the communication skills required to explain methods, interpret results, and justify recommendations for a nontechnical audience. The option to integrate external datasets, such as weather or demographic information, further reinforces the idea that business analysis is strengthened when internal performance data is interpreted within a broader context.

Instructor experience suggests that the

combination of open-ended questions and a large dataset can initially feel challenging for first-year students. However, with light structure early in the project, such as an analysis plan, interim checkpoints, and emphasis on documentation in the workbook, teams can produce high-quality, defensible work. These implementation features also support academic integrity by making student reasoning visible through process artifacts and live explanation rather than relying solely on a final answer.

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APPENDIX A

Sample Data

Field	Value
Date	1/23/2025
Time	10:46:00 AM
Sale ID	30123285576923
Cash Out Location	XPT1
Employee Name	—
Customer Name	Rxxxxx Mxxxxx
Site	Soapy Noble | Niantic
Channel	Retail
Transaction Type	Sale
Transaction Status	Purchased
Line Item Action Type	Sale – Add Product
Product Type	Wash
Product Name	The Works
Quantity	1
Price	23.50
Subtotal	23.50
Tax	0.00
Discount	0.00
Total	23.50
Payment	0.00
Payment (abs)	—

APPENDIX B
Student Handout

To: External Consulting Team – [Your Team Name Here]
From: Matthew Auger, Director of Operations, Soapy Noble Express Car Wash
Date: March 25, 2025
Subject: Strategic Data Review & Recommendations Request

Dear Consulting Team,

We appreciate your partnership with Soapy Noble Express Car Wash. As part of our effort to make more informed, data-driven decisions, we have enlisted your team to conduct a comprehensive business analysis of our operational and sales data. Your findings will be presented directly to Soapy Noble's executive leadership team to help guide strategic planning across our 8 locations in New England.

We've recently upgraded our point-of-sale system and now have access to detailed transactional data. This includes timestamps, location IDs, product sales, payment types, and revenue metrics, all of which are vital to our analysis. However, we believe the most powerful insights come from combining internal data with context from the outside world.

Project Scope

Your primary task is to analyze our transaction dataset, assess performance across locations, and evaluate customer behavior and service usage. To enhance your insights, we strongly encourage you to incorporate relevant external datasets, such as:

- Census and demographic data: Income, population density, car ownership, etc.
- Weather data: Precipitation, temperature, or seasonal patterns that may affect car wash frequency
- Economic data: Consumer spending trends, inflation, fuel prices
- Local events or holidays that might explain spikes or lulls in business

Cross-referencing these external factors with our internal data will help reveal deeper patterns and support more targeted recommendations.

Key Questions

Your analysis should address the following:

1. Location Performance
   - Which sites are outperforming or underperforming, and why?
   - Are there external factors (e.g., population, income, traffic volume) influencing this?
2. Customer Usage Patterns
   - What are the busiest times of day and week?
   - How do trends vary across different communities or seasons?
3. Monthly Plan Effectiveness
   - Are monthly plan holders using the service frequently?
   - Are these plans financially beneficial to the company?
4. Service Mix and Pricing
   - Which washes are most popular?
   - Should we consider bundling, upselling, or adjusting pricing?
5. Strategic Recommendations
   - Based on your findings, what operational or marketing changes would you suggest?
   - How can we better tailor offerings to specific locations or customer segments?

Deliverables

Please submit the following:

- An Excel analysis workbook with tables and visuals (e.g., pivot charts)

- A 10–20 slide presentation summarizing your findings and recommendations
- Optional: a dashboard (Excel or Tableau) for interactive exploration
- Clear explanations of how any external data informed your conclusions

Your final deliverable should be professional, insightful, and accessible to business decision-makers without a technical background.

What We're Looking For

We value:

- Accuracy and clarity in data analysis
- Thoughtful integration of external data for added context
- Actionable recommendations grounded in evidence
- Strong visuals and concise messaging

This is a real-world consulting engagement. We are relying on your work to help us elevate our business strategy and customer experience.

Thank you again for your collaboration. We look forward to your analysis and the insights you uncover to help Soapy Noble continue to deliver Noble Service and a Quality Wash across New England.

