INFORMATION SYSTEMS EDUCATION JOURNAL

Volume 24, No. 5
September 2026
ISSN: 1545-679X

In this issue:

iscap
Information Systems & Computing Academic Professionals

The **Information Systems Education Journal** (ISEDJ) is a double-blind peer-reviewed academic journal published by **ISCAP** (Information Systems and Computing Academic Professionals). Publishing frequency is five times per year. The first year of publication was 2003.

ISEDJ is published online (https://isedj.org). Our sister publication, the Proceedings of the ISCAP Conference (https://iscap.us/proceedings) features all papers, abstracts, panels, workshops, and presentations from the conference.

The journal acceptance review process involves a minimum of three double-blind peer reviews, where both the reviewer is not aware of the identities of the authors and the authors are not aware of the identities of the reviewers. The initial reviews happen before the ISCAP conference. All papers, whether award-winners or not, are invited to resubmit for journal consideration after applying feedback from the Conference presentation. Award winning papers are assured of a publication slot; however, all re-submitted papers including award winners are subjected to a second round of three blind peer reviews to improve quality and make final accept/reject decisions. Those papers that are deemed of sufficient quality are accepted for publication in the ISEDJ journal. Currently the target acceptance rate for the journal is under 35%.

Information Systems Education Journal is pleased to be listed in the Cabell's Directory of Publishing Opportunities in Educational Technology and Library Science, in both the electronic and printed editions. Questions should be addressed to the editor at editor@isedj.org or the publisher at publisher@isedj.org. Special thanks to volunteer members of ISCAP who perform the editorial and review processes for ISEDJ.

2026 ISCAP Board of Directors

INFORMATION SYSTEMS EDUCATION JOURNAL

Editors

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

Abraham Abby Sen
aabbysen@wtamu.edu

Jeen Mariam Joy
jjoy@wtamu.edu

Murray Jennex
mjennex@wtamu.edu

Kareem Dana
kdana@wtamu.edu

Jeffry Babb
jbabb@wtamu.edu

West Texas A&M University
Canyon, TX 79016

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

Recommended Citation: Abby Sen, A., Joy, J., Jennex, M., Dana, K., Babb, J., (2026). Human - AI Collaboration in Knowledge Transfer: A Research Agenda integrating Knowledge Management. *Information Systems Education Journal*, v24(n5) pp 29-48. DOI# https://doi.org/10.62273/XDWF4576

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

Abraham Abby Sen, Jeen Mariam Joy, Murray Jennex, Kareem Dana and Jeffry Babb

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.

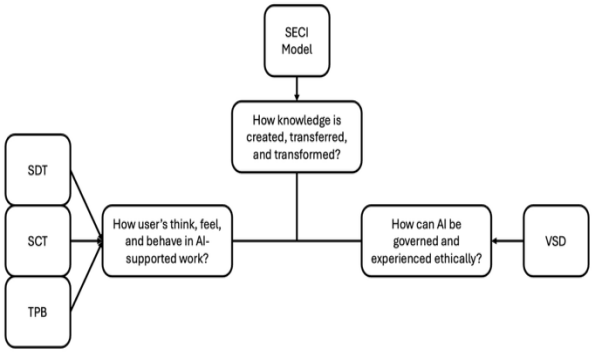

Figure 1: Conceptual Model

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 Governance 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.

8. ACKNOWNLEDGEMENTS

The authors would like to thank the undergraduate students who participated in the feasibility experiment reported in this paper for their time, engagement, and thoughtful contributions. We gratefully acknowledge Carter Cherry ccherry1@buffs.wtamu.edu, Alana Strong amstrong1@buffs.wtamu.edu, Angel Flores aflores13@buffs.wtamu.edu, and Tamaya Thomas tathomas4@buffs.wtamu.edu.

