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Reframing Avatar-Mediated Instruction in Higher Education: A Theory-Building Integrative Review

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Abstract

As Artificial Intelligence (AI)-enabled avatars rapidly enter higher education classrooms—particularly in asynchronous formats—faculty, instructional designers, and administrators face a critical challenge: how to understand and implement these tools beyond surface-level functionality. Despite growing adoption, the literature remains fragmented, offering limited guidance on how epistemic trust, learner identity, and institutional strategy intersect in avatar-mediated instruction. This paper addresses that gap through a theory-building integrative review that synthesizes interdisciplinary literature from instructional technology, psychology, sociology, and organizational studies. The review develops a synthesized framework of epistemic trust, learner identity, and organizational readiness for AI avatar integration. This framework helps educators and institutional leaders better understand how AI avatars influence learner engagement, reshape digital identity formation, and drive transformation in knowledge management processes. The analysis identifies key conceptual variables and moderating factors—including gender, AI familiarity, social presence, avatar design features, and institutional culture—that shape both learner trust and organizational response to AI-mediated communication (AMC). These elements together position AMC not as a passive technological tool, but as a cognitive and pedagogical shift with implications for instructional practice, organizational systems, and equitable AI integration. Rather than presenting empirical results, this paper lays the conceptual groundwork for future research. The frameworks offered here are designed to inform evidence-based inquiry, support faculty and instructional design practice, and guide institutional policy as higher education evolves toward AI-enabled knowledge ecosystems.

Keywords: AI avatars, Epistemic trust, Asynchronous instruction, Learner identity, Social Identity Theory, AI in higher education, AI-mediated communication (AMC)

1. Introduction

This concept paper explores the literature on the topic of AI avatars and their developing use as instructional agents in asynchronous higher education environments. Avatars are paired with synthetic voices designed to simulate human teaching presence and deliver flexible, on-demand instruction with an eye toward meeting the need for quality instruction in situations of limited resources and expert personnel (Fink et al., 2024).

1.1 Background of the Study

The rapid evolution of artificial intelligence (AI) technologies in education marks a pivotal shift in how learners engage with instruction. We have entered what Ng et al. (2021a) describe as the age of the "democratization of …AI technologies" (p. 506). This includes access to, and integration of, AI tools as they reshape learning environments across the globe. AI-driven applications are now central to what the World Economic Forum (2024) terms *Education 4.0*, a paradigm that emphasizes personalization, flexibility, and technology-augmented teaching. As Hirzel (2023) writes, "This era [Education 4.0] is marked by the synergy of AI with human educators, where AI not only augments teaching but also redefines our understanding of personal worth" (p. 12). New models of education are erupting, such as AI driven Blockchain-based Agile Learning DAOs (BALD), a transition away from traditional pedagogical methods, referred to as "the fabric model" (attainment of knowledge and skills for a degree or certification), to more fluid, lifelong learning models (Hirzel, 2023, p. 14).

These developments demand critical attention to the social and psychological implications of AI integration—particularly when AI agents assume instructional roles within formal educational institutions (Caldwell et al., 2022). As Meyer (2022) posits, these decentralized, AI-driven models "will be the future of educational institutions" (para. 3). Among the most transformative of these tools are AI avatars and synthetic voice, which provide social presence, 24/7 on-demand instruction, and flexible access in asynchronous learning platforms. This revolution in individual access to expert level instruction for all has the potential to solve the 2-sigma problem posited by Bloom (1984). He explained that when the average achieving student was provided individual support, they scored two sigma above the mean of those in the whole class instruction.

1.2 Importance of the Topic

The adoption of AI-mediated communication (AI-MC)—particularly the use of AI avatars as instructors in asynchronous higher education—is accelerating faster than the academic literature can respond. Caldwell et al. (2022) explained, "One of the key challenges lies in understanding, defining, and mapping the problem space itself, which encompasses a broad range of intersecting and interacting domains" (p. 24). Despite early findings that learner engagement and personality traits predict online learning success (Dai et al., 2020), and that AI-driven feedback can outperform human instruction in specific contexts (Arguedas et al., 2024), the broader instructional and institutional implications remain fragmented. Research has yet to address how AMC affects learner trust, faculty pedagogy, or administrative decision-making in a cohesive, field-spanning framework (Choung et al., 2023; Söllner et al., 2016). These dynamics often diverge across disciplines, further complicating interpretation. To address this, a theory-building integrative review is needed to synthesize current evidence and develop a holistic conceptual model that informs research, policy, and practice in AI-enabled higher education.

1.3 Purpose

The purpose of this paper is to explore the literature on the use of AI avatars in asynchronous higher education, identify relevant conceptual frameworks, and develop a synthesized model that helps clarify where this emerging instructional practice fits within existing and evolving academic thought. This integrative approach highlights how key ideas—like epistemic trust, learner identity, and institutional adaptation—intersect in the design and use of avatar-mediated instruction. The resulting framework is meant to guide future research, support faculty and instructional designers in understanding practical steps to embed AMC in course design and help higher education leaders shift their perspective—from viewing avatar-mediated communication (AMC) as just another technology tool to recognizing it as a conceptual strategy that informs institutional policies and practices.

1.4 Organization

To guide this conceptual analysis, the paper is organized into four domains that reflect key areas shaping how AMC functions in higher education settings: (1) the historical evolution of AI and the emergence of Education 4.0 as a foundation for AMC; (2) the development of epistemic trust in asynchronous learning environments where avatars serve as instructional agents; (3) the role of learner identity and demographic factors—such as gender and AI familiarity—in shaping trust and engagement with avatar instructors; and (4) institutional adaptation and knowledge management processes (KMP), with attention to how AI avatars are influencing organizational practices under the broader paradigm of Economy 5.0. Each section explores relevant questions, identifies gaps in the literature, and provides implications for higher education. Together, these domains inform the development of a conceptual framework that synthesizes concepts and theories across fields.

1.5 Guiding Questions

Each domain is framed by guiding research questions that explore themes of trust, learner identity, and institutional change. The review also considers moderating variables identified in the literature—such as gender identity, which influences perceptions of credibility in STEM instruction, and AI familiarity, which may shape students' task self-efficacy in digital learning contexts (Hanson, 2017; Hanson & Yu, 2020). By exploring these questions through a theory-building integrative review, the paper provides the foundation for future studies that will examine these relationships in real instructional settings. Appendix 1 presents the four conceptual domains and their associated research questions.

2. Methodology and Design

2.1 Conceptual Approach

This paper employs a theory-building integrative literature review to explore how AMC is conceptualized in asynchronous higher education. An integrative review is "a form of research that synthesizes past studies to generate new theoretical frameworks or perspectives" (Torraco, 2016, p. 408). This approach is well suited to emerging, interdisciplinary topics where studies are often dispersed across fields or lack unified conceptual grounding. As Whittemore and Knafl (2005) explain, integrative reviews allow for the inclusion of diverse methodological traditions, enabling a comprehensive and flexible synthesis of relevant literature.

This review organizes selected research across education, communication, and AI ethics to clarify conceptual boundaries, surface gaps in the literature, and generate a model for future empirical research. Its purpose is not to catalog all literature on AI in education, but to develop a coherent framework to guide critical understanding and application of AMC in higher education settings.