Sincerely,
Matthew Auger
Director of Operations
Soapy Noble Express Car Wash
https://soapynoble.com

APPENDIX C
Scoring Rubric

Evaluation Criteria -- Presentation

Category	1	2	3	4
Content Preparedness	Presentation of content is disjointed and incoherent; little evidence of preparation.	Content shows problems with succinct presentation; more preparation of the material is necessary.	Content is presented succinctly for the most part. Preparation is evident.	Content throughout the presentation is well presented succinctly; presentation is well-prepared and has obviously been well rehearsed.
Organization	Introduction does not give overview; organization is unclear, or presentation ends without conclusion.	Some overview is given; connection between introduction and presentation is sometimes unclear; conclusion is limited OR no introduction /overview or no conclusion.	Mostly effective introduction or overview of presentation; conclusion is appropriate.	Strong and engaging introduction provides overview of presentation; presentation supports introduction; conclusion reinforces main points in memorable fashion.
Visual Support	Visuals do not include graphs or tables to support the presentation; graphics are unattractive, detract from the content of the presentation OR No theme/content-related graphics used.	Visuals (graphics, graphs and tables) could have been used more effectively to support the content of the presentation.	Most visuals are attractive; graphs and tables generally enhance the presentation; graphics are theme-topic related.	Visuals are attractive and effectively enhance the presentation; graphs and tables illustrate important points effectively; graphics are theme/topic-related.
Collaboration	No evidence of team work; no transitions made to next/previous speaker or topics.	Some evidence of team work; some transitions made to next/previous speaker or topics.	Evidence of team work; transitions to next/previous speaker or topics made for the most part.	Presenters worked as part of a team, providing effective transitions to next/previous speaker or making references to previous /next topics.
Presentation Delivery	Presenters do not communicate interest in topic; maintain little eye contact; do not use facial expressions and gestures effectively; inappropriate posture and/or appearance.	Presenters have difficulty communicating interest in topic and maintaining eye contact. Some facial expressions, gestures, posture, or appearance may not be appropriate.	Presenters communicate interest in topic, maintain eye contact for the most part; use appropriate facial expressions, gestures, and posture. Appearance is appropriate.	Presenters communicate interest in topic with energy and poise, maintain eye contact with audience, use facial expressions and effectively; posture and appearance convey confidence and credibility.

Guideline for the Content

Category	1	2	3	4
Presentation	The presentation failed to identify most problems and opportunities in the case. The presentation is vague and would not lead to useful analysis.	The presentation has identified some of the key problems/opportunities of the case. The presentation is general and only addresses some of the issues.	The presentation has identified most of the key opportunities of the case.	The presentation has identified all the key problems/opportunities of the case in a clear and concise way
Quality of Data Analysis	The analysis is superficial or simplistic. It does not cover most dimensions and does not go into details.	The data analysis is somewhat incomplete and only covers some dimensions and some details.	The data analysis is thorough for the most part. Data is analyzed from major dimensions. Data is analyzed in detail most of time.	The data analysis is thorough. Data is analyzed from many possible dimensions and in great detail.
Summary of Data Analysis	Summary of data analysis is incomplete or simplistic. The presenters fail to highlight any significant/interesting findings.	Summary of data analysis is somewhat incomplete and only covers a few significant findings.	Summary of data analysis is complete for the most part. The presenters are able to highlight most significant/interesting findings.	Summary of data analysis is complete. The presenters are able to highlight all significant/interesting findings.
External Data	The team failed to use any data beyond what was supplied to them.	The team used fairly limited external data which failed to present any new findings.	The external data used was appropriate and provided valuable additional insights.	Multiple external data sources were combined in the analysis allowing for advanced findings.
Team Recommendations	Recommendations fail to provide any insight on any analysis.	Recommendations are very limited and simplistic in nature.	Recommendations provide some insight on from the data analysis.	Recommendations were thoughtful, complete and insightful.