9. REFERENCES

Abdel-Karim, B., Pfeuffer, N., Carl, K. V., & Hinz, O. (2023). How AI-Based Systems Can Induce Reflections: The Case of AI-Augmented Diagnostic Work. MIS Quarterly, 47(4), 1395-1424. https://doi.org/10.25300/misq/2022/16773

Abby Sen, A., Joy, J. M., & Jennex, M. E. (2025). Towards Navigating Ethical Challenges in AI-Driven Healthcare Ad Moderation. Computers, 14(9), 380.

Abby Sen, A., Joy, J., & Jennex, M. (2025). Illuminating Ethical Dilemmas in AI-Driven

Regulation of Healthcare Marketing on Social Media.

Al-Emran, M., AlQudah, A. A., Abbasi, G. A., Al-Sharafi, M. A., & Iranmanesh, M. (2024). Determinants of Using AI-Based Chatbots for Knowledge Sharing: Evidence From PLS-SEM and Fuzzy Sets (fsQCA). IEEE Transactions on Engineering Management, 71, 4985-4999. https://doi.org/10.1109/tem.2023.3237789

Alsafari, B., Atwell, E., Walker, A., & Callaghan, M. (2024). Towards effective teaching assistants: From intent-based chatbots to LLM-powered teaching assistants. Natural Language Processing Journal, 8. https://doi.org/10.1016/j.nlp.2024.100101

Asghar, M. Z., Barbera, E., Rasool, S. F., Seitamaa-Hakkarainen, P., & Mohelská, H. (2022). Adoption of social media-based knowledge-sharing behaviour and authentic leadership development: evidence from the educational sector of Pakistan during COVID-19. Journal of Knowledge Management, 27(1), 59-83.

Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). (2021). Artificial intelligence in organizations: Implications for information systems research. Journal of the Association for Information Systems, 22(2), 10., 22(2), 10.

Benbya, H., Strich, F., & Tamm, T. (2024). Navigating Generative Artificial Intelligence Promises and Perils for Knowledge and Creative Work. Journal of the Association for Information Systems, 25(1), 23-36. https://doi.org/10.17705/1jais.00861

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. MIS Quarterly, 45(3).

Breitwieser, J., & Brod, G. (2022). The Interplay of Motivation and Volitional Control in Predicting the Achievement of Learning Goals: An Intraindividual Perspective. Journal of Educational Psychology, 115(5), 1048-1061. https://doi.org/10.1037/edu0000738

Chandra, S., Shirish, A., & Srivastava, S. C. (2022). To Be or Not to Be …Human? Theorizing the Role of Human-Like Competencies in Conversational Artificial Intelligence Agents. Journal of Management Information Systems, 39(4), 969-1005. https://doi.org/10.1080/07421222.2022.2127441

Chowdhury, T., & Oredo, J. (2022). AI ethical biases: normative and information systems development conceptual framework. Journal of Decision Systems, 32(3), 617-633. https://doi.org/10.1080/12460125.2022.2062849

Chu, M.-N. (2023). Assessing the Benefits of ChatGPT for Business: An Empirical Study on Organizational Performance. IEEE Access, 11, 76427-76436. https://doi.org/10.1109/access.2023.3297447

Cradduck, L., Gregory, M. A., & Campbell, L. H. (2022). University Students' Engagement with Devices and Technology: A Comparison of Pre- and Post-COVID-19 Student [Article]. Journal of Telecommunications & the Digital Economy, 10(2), 236-266. https://doi.org/10.18080/jtde.v10n2.594

Curzon, J., Kosa, T. A., Akalu, R., & El-Khatib, K. (2021). Privacy and Artificial Intelligence. IEEE Transactions on Artificial Intelligence, 2(2), 96-108. https://doi.org/10.1109/tai.2021.3088084

Cuthbert, G., & Dörfler, V. (2024, January). Dubito Ergo Sum: Exploring AI Ethics. In HICSS 57: Hawaii International Conference on System Sciences, Honolulu, HI: 5587-5596.