2.2 Inclusion Criteria

To identify relevant literature for this review, a multi-source search strategy was used to capture the rapidly evolving scholarship on AI avatars in higher education. Searches were conducted through Elicit.com, Google Scholar, Firefox-based open web exploration, and reference mining from key texts. Given the emerging nature of the field, the search extended beyond peer-reviewed journals to include books, dissertations, conference proceedings, and select policy reports.

Search terms included: AI agents, AI literacy, epistemic trust, AI avatars, gender and trust, asynchronous learning, social presence and AI, knowledge management in higher education, shared identity with AI systems, human-AI teaming, etc. Sources were included if they contributed to the conceptual questions and emerging model; redundant works were excluded, and older sources were only retained if they offered foundational insight.

3. Conceptual Foundations and Historical Context

3.1 Key Terms and Conceptual Definitions

Before turning to the first conceptual domain, this section defines several key terms used throughout the review. Given the interdisciplinary nature of AI-mediated instruction and the technical specificity of emerging constructs, these definitions serve as a foundation for the analysis that follows. Each term is drawn from existing literature but adapted for use within the context of higher education and AMC.

AI-mediated communication (AI-MC) refers to interactions in which a computational agent generates or modifies messages to achieve communication or instructional goals (Hancick et al., 2020 in Sahebi & Formosa, 2025). *Avatar-mediated communication (AMC)* is a specific form of AI-MC, where a digital figure acts as an instructional proxy. *Epistemic trust* reflects the learner's perception of an instructor's expertise, integrity, and benevolence (Hancock et al., 2011; Fricker, 2021 in Sahebi & Formosa, 2025). *AI literacy* describes the skills and dispositions needed to critically engage with and apply AI tools in education and work (Laupichler et al., 2022; WEF, 2024). *Social identity theory* (Tajfel & Turner, 1979; Teng et al., 2023) and the *CASA framework* (Reeves & Nass, 1996) further guide how learners respond to and interpret AI avatars as social and instructional agents. Additional technical and theoretical terms are defined in Appendix 3 to support accessibility and consistency across this review.

Next, as Torraco (2016) notes, an integrative literature review often begins by tracing a topic's historical development to clarify its current state and conceptual maturity. The purpose of reviewing historical context is not simply to describe the past, but to highlight what has changed, what remains unresolved, and what directions merit further development. With this aim, the next section introduces key concepts and historical trends that form the foundation for understanding AI-mediated instruction in higher education.

3.2 Historical and Conceptual Evolution of AI in Education

The development of AI-mediated instruction flows out of rapid technological advances in communication, cognition, and literacy. This section traces evolution from face-to-face to computer-mediated communication (CMC) and ultimately to more complex interactions involving AI agents and avatars (Sahebi & Formosa, 2025; Teng et al., 2023). We then consider how national and international policy frameworks have shaped the adoption of AI in education (UNESCO, n.d.; OECD, 2023) and review emerging definitions of AI literacy that inform learner readiness and engagement (Laupichler et al., 2022; Tenório et al., 2023). Together, these developments frame the conceptual grounding for understanding avatar-mediated instruction in online asynchronous environments in higher education.

3.2.1 From CMC to AMC: The Rise of AI-Mediated Communication

Human literacy requirements have changed over time with the changing skills needed to be successful in the workplace, with the most recent developments relating to how human-to-human interactions have changed. As digital literacies developed, new paradigms also developed, such as Computer Mediated Communication (CMC), where the computer separates the human-to-human interface and provides remote access in real time and asynchronously. As AI enabled tools entered the scene, Sahebi and Formosa (2025) coined a term Artificial Intelligence-Mediated Communication (AI-MC), and their research explored the impact AI-MC may have on epistemic trust in online communications.

In the current technological landscape, more than one billion people are regularly using Avatars, enabled by AI algorithms, to interact with one another, coined Avatar Mediated Communication (AMC), creating yet another level of separation in the human-to-human interaction (Teng et al., 2023). Further, researchers have studied the characteristics of Avatars to identify key variables influencing user perceptions and behaviors; reporting both the characteristics of the user and the avatar are context dependent and influenced through situated interactions. For example, depending upon the ability to personalize a chosen avatar, the user-avatar interaction can vary along a spectrum from viewing the avatar as an object or tool performing a computer mediated action, to viewing the avatar as oneself (Ethopoeia – "putting one's role in the place of another"). Avatars have been shown to influence users in profound ways, including affecting the user's actions in subsequent face-to-face interactions with humans (Proteus effect – "aligning their actions with the nature of the avatar they use") (p. 1174). AMC changes behaviors including intentions to continue, as well as psychological and behavioral engagement. The following sections explore the global response to the changing workplace skills and their related literacies in educational settings.

3.2.2 Global Policy Priorities for AI in Education

Schools and governments globally are promoting AI literacy with slogans such as "AI for everyone…" (Norwegian Ministry of Local Government and Modernisation*,* 2020, p. 44) and the promise of "AI for all," with a human-centered approach, suggesting these technologies will help reach the 2030 Agenda for Sustainable Development goals (UNESCO, n.d., para. 2). The Organisation for Economic Co-operation and Development (OECD) (2023) has established international Guidelines for Effective and Equitable Use of AI in Education.

However, there are major issues resulting from the introduction of AI ranging from "ethics of AI, AI in education, gender equality, to capacity building for governments and judiciary" (UNESCO, n.d., para. 2). AI enabled tools include such a vast array of uses and applications that the user's resources, worldview, and goals highly influence the diversity of the applications in contexts. For example, Hirzel (2023) provides an overview of the educational focus for the use of AI by country, with the US notably focusing on AI literacy. Refer to Appendix 2 for AI in education focus by Country resources and priorities.

3.2.3 Evolving Definitions and Dimensions of AI Literacy

Canada and the United States have taken the lead in AI literacy research (Tenório et al., 2023) with the literature yet to find a common answer to "What is AI literacy?" (Laupichler et al., 2022, p. 5). Baskara (2025) described AI literacy for K-12 through university students as a multidimensional competence that encompasses the technical understanding, practical applications, critical evaluation, and ethical considerations of AI systems and technologies in academic, professional, and everyday contexts. It extends beyond mere technical skills to include both cognitive and societal dimensions, preparing students to effectively navigate, contribute to, and critically engage with AI-integrated environments (Ng et al., 2021a & 2021b).

A review of the literature reveals a variety of AI literacy skills that can be categorized into a variety of cognitive categories based upon Bloom's (1984) Taxonomy–know and understand AI, use and apply, and evaluate and create. This aligns well with Dai et al.'s (2020) description of basic literacies as "a user's ability to access, analyze, and use information to achieve an intended purpose" (p. 3). Long and Magerko's (2020) definition of AI literacy has been the most cited in subsequent publications on the topic (Refer to the definitions in Appendix 3). Laupichler et al. (2022) reviewed the literature on AI literacy and noted the needs are differentiated by target group; therefore, the definition should diverge for each group. AI literacy definitions generally refer to competencies that the general public — specifically non-experts without backgrounds in information technology or science — should develop (Laupichler et al., 2022).

Dai et al. (2020) developed an AI instrument to measure primary students' readiness for AI. However, they found AI literacy did not predict users' readiness to use AI. Mediators to AI readiness included one's confidence and perceptions of AI's relevance. These findings open the door to explore further the key concepts surrounding these disruptive technologies and their influence on teaching, learning and leadership in the AI age.