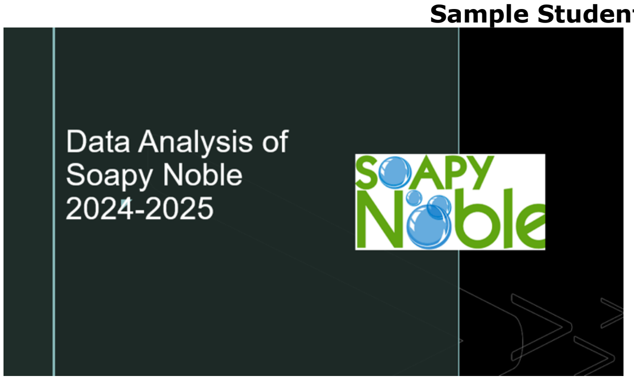
Case Competition -- Evaluation Form

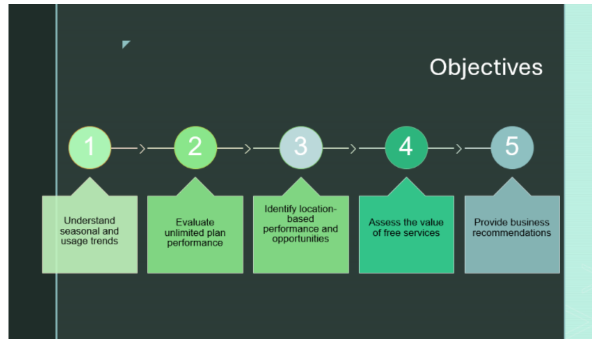
Evaluator Name: ____

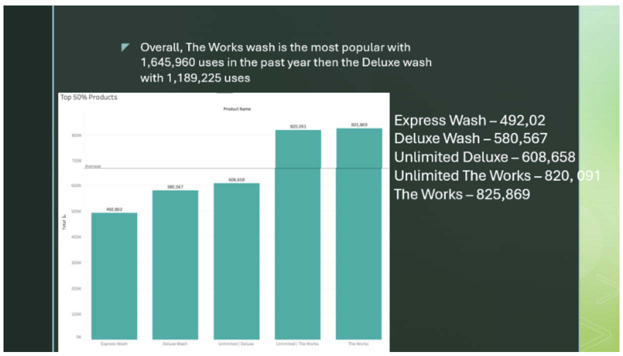
	Presentation					Content					
Team	***Content Preparedness (1-4)***	***Organization (1-4)***	***Visual Support (1-4)***	***Collaboration (1-4)***	***Presentation Delivery (1-4)***	***Presentation (1-4)***	***Quality of Data Analysis (1-4)***	***Summary of Data Analysis (1-4)***	**External Data (1-4)**	***Recommend (1-4)***	***Total (10-40)***
1											
2											
3											
4											
5											
6											