Falebita, O. S., & Kok, P. J. (2024). Artificial Intelligence Tools Usage: A Structural Equation Modeling of Undergraduates' Technological Readiness, Self-Efficacy and Attitudes. Journal for STEM Education Research. https://doi.org/10.1007/s41979-024-00132-1

Faraj et al. (2018) Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of artificial intelligence. Information and Organization, 28(1), 62–70. https://doi.org/10.1016/j.infoandorg.2018.02.003

Fink, M. C., Robinson, S. A., & Ertl, B. (2024). AI-based avatars are changing the way we learn and teach: benefits and challenges. Frontiers in Education, 1-8.

Fischer, B., Guerrero, M., Guimón, J., & Schaeffer, P. R. (2020). Knowledge transfer

for frugal innovation: where do entrepreneurial universities stand? Journal of Knowledge Management, 25(2), 360-379. https://doi.org/10.1108/jkm-01-2020-0040

Fu-Yun, Y., & Chun-Ping, W. (2016). Predictive Effects of the Quality of Online Peer-Feedback Provided and Received on Primary School Students' Quality of Question-Generation. Educational Technology & Society, 19(3), 234-246.

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2021). Will Humans-in-the-Loop Become Borgs? Merits and Pitfalls of Working with AI. MIS Quarterly, 45(3), 1527-1556. https://doi.org/10.25300/misq/2021/16553

García Lozano, M., Brynielsson, J., Franke, U., Rosell, M., Tjörnhammar, E., Varga, S., & Vlassov, V. (2020). Veracity assessment of online data. Decision Support Systems, 129. https://doi.org/10.1016/j.dss.2019.113132

Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P. (2023). Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review. Education Sciences, 13(12), 1216.

Gupta, R., Nair, K., Mishra, M., Ibrahim, B., & Bhardwaj, S. (2024). Adoption and impacts of generative artificial intelligence: Theoretical underpinnings and research agenda. International Journal of Information Management Data Insights, 4(1). https://doi.org/10.1016/j.jjimei.2024.100232

Hase, A., & Kuhl, P. (2024). Teachers' use of data from digital learning platforms for instructional design: a systematic review. Educational Technology Research & Development, 72(4), 1925-1945. https://doi.org/10.1007/s11423-024-10356-y

Hidayat-ur-Rehman, I. (2024). Examining AI competence, chatbot use and perceived autonomy as drivers of students' engagement in informal digital learning [Article]. Journal of Research in Innovative Teaching & Learning (JRIT), 17(2), 196-212. https://doi.org/10.1108/JRIT-05-2024-0136

Jarrahi (2018) Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jo, H. (2024). From concerns to benefits: a comprehensive study of ChatGPT usage in education. International Journal of Educational Technology in Higher Education, 21(1), 1-29.

Kankanhalli, A. (2024). Peer Review in the Age of Generative AI. Journal of the Association for Information Systems, 25(1), 76-84. https://doi.org/10.17705/1jais.00865

Kim, J., Hong, L., & Evans, S. (2024). Toward measuring data literacy for higher education: Developing and validating a data literacy self-efficacy scale. Journal of the Association for Information Science and Technology, 75(8), 916-931. https://doi.org/10.1002/asi.24934

Kong, S.-C., & Yang, Y. (2024). A Human-Centered Learning and Teaching Framework Using Generative Artificial Intelligence for Self-Regulated Learning Development Through Domain Knowledge Learning in K–12 Settings. IEEE Transactions on Learning Technologies, 17, 1562-1573. https://doi.org/10.1109/tlt.2024.3392830

Kwon, Y., & Lee, Z. (2024). A hybrid decision support system for adaptive trading strategies: Combining a rule-based expert system with a deep reinforcement learning strategy. Decision Support Systems, 177. https://doi.org/10.1016/j.dss.2023.114100

Lebovitz, S., Levina, N., & Lifshitz-Assa, H. (2021). Is AI Ground Truth Really True? The Dangers of Training and Evaluating AI Tools Based on Experts' Know-What. MIS Quarterly, 45(3), 1501-1526. https://doi.org/10.25300/misq/2021/16564

Legault, L., Green-Demers, I., Grant, P., & Chung, J. (2007). On the self-regulation of implicit and explicit prejudice: a self - determination theory perspective. Pers Soc Psychol Bull, 33(5), 732-749. https://doi.org/10.1177/0146167206298564

Leonardi, P. (2023). Affordances and Agency: Toward the Clarification and Integration of Fractured Concepts. MIS Quarterly, 47(4).