The following sections review the conceptual foundations of AI-mediated instruction and its influence on user trust and identity. Refer to Appendix 4 for a table summarizing the key theories and their interrelationships as they developed over time.

3.3 AI Avatars as Online Instructors

As AI avatars increasingly serve as instructional agents in higher education, it is essential to examine their perceived credibility and pedagogical function in asynchronous learning environments. Within the evolving climate of Education 4.0, human instructors are turning to AI-powered tools—such as avatars, bots, and synthetic voice interfaces—to scale instruction and provide 24/7 access beyond what is possible for a single teacher (Hendriks et al., 2015). These systems are not simply technical enhancements; they represent a conceptual shift in how instruction is delivered, perceived, and socially constructed.

This shift brings renewed attention to the psychological and social implications of AI-mediated instruction. As the concept of AI literacy continues to evolve, so too does our understanding of interaction, identity, and trust in digital learning spaces. Hirzel (2023) observed that "this era [Education 4.0] is marked by the synergy of AI with human educators, where AI not only augments teaching but also redefines our understanding of personal worth" (p. 12). Importantly, learners are not neutral consumers of avatar-based instruction. Research shows that students implicitly assess digital agents and voices along the same epistemic dimensions—expertise, integrity, and benevolence—once reserved for human instructors (Edwards et al., 2019; Hendriks et al., 2015). Users often attribute social meaning to digital agents and respond to them as if they were human—a phenomenon explained by the Computers as Social Actors (CASA) framework (Reeves & Nass, 1996; Nass et al., 1996). This framework is explored in more detail in Section 4.3, where its relevance to avatar-mediated instruction and trust formation is examined. The psychological disposition of viewing digital agents as entities that possess human-like characteristics is known as anthropomorphism. The literature consistently shows that embedding human characteristics into AI transforms user engagement, enhances trust, and impacts consumer attitudes across a variety of sectors (Chaturvedi, Verma, Srivastava, Khot, 2025; Salles, Evers, & Farisco, 2020).

Empirical evidence on the instructional effectiveness of AI avatars is rapidly emerging. Schiefelbein (2023) reported that "hyper-realistic avatars have the potential to be just as engaging, trusted, and effective for information retention as a real human on video" (p. 45). Similarly, Arkün-Kocadere and Özhan (2024) found no significant differences in engagement or performance between students receiving instruction from a human versus an AI avatar. However, researchers also caution that design matters. Krauter (2024) described a negative response when avatars appeared "excessively" realistic but exhibited subtle flaws, producing a phenomenon known as the *Uncanny Valley* (p. 342a). Learners may experience discomfort, fear, or disengagement when faced with avatars that look nearly—but not quite—human (Baake, 2025; Byrne, 2025; MacDorman et al., 2009; Shahini, 2025).

A large-scale experimental study involving over 72,500 participants found that disclosure of an avatar's AI nature in video games actually heightened effort intensity compared to non-disclosed AI companions. This contradicts the intuitive assumption that knowing one is interacting with an artificial entity might reduce engagement (Visser et al., 2024). Although this study was conducted in a game setting, Students might also engage more intensely (e.g., focus harder, respond faster) if they know the "teacher" or "guide" is an AI, because it could lower pressure ("I'm not being judged by a human") or increase novelty ("an AI is helping me"). However, if students think the AI avatar is less capable or less authoritative than a human teacher, it could hurt engagement instead.

Taken together, these findings suggest that while AI avatars may offer powerful instructional benefits, their successful integration depends on thoughtful design and attention to learner psychology. As students increasingly interact with AI in place of human instructors, the question is no longer whether avatars can teach—but how learners come to trust, accept, and learn from them (Kim et al., 2022).

3.4 Psychological and Social Dimensions of Trust in Avatar-Mediated Communication

This section expands the trust construct by drawing on emerging research in artificial psychology, digital sociology, and communication theory to better understand how AMC influences learner engagement and behavior. These perspectives inform the deeper social foundations of epistemic trust and set the stage for later sections that explore identity, knowledge sharing, and institutional adaptation.

The shift from human-to-human interaction to AMC directs the focus to the social and psychological implications of the use of AI as instructors in the context of educational institutions. Psychologically, Wang et al. (2024) noted feedback loops resulting from the use of AI can affect one's "personal and social identities," influencing attitudes such as trust and technology acceptance (p. 2). Edwards et al. (2019) observed that learners often assign social meaning to non-human agents during online communication, gaining a sense of personal worth from their interactions—similar to human relationships grounded in social identity theory. Teng et al. (2023) reported that AMC changes behaviors, such as psychological and behavioral engagement, through social presence.

Fehrenbacher and Weisner (2024) drew on social psychology and CMC theories to test coworkers' willingness to share knowledge (KS). They found co-workers were less responsive to requests from avatars versus human photo representations of unknown coworkers in a virtual setting, noting that "successful collaboration in the virtual world is shaped by aspects of social identity" (p. 2).

These behavioral and identity-based findings are prompting scholars to theorize new psychological and sociological frameworks for understanding AI-mediated human interaction. Yu (2023) explained that many of the pioneers of AI research received training in psychology or were inspired by cognitive science or neuroscience, suggesting a new field of study – artificial psychology, "envisioning an AI system capable of reasoning about emotions, adapting to humans, and constructing knowledge representations based on experiences" (para. 1). Matochová and Kowalikova (2024) wrote that the discipline of digital sociology has yet to address the impact of AI on social structures, relationships, cultures, and identity (p. 178). These developments raise a central question in AI-mediated instruction: can learners trust AI to care, act fairly, and teach competently in ways that support academic credibility and relational engagement?

3.4.1 Muenster Epistemic Trustworthiness Inventory

To conceptually frame how learners evaluate trust in AI avatar instructors, the literature draws on the Muenster Epistemic Trustworthiness Inventory (METI), developed by Hendriks et al. (2015). The METI identifies three interrelated dimensions of epistemic trust: expertise (perceived competence), integrity (perceived honesty and fairness), and benevolence (perceived care and goodwill). While originally designed to assess perceptions of human information sources, these dimensions offer a useful conceptual lens through which to examine how trust operates in AI-mediated instructional contexts—particularly where avatars or synthetic agents act as surrogates for human teachers. While the METI framework offers a structured way to conceptualize epistemic trust, it does not fully account for the psychological and social factors that shape how learners interpret and relate to AI avatar instructors. Trust in AI is not purely cognitive—it is relational, contextual, and shaped by the user's identity, emotional response, and perceived social presence of the agent.

In AMC, trust is not derived solely from the technology itself but is shaped by how users interpret relational and social cues in the learning environment. Sahebi and Formosa (2025) argue that epistemic trust in AI-MC may ultimately reflect learners' judgments not just about the agent's output, but about the human actors behind the AI—those who designed, selected, or deployed the system in educational settings. This highlights the need to evaluate AI systems not only for informational reliability, but also for their perceived fairness and relational alignment with learners' expectations.

Although the METI is typically applied in empirical settings, its multidimensional framing supports a conceptual understanding of how learners might judge the credibility and instructional authority of AI avatars. As Goldbach et al. (2019) note, much of the existing research focuses on learners' intention to use AI systems, but relatively few studies have explored the judgments that underlie sustained engagement, particularly in asynchronous or avatar-mediated formats. In these contexts, METI's trust constructs help frame the psychosocial processes that may influence learners' willingness to engage, accept feedback, and persist in AI-mediated learning environments.