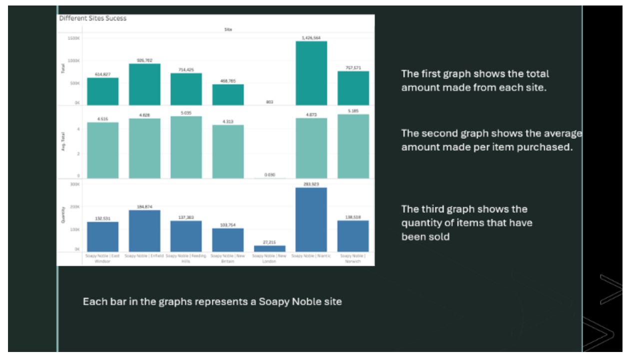
Comments

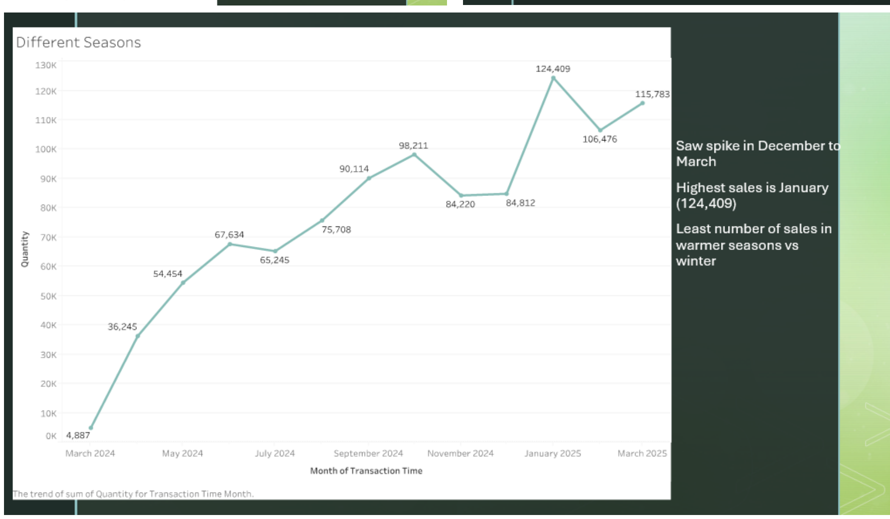
APPENDIX D
Sample Student Presentation

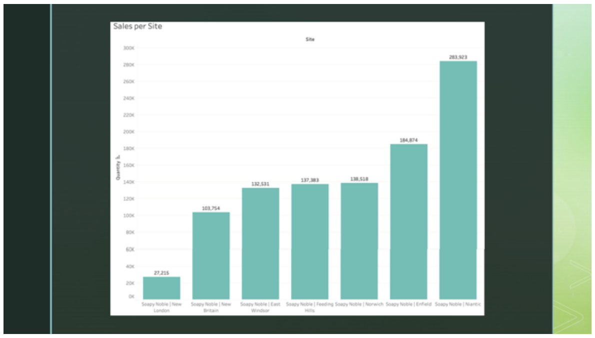


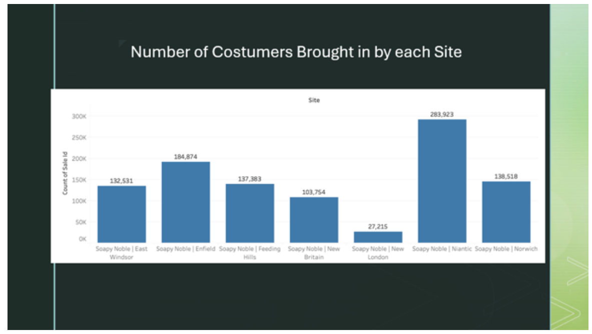


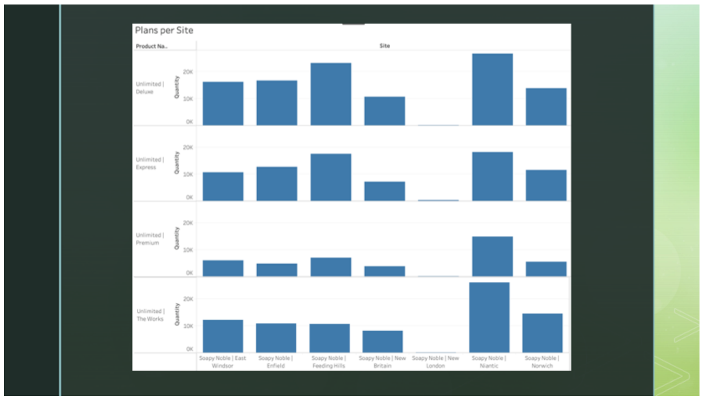


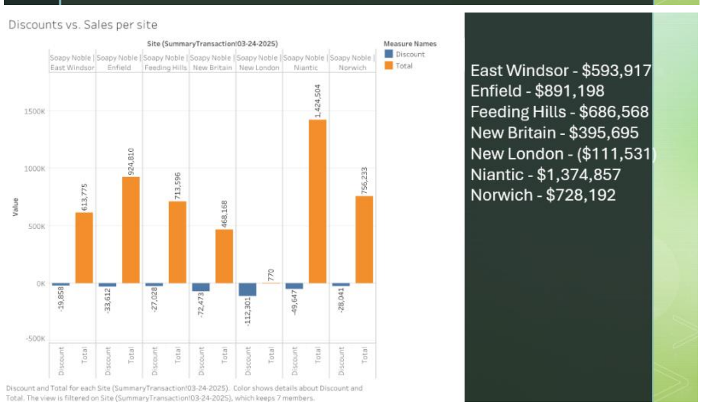




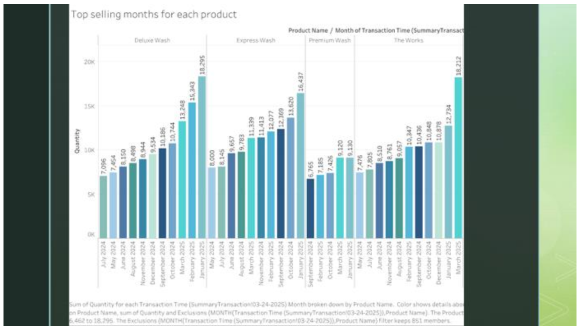

Sales per Site
Site
283,923
184,874
137,383
138,518
132,531
103,754
27,215

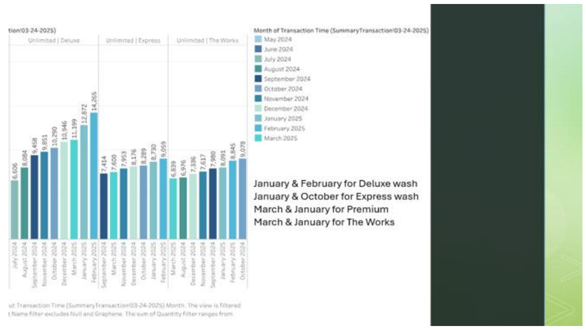

Number of Costumers Brought in by each Site
Site
132,531
184,874
137,383
103,754
27,215
283,923
138,518

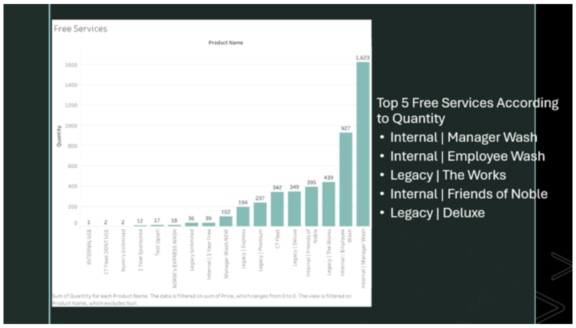

Plans per Site


Discounts vs. Sales per site
Measure Names
Discount
Total
613,775
924,810
713,596
468,168
770
1,424,504
756,233
-19,858
-33,612
-27,028
-72,473
-112,301
-49,647
-28,041
East Windsor - $593,917
Enfield - $891,198
Feeding Hills - $686,568
New Britain - $395,695
New London - ($111,531)
Niantic - $1,374,857
Norwich - $728,192