Li, J., Larsen, K., & Abbasi, A. (2020). TheoryOn: A Design Framework and System for Unlocking Behavioral Knowledge Through Ontology Learning. MIS Quarterly, 44(4), 1733-1772. https://doi.org/10.25300/misq/2020/15323

Lijie, H., Mat Yusoff, S., & Mohamad Marzaini, A. F. (2024). Influence of AI-driven educational tools on critical thinking dispositions among university students in Malaysia: a study of key factors and correlations. Education and Information Technologies. https://doi.org/10.1007/s10639-024-13150-8

Lin, L.-S., Lin, Y.-S., Li, D.-C., & Liu, Y.-H. (2023). Improved learning performance for small datasets in high dimensions by new dual-net model for non-linear interpolation virtual sample generation. Decision Support Systems, 172. https://doi.org/10.1016/j.dss.2023.113996

Liu, D., Yoon, V. Y., & Sen, A. A. (2026). Embedding CAs in Organizational Ecosystems: Accomplishments and Future Research. IEEE Transactions on Engineering Management.

Maita, I., Saide, S., Putri, A. M., & Muwardi, D. (2024). Pros and Cons of Artificial Intelligence–ChatGPT Adoption in Education Settings: A Literature Review and Future Research Agendas. IEEE Engineering Management Review, 52(3), 27-42. https://doi.org/10.1109/emr.2024.3394540

Manuel, P.-M., Pilar, A.-M., María Dolores, R.-M., Mp, D., Sara, P., & M. Pilar, M.-J. (2019). Characterization of biodiesel using virtual laboratories integrating social networks and web app following a ubiquitous- and blended-learning. Journal of Cleaner Production, 215, 399-409.

Mario, L., & Roberto, C. (2023). The Impact of Changing Environment on Undergraduate Mathematics Students' Status. European Journal of Science and Mathematics Education, 11(4), 672-689.

Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. . Organization science, 5(1), 14-37.

Popenici, S. (2023). The critique of AI as a foundation for judicious use in higher education. Journal of Applied Learning & Teaching, 6(2). https://doi.org/10.37074/jalt.2023.6.2.4

Pirham, S., Khaddapi, M., & Rahmawati, R. (2025). Association of Perceived Benefits and Ease of Use on Quality of Palopo City Government Information System Through User Satisfaction. Studi Ilmu Manajemen dan Organisasi, 6(1), 21-38.

Raisch & Krakowski (2021) Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 46(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Rudolph, J., Bin Mohamed Ismail, M. F., & Popenici, S. (2024). Higher Education's Generative Artificial Intelligence Paradox: The Meaning of Chatbot Mania. Journal of University Teaching & Learning Practice, 21(6), 1-35. https://doi.org/10.53761/54fs5e77

Sanusi, I. T., Ayanwale, M. A., & Chiu, T. K. F. (2023). Investigating the moderating effects of social good and confidence on teachers' intention to prepare school students for artificial intelligence education. Education and Information Technologies, 29(1), 273-295. https://doi.org/10.1007/s10639-023-12250-1

Sarker, S., Susarla, A., Gopal, R., & Thatcher, J. B. (2024). Democratizing Knowledge Creation Through Human-AI Collaboration in Academic Peer Review. Journal of the Association for Information Systems, 25(1), 158-171. https://doi.org/10.17705/1jais.00872