3.4.2 Conceptual Model of Epistemic Trust in AI Mediated Interactions

The conceptual model, developed in this review, builds on the METI framework to show how social presence may shape learners' trust in AI avatar instructors. In asynchronous environments, where relational cues are often limited, the perception that an instructor is real, accessible, and emotionally attuned—core features of social presence—can influence learners' judgments of expertise, integrity, and benevolence (Borup et al., 2012; Thomas et l., 2017a & b; Wang et al., 2024).

These perceptions are further shaped by learner characteristics such as gender, AI familiarity, year of study, and academic major, which may moderate how trust is formed (Ma et al., 2025). Research in online education and AI-enhanced instruction supports the idea that fostering social presence can enhance engagement and deepen learners' trust in both human and artificial agents (Borup et al., 2012 & 2013; Kim et al., 2021b). These theorized relationships can be viewed as variables in empirical studies along with moderators influencing student trust in AI-mediated interactions in online environments. Figure 1 illustrates how the "social presence" of an AI-avatar teacher in an online environment shapes students' trust. When an AI avatar seems more human and emotionally aware, students are more likely to believe it is knowledgeable (expertise), honest (integrity), and genuinely helpful (benevolence).

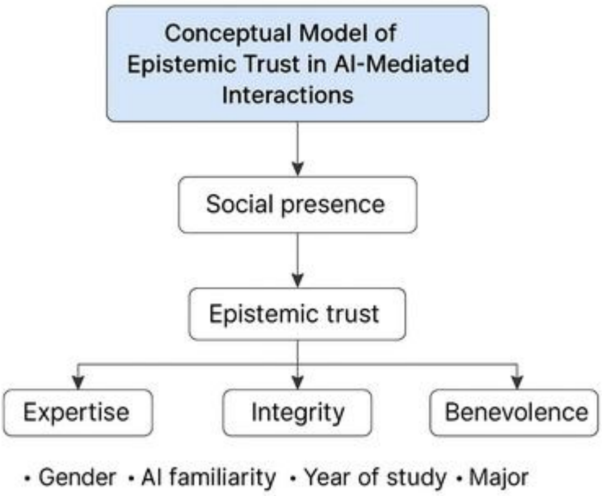

Figure 1. Conceptual Model of Epistemic Trust in AI-enabled Instruction

Note: No firm relationships are suggested in this integrative review, and the models developed lay the foundation for subsequent empirical studies. Future models will include additional annotations of test results confirming or modifying the proposed model relationships. In Figure 1, the downward flow suggests the influence of each proposed construct on the next. Social presence influences students' epistemic trust in the teacher. Epistemic trust, described in the METI framework, includes students' perceptions of the teachers' expertise, integrity, and benevolence. However, these are potentially moderated by the students' characteristics such as, but not limited to, gender, AI familiarity, year of study in school, and student's major area of study. Therefore, no arrow points to the moderators, which are yet to be tested before positioning them in the model. Refer to Figure 3 for suggested empirical relationships found in the literature.

The following sections will discuss more fully the findings in the relevant literature relating proposed moderators and variables of social presence and epistemic trust.

3.5 Gendered Patterns in AI Perception

Gender, as a central component of learner identity, significantly shapes how students interpret and emotionally engage with emerging technologies—particularly those, like AI avatars, that simulate social presence in asynchronous instruction (Belt & Lowenthal, 2022; Belt & Lowenthal, 2023a; Kim et al., 2021a). This dynamic becomes especially salient in the era of Education 4.0, where AI is increasingly embedded into the instructional core, shifting pedagogical paradigms and necessitating inclusive approaches to technology-mediated learning (Sahebi & Formosa, 2025; WEF, 2024).

If AI is to foster equitable trust, instructional design must go beyond functional access and address *relational equity*—the ways in which learners from diverse backgrounds perceive credibility, social cues, and emotional alignment in AI instructors (Hanson & Yu, 2024). However, persistent barriers to AI literacy remain, particularly among students from underrepresented groups—including gender and ethnic minorities and those from low socioeconomic backgrounds—due to lower exposure to AI technologies (Ng et al., 2021). Figure 2 visually summarizes the sociocultural and cognitive factors contributing to gendered differences in AI perception, which underpin later discussions of engagement and trust in AMC and how gender plays a big part in AI perception in online classes. This "relational equity" difference can cause students to see and trust AI instructors differently.

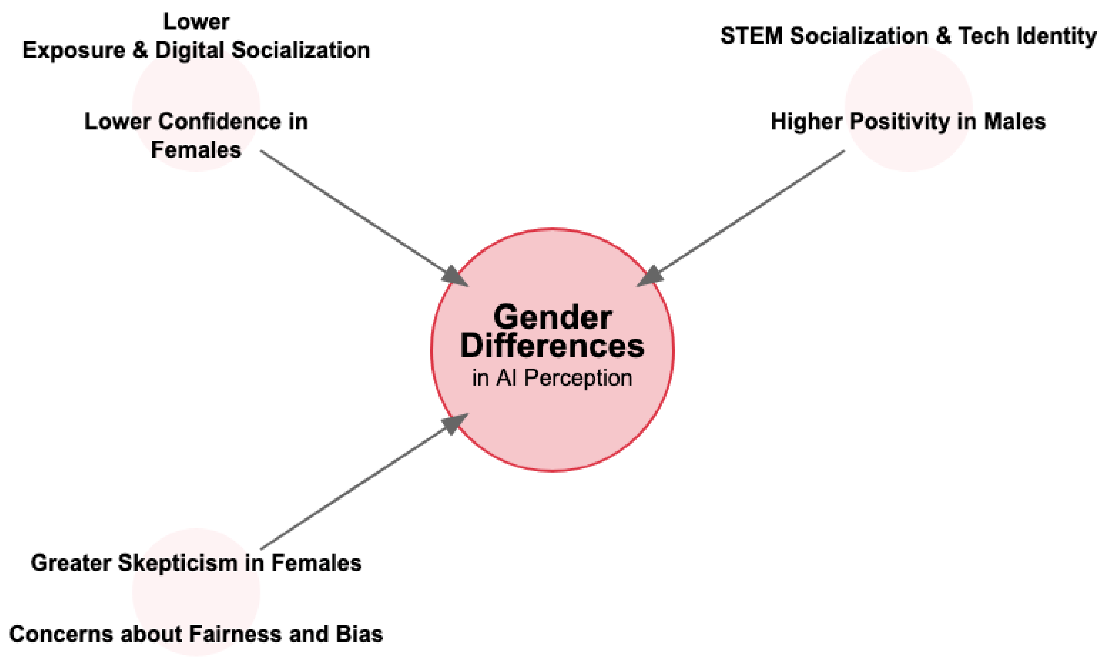

Figure 2. Gender Differences in Perceptions Related to AI

Note. The proposed relationships between gender and perceptions of trust in AI are based upon a review of the relevant literature, which suggests females show greater skepticism and have lower confidence in AI than males. Lower confidence may be the result of reduced exposure and digital socialization in females. Increased skepticism potentially results from issues related to fairness and bias experienced by females in society. Males show higher positivity toward AI, which potentially results in higher STEM socialization and a "tech" mentality.