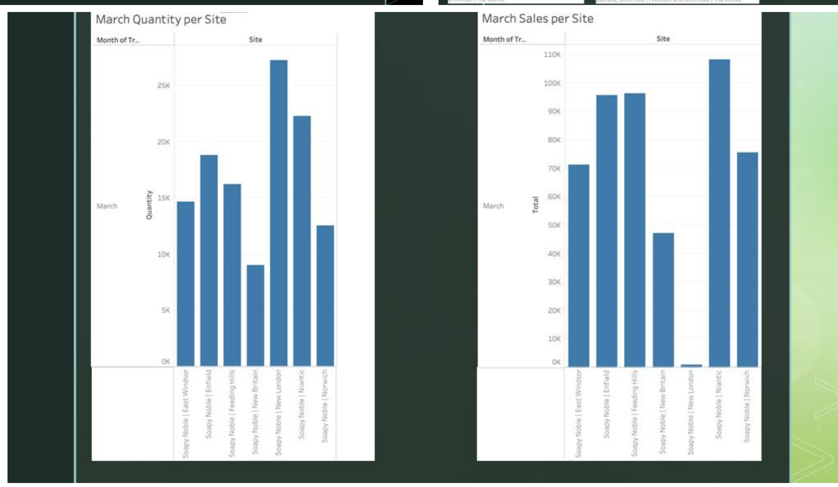

Discounts and Total for Each Month
Month of Transaction Time
Total
Discount
600K
400K
200K
0K
-50K
-100K
March 2024
April 2024
May 2024
June 2024
July 2024
August 2024
September 2024
October 2024
November 2024
December 2024
January 2025
February 2025
March 2025

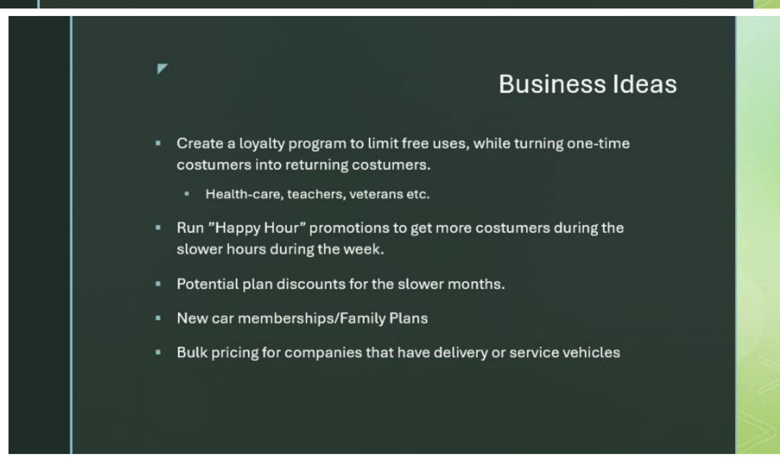

Top selling months for each product
Deluxe Wash
Express Wash
Premium Wash
The Works


Unlimited | Deluxe
Unlimited | Express
Unlimited | The Works
January & February for Deluxe wash
January & October for Express wash
March & January for Premium
March & January for The Works


Free Services
Top 5 Free Services According to Quantity
• Internal | Manager Wash
• Internal | Employee Wash
• Legacy | The Works
• Internal | Friends of Noble
• Legacy | Deluxe


Unlimited Plan Usage
Unlimited Plan Payment
Premium- $4.6025 per wash
Express - $2.90 per wash
The works - $4.815 per wash
Deluxe - $ 3.723 per wash
Premium - $20 Single Wash
Express - $10 Single Wash
The works - $25 Single Wash
Deluxe - $15 Single Wash


March Quantity per Site
March Sales per Site


Business Ideas
Create a loyalty program to limit free uses, while turning one-time costumers into returning costumers.
Health-care, teachers, veterans etc.
Run "Happy Hour" promotions to get more costumers during the slower hours during the week.
Potential plan discounts for the slower months.
New car memberships/Family Plans
Bulk pricing for companies that have delivery or service vehicles