Schmitt, A., Zierau, N., Janson, A., & Leimeister, J. M. (2023). The Role of AI-Based Artifacts' Voice Capabilities for Agency Attribution. Journal of the Association for Information Systems, 24(4), 980-1004. https://doi.org/10.17705/1jais.00827

Schwartz, D., & Te'eni, D. (2024). AI for Knowledge Creation, Curation, and Consumption in Context. Journal of the Association for Information Systems, 25(1), 37-47. https://doi.org/10.17705/1jais.00862

Sen, A. A., Joy, J. M., Jennex, M., Babb, J., & Dana, K. (2025). The Missing Link: Knowledge Management in AI-Powered Education Frameworks. Innovations in Pedagogy and Technology, 1(3), 67-81.

Sen, A. A., Joy, J. M., Jennex, M. E., & Babb, J. (2026). Toward Bridging the Knowledge Management Gap in Assessment Literacy: Artificial Intelligence as a Catalyst for Change. In Navigating Inequities and Social

Justice in the Age of Artificial Intelligence (pp. 19-36).

Soliman, W., & Siponen, M. (2022). What Do We Really Mean by Rigor in Information Systems Research?. In Proceedings of the Annual Hawaii International Conference on System Sciences. University of Hawai'i at Manoa.

Stevens, M., & Elen, J. (2023). 'Picturing' instruction: an exploration of higher education students' knowledge of instruction. Studies in Higher Education, 49(2), 206-220. https://doi.org/10.1080/03075079.2023.2227647

Sturm, T., Gerlacha, J., Pumplun, L., Mesbah, N., Peters, F., Tauchert, C., Nan, N., & Buxmann, P. (2021). Coordinating Human and Machine Learning for Effective Organization Learning. MIS Quarterly, 45(3), 1581-1602. https://doi.org/10.25300/misq/2021/16543

Thomas, A. (2024). Digitally transforming the organization through knowledge management: a socio-technical system (STS) perspective. European Journal of Innovation Management, 27(9), 437-460.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal Computing: Toward a Conceptual Model of Utilization1. MIS quarterly, 15(1), 125-143.

Tremblay, M. C., Kohli, R., & Forsgren, N. (2021). Theories in flux: Reimagining theory building in the age of machine learning. . MIS Quarterly, 45(1), 455-459.

Ujjwal, B., & Samit, B. (2024). ML-Based Intelligent Real-Time Feedback System for Blended Classroom. Education and Information Technologies, 29(4), 3923-3951. https://doi.org/10.1007/s10639-023-11949-5

Vaast, E., & Pinsonneault, A. (2021). When Digital Technologies Enable and Threaten Occupational Identity: The Delicate Balancing Act of Data Scientists. MIS Quarterly, 45(3), 1087-1112. https://doi.org/10.25300/misq/2021/16024

Wang, F., King, R. B., Chai, C. S., & Zhou, Y. (2023). University students' intentions to learn artificial intelligence: the roles of supportive environments and expectancy–value beliefs. International Journal of Educational Technology in Higher Education, 20(1).

Wilson, H. J., & Daugherty, P. R. (2024). Embracing Gen AI at Work [Article]. Harvard Business Review, 102(5), 151-155.

Wong, P. P. Y., Wong, G. W. C., Techanamurthy, U., Mohamad, W. S. B., Febriana, A., & Chong, J. C. M. (2022). Using Social Mobile Learning to Stimulate Idea Generation for Collective Intelligence among Higher Education Students. Knowledge Management & E-Learning, 14(2), 150-169.

Xue, M., Cao, X., Feng, X., Gu, B., & Zhang, Y. (2022). Is College Education Less Necessary with AI? Evidence from Firm-Level Labor Structure Changes. Journal of Management Information Systems, 39(3), 865-905. https://doi.org/10.1080/07421222.2022.2096542

Yang, Y., & Subramanyam, R. (2022). Extracting Actionable Insights from Text Data: A Stable Topic Model Approach. MIS Quarterly, 47(3), 923-954. https://doi.org/10.25300/misq/2022/16957

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.