3.6 Conceptualizing Gendered Trust in AMC

User identity—particularly gender, AI familiarity, and self-efficacy in technology use—has been shown to significantly shape learner attitudes in AI acceptance models (Gursoy et al., 2019; Goldbach et al., 2019; Tsai et al., 2019). Research consistently shows that "the paths from AI anxiety to perceived ease of use and from perceived ease of use to perceived usefulness are moderated by gender" (Zhang et al., 2023, p. 1). Figure 3 provides a model of moderators and mediators and risks related to epistemic trust in AI-MC.

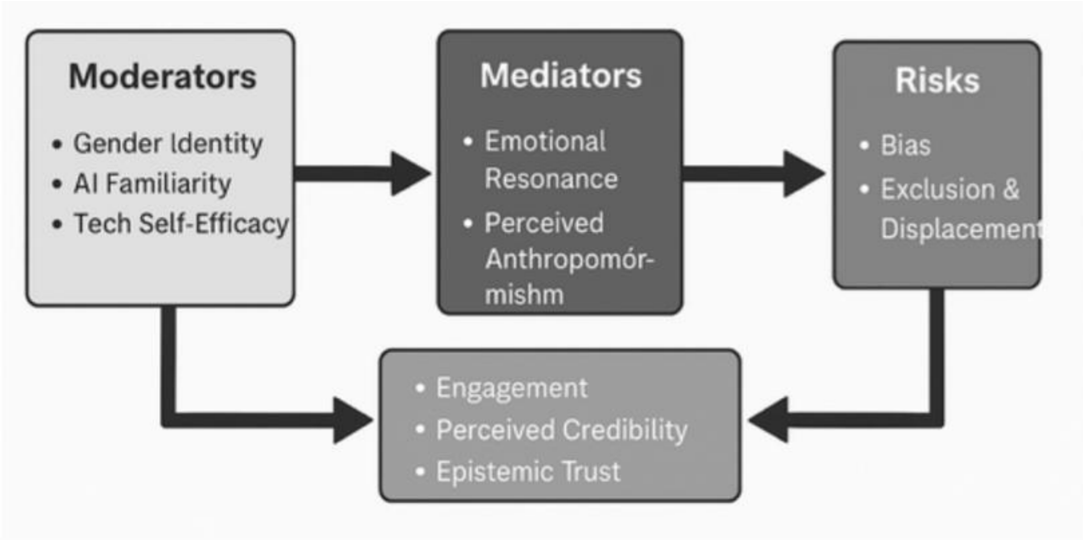

Figure 3. Gendered Trust in AI-MC

Note. The diagram provides a framework for understanding how different students might develop trust in AI systems, such as AI avatar instructors. This model is crucial for designing equitable and effective learning experiences.

Across studies on technology acceptance, male-identifying participants tend to assign more positive social qualities to AI systems and report greater familiarity, comfort, and confidence when using emerging digital tools (Cheryan et al., 2017; Kim et al., 2021; Seo et al., 2021a & b; Tan, 2024b). Dai et al. (2020) found that male students expressed stronger readiness and perceived relevance of AI, which likely reflects broader cultural alignment between dominant male gender norms and STEM-related identities—norms that often position men as "default" users or creators of technology (Belt & Lowenthal, 2023b).

In contrast, female and nonbinary learners tend to prioritize emotional resonance and interpersonal cues when evaluating AI-mediated communication and often approach AI with more scrutiny and critical reflection—particularly in high-stakes educational settings where perceptions of bias or misalignment can impact engagement and trust (Shahini, 2025). These relational dimensions can either support or erode trust, depending on how effectively the AI conveys social presence (Belt & Lowenthal, 2023a; Borup et al., 2012 & 2013; Cheryan et al., 2017; Tan et al., 2021a & b). For instance, Shahini found that female learners reported greater trust than males in AI instructors when the avatar displayed high levels of anthropomorphism.

As AI becomes further integrated into academic and professional environments, concerns around algorithmic bias present a significant risk—especially for women. AI instructors may unintentionally replicate exclusionary cues embedded in training data or system design. Beyond the classroom, broader structural inequities are amplified by automation: both the IMF and the Institute for Women's Policy Research have projected that women are disproportionately at risk for job displacement due to AI (UNESCO, 2020). These projected trends compound existing issues. As Cheryan et al. (2017) argue, persistent structural and cultural barriers—not lack of ability or interest—continue to deter many women from fully participating in STEM fields.

3.7 Projected Immersive Era: Future Directions for Avatar-Mediated Instruction

While this paper focuses on current uses of AI avatars in asynchronous learning, it is essential to anticipate how trust, presence, and instructional roles may evolve as higher education moves toward increasingly immersive digital environments. The *Projected Immersive Era* (2030+) anticipates the widespread integration of extended reality (XR) technologies—such as virtual, augmented, and mixed reality—into daily educational, professional, and social life. Within this context, AI-powered avatars are expected to take on increasingly social and instructional roles, fostering environments that simulate co-presence and human-like interaction. Although current use of AI avatars in higher education largely occurs in low-immersion formats, such as asynchronous instructional videos, these applications exist on a continuum toward more immersive modalities where trust and relational presence become critical.

In immersive environments, *epistemic trust*—the belief that an information source is competent, honest, and benevolent—has been shown to deepen as immersion increases. For example, Mal et al. (2024) found that immersive VR significantly enhanced users' perceptions of avatar plausibility and trustworthiness, while Rosenberg (2023) warned that such realism may blur users' awareness of persuasive AI influence. Trust is not merely cognitive but behavioral as well: Clements et al. (2023) showed that participants were more likely to follow instructions from avatars they perceived as trustworthy in immersive settings. These findings align with growing concerns about "proxy gaps" in responsibility and the need for frameworks to assess the relational credibility of AI agents (Constantinescu, 2025; Zhou et al., 2022). To evaluate trust in educational AI avatars across both current and emerging contexts, the METI framework remains a valuable tool for assessing learners' perceptions of expertise, integrity, and benevolence (Hendriks et al., 2015; Montag et al., 2023).

4. Theoretical Integration and Conceptual Model Development

This section synthesizes key theoretical perspectives—epistemic trust, social identity theory, and human-computer interaction frameworks—to propose a conceptual model of how learners form trust in AI avatar instructors in asynchronous higher education settings. Drawing from the METI framework, which conceptualizes trust across the dimensions of expertise, integrity, and benevolence (Hendriks et al., 2015), this model integrates broader relational constructs such as social identity (Edwards et al., 2019) and socially responsive design (Reeves & Nass, 1996) to explain learner perceptions. By weaving together these frameworks, the model addresses the domains' guiding questions concerning trust formation, learner identity, and institutional adaptation in AI-mediated instruction. This integrative synthesis moves beyond individual research findings in the literature to build a foundation for future research and design in higher education. Refer to Figure 4 for a visual synthesis of the theoretical lenses that inform the development of the integrated model.