APPENDIX E
Prior ISEDJ Cases

Date	Article Title	Skill 1	Skill 2	Skill 3	Skill 4	Skill 5
25-Nov	Teaching Case: Kibbles & Bytes: Developing a Database for an Animal Shelter Silent Auction	Process Design	Swimlane Diagrams	Database Design		
25-Sep	Teaching Case: Countering the “Plagiarism Slot Machine”: Protecting Creators and Businesses from AI Copyright Infringement	Screen Scraping	Data Pools	Metadata	AI Copyright Infringement	AI Training
25-Jul	Teaching Case: Leveraging Topic Modeling to Predict and Prevent Employee Attrition	Turnover	Latent Dirichlet Allocation	Human Resources	Retention	RapidMiner
25-Jul	Teaching Case: Online Maps and Route-Finding – Huge Success, With Some Nagging Problems ...	Online Maps	Route-finding	Route optimization		
25-May	Teaching Case: Agile Learning in Action: Fostering Students’ Agile Mindsets and Experience with a Classroom Client Project	Agile	Active Learning	Collaboration		
25-Jan	Teaching Case: A Small Accounting Firm Must Meet the Challenge Posed by Artificial Intelligence	Consulting	Artificial intelligence	ChatGPT	Auditing	Accounting
25-Jan	Teaching Case: Cleaning Out the Basement: Designing & Developing a Database to Support an Online Side Hustle Case	Database design	Process design	Swimlane diagrams	Multidisciplinary Project	
24-Nov	Teaching Case: The Southwest Airlines Winter Meltdown - Case studies on risk, technical debt, operations, passengers, regulators, revenue, and brand	Supply Chain	Airline Industry	Risk Management	Scalability	Technical Debt

24-Sep	Teaching Case: A Data Analytics Module Introducing Principles of Social Enterprise and Humanistic Management	Data Analytics	Humanistic Management	Human Dignity	Analytics for Social Good	Data Visualization
24-Sep	Teaching Case: Generative AI in practice: A Teaching Case in the Introduction to MIS class	Generative AI	ChatGPT	Future of work	Prompt engineering	Business process
24-Jul	Teaching Case: How Popular is Your Name? Finding the Popularity of US Names Using Big Data Visualization	Big Data	Visualization	BigQuery	Tableau	
24-Jul	Teaching Case: Teaching Data Literacy Using Titanic Survival Factors	analytics	data literacy	Tableau	Python	Pandas
24-May	Teaching Case: The Agile Student Practice Project: Simulating an Agile Project in the Classroom for a Real-World Experience	Agile	Active Learning	Collaboration		
23-Nov	Teaching Case: Design Thinking: Facilitating Consumer Access to Community Services	Design Thinking	Internet of Things	Systems Thinking		
23-Nov	Teaching Case: Creating a Clear Vision for Rural Healthcare: A Data Analysis Exercise	Big Data Analytics	Healthcare			
23-Sep	Teaching Case: Robotic Process Automation Overdue Collections Case	Robotic Process Automation	Business Process Improvement	Business Process Reengineering		
23-Sep	Teaching Case: Health Care Management: Preventing Post-Surgical Falls after Hip or Knee Replacement Surgery through Predictive Analytics	Health Care Analytics	Data Science	Predictive Analytics	SAS Enterprise Miner	
23-Sep	Teaching Case: Tax Time: An Interdisciplinary Accounting Analytics Experiential Learning Activity	Accounting Analytics	Data Analytics	Forecasting	Decision Making	Tax Returns

23-Sep	Teaching Case: Using Supervised Machine Learning and CRISP-DM to Predict an Acquittal Verdict	Data Mining	Legal Analytics	CRISP-DM	Analytics Project	R
23-Jul	Teaching Case: Cybersecurity Assessment for a Manufacturing Company Using Risk Registers: A Teaching Case	Cybersecurity Controls	Risk Management	Manufacturing Cybersecurity		
23-Jul	Teaching Case: Yours, mine and ours: Risk assignments, management, and tradeoffs on the road to driverless vehicles	Autonomous Vehicles	Technology Rollout	Risk Management		
23-May	Teaching Case: A Registration System for a Citywide Service Project: A System Design & Development Case	Database Design	Process Design	Swimlane Diagrams		
23-May	Teaching Case: Alexa, Help Me Learn About the Internet of Things!	Internet of Things	Amazon Echo	Automation	Digital Literacy	Active Learning
22-Jun	Bracketology: Predicting Winners from Music March Madness	Python	Data Science	Data Analytics	APIs	Hit Song Science
22-Jun	An Experiential Learning Project using Sentiment Analysis of Twitter Posts	Experiential Learning	Analytics	Sentiment Analysis	Twitter	
22-Jun	Interacting with Bloomberg Terminal from an Information Technology Perspective	Bloomberg Terminal	Digital Literacy	Career Skills	Business Education	
22-Jun	An IT Start-Up meets a Conglomerate - the Integration Challenge	IT Strategy	Change Management	Merger and Acquisition	Software as a Service	Integration
22-Jun	Here We Grow Again! An Expansion for Mark's Doggy Day Care: A Database Design and Development Case	Process Modeling	Systems Analysis	Database Design		
22-Jun	100 Million Doses in 100 Days: Analyzing the COVID-19 Vaccination Supply Chain	Data Analytics	Visual Analytics	Supply Chain Management	Experiential Learning	