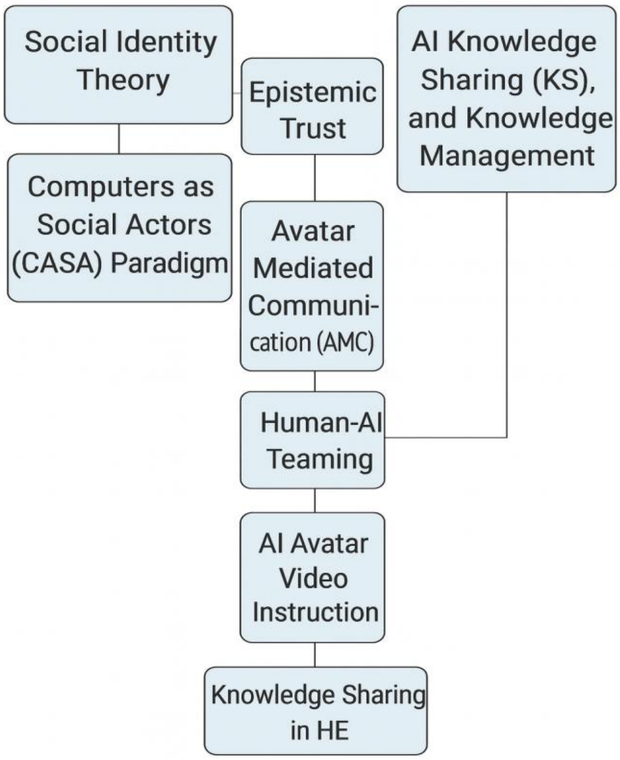

Figure 4. Theoretical and Conceptual Model for AMC Developed from the Integrative Review

Description: The first sections of this integrative review build the readers understanding of the use and development of AI in education. The subsequent sections focus more narrowly on AMC and follow the organization provided in Figure 4. The diagram presents the theoretical and conceptual model of how established theories connect to the practical application of AI in education. This model effectively maps the foundational concepts that justify and guide research into using AI avatars for teaching and learning.

4.1 Extending METI to AI-Avatar Mediated Instruction

The METI (Measures of Epistemic Trustworthiness Instrument) framework—grounded in perceived expertise, integrity, and benevolence (Hendriks et al., 2015)—offers a valuable foundation for assessing trust in educational contexts. In this concept paper, METI is extended to theorize how learners form judgments of trust in AI avatar instructors, particularly in asynchronous environments where traditional relational cues are limited. Unlike human instructors, AI avatars depend on socially programmed scripts and visual cues to establish presence, which reshapes how learners assess credibility.

By applying METI to AMC, this paper reframes trust as both a relational and cognitive construct, shaped by the learner's prior experiences, identity characteristics, and the avatar's perceived presence. Building on findings by Vallis et al. (2023), which show that students valued consistency but missed human interactivity in AI avatar instruction, this extension emphasizes the need for instructional designs that balance technical delivery with emotional and relational resonance. These insights directly inform the conceptual model proposed in Figure 4.1, where METI serves not only as an evaluative framework but also as a theoretical scaffold for understanding epistemic trust development in AI-mediated instruction.

4.2 Social Identity Theory (SIT)

Social Identity Theory (SIT) suggests individuals define part of their self-concept through group membership, distinguishing between in-groups and out-groups as a source of belonging and self-worth (Edwards et al., 2019). In educational contexts, shared identity increases task efficiency, trust, and persistence (Gutoreva, 2024; Jeon, 2021). Teng et al. (2023) emphasized that social identification strengthens interpersonal ties and contributes to well-being and trust—key outcomes in avatar-mediated learning.

As AI systems and avatars increasingly mediate communication, SIT provides a lens for examining whether learners perceive these non-human agents as part of their instructional "in-group." This framing informs how trust is constructed in asynchronous settings, where social presence and identity cues are digitally mediated (Mirababaie, 2021).

The notion of the extended-self further supports this idea. Gutoreva (2024) described how individuals form social experiences in artificial environments, developing symbiotic relationships with AI. Jeon (2024) noted users may perceive avatars as both collaborative actors and functional tools. As a result, individuals engage in "virtually extended identification," enhancing confidence and self-view through perceived affiliation with the AI (Mirbabaie et al., 2021, p. 32).

Importantly, long-term collaboration with virtual assistants can erode identification with human teams, particularly when users over-identify with AI agents (Mirbabaie et al., 2021). To mitigate this, Teng et al. (2023) recommend intentional design strategies—such as team-based tasks and human connection points—that maintain learners' social identification with peers and instructors. These design features are essential for sustaining trust and well-being in AI-enhanced educational environments.

4.3 Computers as Social Actors (CASA)

The CASA paradigm (Reeves & Nass, 1996) explains how users instinctively apply social heuristics to computer-based agents, attributing human traits—such as expertise, personality, or emotion—to non-human interfaces. In this context, AI avatars function not merely as tools but as social actors, influencing learner perceptions in ways that parallel human interaction (Guzman, 2018; Edwards et al., 2019).

This framework provides a valuable theoretical bridge for applying the METI model to AI-mediated instruction. Learners evaluate AI avatars not just for technical accuracy but for epistemic trustworthiness, inferred from social cues that simulate human presence. Kitsios and Kamariotou (2021) emphasized that motivation to engage with AI tools depends in part on perceived emotional alignment and cognitive congruence—core social factors described in the CASA framework.

Research supports the preceding view. Specifically, Teng et al. (2023) and Fehrenbacher and Weisner (2024) found that learners' engagement and trust in AI avatars are shaped by how well those avatars match expected social roles. These findings align with CASA's central claim that social presence—even when artificially rendered—can trigger deeply human responses.

Thus, CASA helps explain how and why learners form trust judgments in avatar-mediated instruction. It reinforces the need for AI design that integrates relational cues aligned with learners' expectations for competence, care, and fairness—paralleling the dimensions of expertise, benevolence, and integrity embedded in the METI framework.

4.4 Knowledge Sharing, Management, and AI-Mediated Instruction

Beyond individual learner engagement, the use of AI avatars in higher education challenges institutions to rethink knowledge sharing (KS) and knowledge management (KM) practices. In this context, avatars act not just as delivery tools, but as epistemic agents—digital entities that shape, encode, and transfer knowledge through AI-MC (Nakash & Bolisani, 2024).

As Hirzel (2023) explains, knowledge in AI-enhanced platforms is no longer solely human-driven. Instead, it is co-constructed through continuous interaction with autonomous systems, shifting the traditional model of content transmission toward one of relational engagement and value co-creation (Hentzen et al., 2021). This reframing moves beyond ICT-based diffusion models and positions AI avatars as active agents in the knowledge lifecycle.

However, extracting value from AI integration is not automatic. Human perceptions and organizational context shape how AI is adopted and trusted (Kitsios & Kamariotou, 2025). In higher education, trust in AI as a knowledge intermediary is a critical variable in how learners evaluate digital content and how faculty adopt AI strategies.

As Lei et al. (2024) note, AI may be revolutionizing higher education, but institutional barriers—such as culture, readiness, and entrenched processes—limit its transformative potential. To overcome these constraints, scholars advocate for a cognitive strategy that repositions AI from being merely a technological tool to a pedagogical and epistemological partner in learning (Lei et al., 2024).

4.5 Human-AI Teaming (HAT): A Cognitive and Strategic Shift

This section examines Human-AI Teaming (HAT) as a paradigm shift in conceptualizing the relationship between humans and artificial intelligence, with specific application to AI avatars in higher education contexts. HAT represents a fundamental reconceptualization of Human-Computer Interaction (HCI). Rather than viewing AI as merely a tool for automation, HAT repositions AI as a collaborative cognitive agent (Dellermann et al., 2021). In this framework, AI systems and human agents work together to accomplish shared goals, combining their respective strengths to outperform what either could achieve alone (Xu & Gao, 2024). This paradigm shift is particularly relevant to AI avatars in higher education, where traditional notions of instructional technology are being challenged by more relational and dynamic forms of human-AI interaction. The HAIJCS model (Human-AI Joint Cognitive Systems) emphasizes shared situation awareness, decision-making, and control, modeling AI as a teammate embedded within complex cognitive tasks—not simply a delivery mechanism. This paradigm is especially relevant in higher education, noting the interrelationships of instructional design, learner trust, and identity development previously discussed (National Academies of Sciences, 2021).

Moving to the next transformation in AI-MC, HAT recognizes that AI systems function best when integrated as cognitive teammates—agents that dynamically support human educators (Zhou et al., 2022). The HAT literature emphasizes that AI must operate within Human-Centered AI (HCAI) frameworks including institutional readiness, digital equity, and cognitive strategies (Xu & Gao, 2024). Digital equity requires inclusion and cognitive alignment—for example avatar agents can be designed with social presence, cultural responsiveness, and pedagogical alignment with needs of underrepresented learners in STEM.

By embedding HAT principles into institutional policies, instructional design frameworks, and trust development models, higher education can more effectively transition from AI as a content tool to AI as a pedagogical collaborator. This aligns with the broader conclusion that AI avatars must be approached not simply as instructional technologies, but as cognitive shifts that reconfigure knowledge sharing, learning agency, and instructional identity.

AI avatars, when positioned solely as deliverers of pre-scripted content, risk reducing the human actor to a passive recipient. Faculty and administrators can transform their understanding of AI-mediated instruction as a tool to a form of cognitive teaming—where the AI agent complements human decision-making, instructional framing, and ethical considerations of inclusion.

5. Gaps and Implications

5.1 Gaps

Although AI avatars are becoming increasingly common in higher education, significant gaps remain in understanding how students form perceptions of trust and instructional credibility in asynchronous learning environments. Few studies explore how these perceptions develop in the absence of face-to-face interaction or real-time feedback. Moreover, research on learner characteristics—such as academic year, gender, major, or prior exposure to AI—is still emerging and lacks clear consensus.

Belt and Lowenthal (2023a) emphasize the importance of facilitation style and transparency in building trust during synchronous video instruction, but whether these cues translate to asynchronous, scripted environments remains unclear. Studies by Cheryan et al. (2017) and Belt and Lowenthal (2023b) have begun exploring STEM identity and relational trust for underrepresented learners; however, findings related to gender and identity remain mixed in AI-mediated instruction.

Beyond learner-level variation, gaps also exist at the institutional level. Scholars note that institutions must evolve from static repositories of knowledge to dynamic, AI-enabled ecosystems—but few studies address how higher education institutions are adapting their cultures, infrastructures, and pedagogical frameworks to support this shift (Lei et al., 2024;

Ling et al., 2014; Taherdoost & Madanchian, 2023; Kitsios & Kamariotou, 2021).

Finally, Edwards et al. (2019) call attention to the lack of integration between Social Identity Theory (SIT) and Human–Robot Interaction (HRI) research in educational settings. As AI tools become more pervasive in learners' environments, understanding how in-group affiliation and identity salience influence trust in AI avatars represents a critical frontier for future research. These gaps point to several urgent priorities for inquiry, which are addressed in the recommendations that follow.

5.2 Implications

The findings of this integrative review suggest that AMC in higher education carries distinct implications for learners, faculty, and administrators. As shown in Figure 5, AMC has the potential to support differentiated instruction and enhance learner autonomy through 24/7 access to AI avatars. However, it also introduces risks—particularly the reduction of human connection and the possibility of undermining student agency when AI systems are perceived as authoritative or opaque.

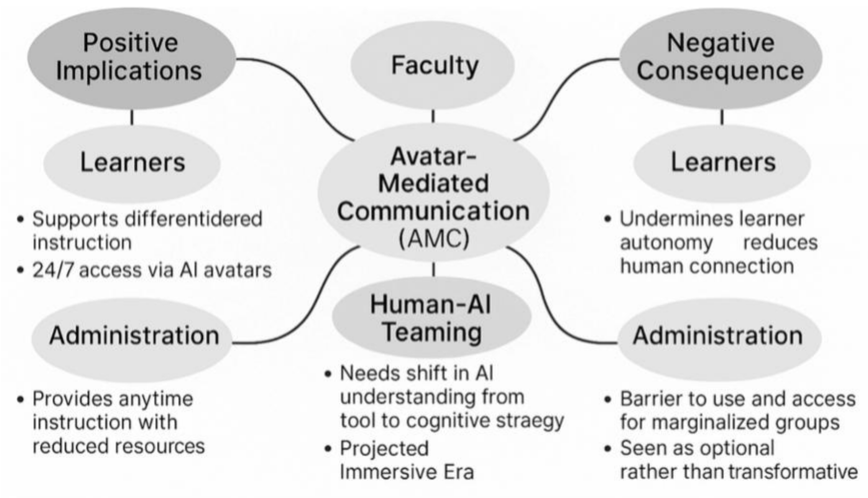

Figure 5. Implications for the Learner, Faculty, and Administrator Synthesized from the Literature on the Impact of AMC in HE

Note. This diagram provides a synthesized overview of the implications of using AMC in higher education. This framework lays out the opportunities and the potential pitfalls for key stakeholders: learners, faculty, and administrator.

Faculty may benefit from increased instructional productivity and new forms of engagement, but it will require a shift in their understanding of AI as a technological tool to a pedagogical strategy grounded in social cognition. For administrators, AMC offers a scalable solution for providing instruction with reduced resources but also raises equity concerns if digital access and training are not equitably distributed. The synthesis of these findings underscores the need for coordinated, stakeholder-specific strategies that integrate AI tools thoughtfully into educational ecosystems, ensuring that AMC is not merely adopted as a convenience, but understood as a transformative shift in instructional communication and design.

Understanding AI avatars as teammates, rather than tools, shifts the instructional design process (Hanshaw & Hanson, 2019). Faculty must think of collaboration protocols, information processing roles, and shared decision-making within digital learning environments. This reconceptualization requires new approaches to course design and development. Trust in AI instructors depends not only on perceived expertise or visual realism but also on whether the AI agent is perceived as working with the learner—not replacing or surveilling them. Teaming models highlight the importance of human-led governance, where instructors, designers, and institutions retain epistemic control and ensure that AI decisions are interpretable, adaptable, and justifiable in educational terms.

5.3 Translating Conceptual Insights into Empirical Design

Building on the theoretical foundations established in this review, this section outlines a proposed research design that translates the conceptual model into an empirical study. The purpose is to validate and refine the integrated framework by investigating how learners in asynchronous higher education settings perceive trust in AI avatar instructors—an inquiry central to the conceptual questions that guided this integrated review.

Given the multidimensional nature of epistemic trust—including learners' perceptions of expertise, integrity, and benevolence—a mixed-methods approach is both appropriate and necessary. As Choi and Clark (2021) observe, trust formation in digital instructional environments reflects not only measurable behavioral patterns but also personal, relational, and interpretive processes. These processes are shaped by identity-based factors and emotional responses that cannot be fully captured by quantitative measures alone.