21-Feb	Viral Scalability - Coping with Sudden Demand Swings	Scalability	Coronavirus	Cybersecurity		
21-Feb	Can you Predict the Money Laundering Cases?	Anti-Money Laundering	Business Analytics	Predictive Analytics	SAS Enterprise Miner	
21-Feb	GlobePort faces a Knowledge Gap in its Business Process Outsourcing	Knowledge Management	Process Management	Business Process Outsourcing	Collaboration Systems	
21-Feb	TheatreWorks of Southern Indiana: A Database Design Case	systems analysis and design data model	Data Flow Diagram	Data Dictionary		
20-Apr	Styles by Ashley: A System Design and Development Case	Process Design	Swimlane Diagrams	Database Design	Request for Proposal	
20-Apr	Ethics and Data Manipulation	Ethics	Data Analysis	Research	Decision Making	
20-Apr	Software Business Models	Teamwork	Comm	Info. process	Critical Thinking	Problem Solving
20-Apr	Broadband Connectivity In "Flyover Country"	Computer Info Systems	MIS	Legislation	Ethics	Net Neutrality
20-Apr	Ethical Coding: Privacy, Ethics & Law in Computing	Ethics	Data Security	Compliance with Industry Standards		
20-Apr	A Taste of Microsoft Data Analytics in Introductory MIS Curriculum to Encourage Analytics Skills and Knowledge	Big Data	Analytics	Data Visualization		

Article Title	Level	Data Supplied?	Data Format	Real World?	Link
Teaching Case: Kibbles & Bytes: Developing a Database for an Animal Shelter Silent Auction	Upper/Grad	No	Screenshots	Yes	https://isedj.org/2025-23/n6/ISEDJv23n6p53.pdf
Teaching Case: Countering the "Plagiarism Slot Machine": Protecting Creators and Businesses from AI Copyright Infringement	Upper	No	Not Available	Yes	https://isedj.org/2025-23/n5/ISEDJv23n5p53.pdf
Teaching Case: Leveraging Topic Modeling to Predict and Prevent Employee Attrition	Upper	No	Screenshots	Yes	https://isedj.org/2025-23/n4/ISEDJv23n4p69.pdf
Teaching Case: Online Maps and Route-Finding – Huge Success, With Some Nagging Problems ...	Grad	Yes	URL Link	Yes	https://isedj.org/2025-23/n4/ISEDJv23n4p22.pdf
Teaching Case: Agile Learning in Action: Fostering Students' Agile Mindsets and Experience with a Classroom Client Project	Upper	No	Not Available	Yes	https://isedj.org/2025-23/n3/ISEDJv23n3p41.pdf
Teaching Case: A Small Accounting Firm Must Meet the Challenge Posed by Artificial Intelligence	Upper	No	Not Available	Yes	https://isedj.org/2025-23/n1/ISEDJv23n1p46.pdf
Teaching Case: Cleaning Out the Basement: Designing & Developing a Database to Support an Online Side Hustle Case	Upper	No	Metrics discussed, but no data given	Yes	https://isedj.org/2025-23/n1/ISEDJv23n1p23.pdf

Teaching Case: The Southwest Airlines Winter Meltdown - Case studies on risk, technical debt, operations, passengers, regulators, revenue, and brand	Upper	No	Not Available	Yes	https://isedj.org/2024-22/n5/ISEDJv22n5p59.pdf
Teaching Case: A Data Analytics Module Introducing Principles of Social Enterprise and Humanistic Management	Intro	No	Data mentioned, but no link	Yes	https://isedj.org/2024-22/n4/ISEDJv22n4p62.pdf
Teaching Case: Generative AI in practice: A Teaching Case in the Introduction to MIS class	Intro	No	Not Available	Yes	https://isedj.org/2024-22/n4/ISEDJv22n4p29.pdf
Teaching Case: How Popular is Your Name? Finding the Popularity of US Names Using Big Data Visualization	Intro	No	Data mentioned, but no link	Yes	https://isedj.org/2024-22/n3/ISEDJv22n3p61.pdf
Teaching Case: Teaching Data Literacy Using Titanic Survival Factors	Intro	Yes	URL Link	Yes	https://isedj.org/2024-22/n3/ISEDJv22n3p25.pdf
Teaching Case: The Agile Student Practice Project: Simulating an Agile Project in the Classroom for a Real-World Experience	Intro	No	Screenshots	Yes	https://isedj.org/2024-22/n2/ISEDJv22n2p70.pdf
Teaching Case: Design Thinking: Facilitating Consumer Access to Community Services	Upper	No	Not Available	Yes	https://isedj.org/2023-21/n5/ISEDJv21n5p60.pdf

Teaching Case: Creating a Clear Vision for Rural Healthcare: A Data Analysis Exercise	Upper/Grad	Yes	Google Sheet	Yes	https://isedj.org/2023-21/n5/ISEDJv21n5p12.pdf
Teaching Case: Robotic Process Automation Overdue Collections Case	Upper	No	Screenshots	Yes	https://www.isedj.org/2023-21/n4/ISEDJv21n4p53.html
Teaching Case: Health Care Management: Preventing Post-Surgical Falls after Hip or Knee Replacement Surgery through Predictive Analytics	Intro	No	Screenshots	Yes	https://isedj.org/2023-21/n4/ISEDJv21n4p46.pdf
Teaching Case: Tax Time: An Interdisciplinary Accounting Analytics Experiential Learning Activity	Upper	Yes	URL Link	Yes	https://isedj.org/2023-21/n4/ISEDJv21n4p37.pdf
Teaching Case: Using Supervised Machine Learning and CRISP-DM to Predict an Acquittal Verdict	Upper	Yes	URL Link	Yes	https://isedj.org/2023-21/n4/ISEDJv21n4p23.pdf
Teaching Case: Cybersecurity Assessment for a Manufacturing Company Using Risk Registers: A Teaching Case	Upper	No	Not Available	Yes	https://isedj.org/2023-21/n3/ISEDJv21n3p62.pdf
Teaching Case: Yours, mine and ours: Risk assignments, management, and tradeoffs on the road to driverless vehicles	Upper	Yes	URL Link	Yes	https://isedj.org/2023-21/n3/ISEDJv21n3p50.pdf

Teaching Case: A Registration System for a Citywide Service Project: A System Design & Development Case	Upper/Grad	No	Screenshots	No	https://isedj.org/2023-21/n2/ISEDJv21n2p82.pdf
Teaching Case: Alexa, Help Me Learn About the Internet of Things!	Intro	No	Not Available	Yes	https://isedj.org/2023-21/n2/ISEDJv21n2p69.pdf
Bracketology: Predicting Winners from Music March Madness	Upper	No	Coding, heatmap, brackets	Yes	https://isedj.org/2022-20/n3/ISEDJv20n3p44.pdf
An Experiential Learning Project using Sentiment Analysis of Twitter Posts	Intro	No	Screentshots	Yes	https://isedj.org/2022-20/n3/ISEDJv20n3p36.pdf
Interacting with Bloomberg Terminal from an Information Technology Perspective	Upper	No	Screenshots and Readings	Yes	https://isedj.org/2022-20/n3/ISEDJv20n3p27.pdf
An IT Start-Up meets a Conglomerate - the Integration Challenge	Grad	No	Not Available	Yes	https://isedj.org/2022-20/n3/ISEDJv20n3p19.pdf
Here We Grow Again! An Expansion for Mark's Doggy Day Care: A Database Design and Development Case	Upper	No	Screenshots	No	https://isedj.org/2022-20/n3/ISEDJv20n3p12.pdf
100 Million Doses in 100 Days: Analyzing the COVID-19 Vaccination Supply Chain	Upper	Yes	URL Link	Yes	https://isedj.org/2022-20/n3/ISEDJv20n3p4.pdf
Viral Scalability - Coping with Sudden Demand Swings	Upper	No	Diagrams	Yes	
Can you Predict the Money Laundering Cases?	Grad	No	Data mentioned, but no link	Yes	https://isedj.org/2021-19/n1/ISEDJv19n1p16.pdf

GlobePort faces a Knowledge Gap in its Business Process Outsourcing	Upper/Grad	No	Screenshots	Yes	https://isedj.org/2021-19/n1/ISEDJv19n1p9.pdf
TheatreWorks of Southern Indiana: A Database Design Case	Upper	No	Screenshots	Yes	https://isedj.org/2021-19/n1/ISEDJv19n1p4.pdf
Styles by Ashley: A System Design and Development Case	Grad	Yes	Screenshots	No	https://isedj.org/2020-18/n2/ISEDJv18n2p14.pdf
Ethics and Data Manipulation	Upper	No	Not Available	No	https://isedj.org/2020-18/n2/ISEDJv18n2p4.pdf
Software Business Models	Upper	No	Q&A	No	https://isedj.org/2020-18/n2/ISEDJv18n2p22.pdf
Broadband Connectivity In "Flyover Country"	Intro	No	Screenshots	Yes	https://isedj.org/2020-18/n2/ISEDJv18n2p41.pdf
Ethical Coding: Privacy, Ethics & Law in Computing	Upper/Grad	No	Screenshots	Yes	https://isedj.org/2020-18/n2/ISEDJv18n2p50.pdf
A Taste of Microsoft Data Analytics in Introductory MIS Curriculum to Encourage Analytics Skills and Knowledge	Intro	Yes	URL Link	Yes	https://isedj.org/2020-18/n2/ISEDJv18n2p58.pdf