A quantitative phase will draw on validated survey instruments such as the METI framework to assess epistemic trust. This phase will explore how learner characteristics—such as gender, AI familiarity, year of study, and academic major—moderate perceptions of AI instructors. These variables directly support Research Questions 3 and 4 (found in Appendix 1) related to learner identity and the intersection of demographic factors with trust formation. Statistical analyses from this phase will identify patterns and generalizable trends in students' trust perceptions across diverse educational contexts (Zawacki-Richter et al., 2019).

Complementing this, a qualitative phase will involve collecting open-ended responses or conducting semi-structured interviews. These data will illuminate the nuanced and context-rich ways that students interpret and emotionally engage with AI avatar instructors. Trust—especially when influenced by factors such as anthropomorphism or perceived social alignment—often involves subtle cues and relational dynamics that extend beyond the scope of survey data.

Bringing these two strands together, a mixed-methods approach will enhance explanatory power through triangulation (Creswell & Plano Clark, 2018), enabling a fuller understanding of both the breadth and depth of epistemic trust in AI-mediated instruction. The results will not only inform future refinement of the conceptual model but also guide the development of improved instructional design, faculty training, and institutional policies for AI integration.

In short, the conceptual work presented here lays the foundation for a rigorous, empirically grounded exploration of AI avatar instruction in higher education, linking theory to action and establishing a clear pathway for future research.

5.4 Recommendations for Future Research

Building on this paper's conceptual model, the following research directions offer pathways for extending theoretical insights into empirical investigation. These priorities are grouped across three domains: (1) learner identity and instructional design, (2) modality and engagement, and (3) institutional adaptation and equity. Each represents a critical next step for advancing AI-mediated instruction in higher education.

5.4.1 Learner Identity and Trust Dynamics

Future research should explore how learner characteristics—such as gender, race, and AI familiarity—influence trust in avatar-based instruction. Experimental and longitudinal designs could test how avatar features (e.g., voice, gender expression, realism) affect perceptions of expertise, integrity, and benevolence. These studies would extend CASA and SIT frameworks using validated tools such as the METI scale.

5.4.2 Instructional Modality and Trust Trajectories

Comparative studies are needed to evaluate how different delivery modes—such as asynchronous video and mixed reality simulations—shape epistemic trust. Longitudinal or design-based research (DBR) could also track trust development over time and test intervention strategies (e.g., co-teaching models, feedback loops) that enhance learner engagement and instructional credibility.

5.4.3 Faculty Development, Leadership, and Institutional Equity

Organizational-level studies should investigate how faculty and administrators conceptualize AI avatars—not as tools, but as cognitive instructional agents. SoTL-based designs could examine how principal preparation programs address AI-integrated knowledge management (KM) and identify opportunities to align policy, professional learning, and instructional planning with cognitive models of AMC. Additionally, equity-focused research should test whether AI avatars can increase belonging, agency, and self-efficacy for underrepresented students in STEM, or support caregiver engagement in special education contexts.

Further, recently universities worldwide have invested significant resources in faculty professional development on artificial intelligence, primarily emphasizing technical upskilling, but this movement seems to overlook the crucial psychological dimensions of technology adoption—namely, the pervasive human tendency to resist change and maintain the status quo (Miller, 2019). Research within higher education reveals that initial reluctance to use new instructional technologies stems from fear of failure, concerns over increased workload, and apprehensions that technology may devalue traditional teaching roles (Beggs, 2000). In the era of AI, AI is especially perceived as a threat due to potential job displacement (Subaveerapandiyan & Shimray, 2024). To foster acceptance, it is advisable to conduct research on why negative perceptions are formed, and how to cultivate a dynamic, innovative, and resilient academic community capable of thriving in an era of rapid technological transformation.

6. Summary and Conclusion

This concept paper explored the evolving use of AI avatars in asynchronous higher education, with a focus on how learners form perceptions of *epistemic trust* in the absence of live, human interaction. Drawing from four conceptual domains—(1) the historical evolution of AI in education, (2) epistemic trust in asynchronous contexts, (3) learner identity and demographic influences, and (4) institutional adaptation—this integrative review identified the complex psychological, social, and structural factors that shape how students, faculty, and administrators experience and implement AMC.

The synthesis revealed that trust in AI instructors extends beyond technical performance; it is deeply relational and contextual. Learners' perceptions of *expertise*, *integrity*, and *benevolence* are mediated by identity variables such as gender, AI familiarity, academic background, and field of study (Cheryan et al., 2015 & 2017; Belt & Lowenthal, 2023b). At the same time, AMC introduces risks that include social disconnection, cognitive over trust, and misalignment between instructional design and learner identity—especially for students from underrepresented or lower-exposure groups (Teng et al., 2023; Fehrenbacher & Weisner, 2024).

While AI avatars present promising opportunities to expand instructional reach, increase personalization, and support learner autonomy, their use raises foundational questions about knowledge transfer, instructional credibility, and social presence. As highlighted by Lei et al. (2024), Kitsios and Kamariotou (2021), and others, higher education institutions are not yet structurally or culturally aligned to support the epistemic shifts required for AI integration. When faculty and administrators treat AMC as a neutral technology tool—rather than a pedagogical and psychological agent—key opportunities for engagement, inclusion, and innovation may be lost.

The review also underscores that trust in AI, even when warranted, carries cognitive and ethical consequences. As Edwards et al. (2019) caution, AI agents with human-like affect may inadvertently influence beliefs or behaviors in ways that diminish learner autonomy and critical reflection. This finding further supports the need for ethical design, transparency, and ongoing human connection in AI-mediated learning environments.

A paradigm shift is indicated from viewing AI as a tool to understanding it as a collaborative agent in educational contexts. HAT provides a compelling lens to clarify the positioning of AI avatar instruction within the broader instructional ecosystem and develop more inclusive, ethical, and pedagogically sound applications of AI avatars in higher education.

To integrate these insights, the paper proposes a dual-pathway conceptual model that synthesizes the *positive* implications of AMC—such as differentiated instruction, enhanced access, and learner agency—with the *negative* risks of identity exclusion, disengagement, and institutional unpreparedness. This model builds directly from the four guiding research domains and provides a cohesive framework for future empirical research, instructional design, and institutional strategy.

Ultimately, this paper advances a rethinking of AMC—not as a technology alone, but as a conceptual shift in how higher education constructs credibility, fosters identity, and manages knowledge. The models developed herein offer practical and theoretical scaffolds to help institutions move toward a more equitable, learner-centered, and cognitively aligned use of AI avatars in teaching and learning.

6.1 Closing Note

Together, these recommendations aim to extend the contributions of this integrative review by moving from exploratory insight to targeted, theory-informed research. Future inquiries should refine, adapt, and optimize AI-MC systems—particularly AMC—to advance equity, deepen engagement, and enhance instructional effectiveness in higher education.

Declaration of Conflicting Interests

The authors declare no existing conflicts of interest that would undermine the reliability of the outcomes of this paper.

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Author’s Note on AI Contribution

This concept paper was developed in collaboration with an AI assistant (ChatGPT, OpenAI, 2024), which supported the research process as an organizational tool to assist with visualization, APA paper and reference formatting, recommendations for transitions, identification of redundancies, etc. All content generated through AI assistance was critically reviewed and edited by the author to ensure alignment with scholarly standards, field-specific expectations, and ethical authorship practices. No text or results were included without the author’s explicit writing, development, insights, direction, review and approval. The conclusions represent the opinions of the authors.

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Glossary

AI: artificial intelligence.

AI-MC: artificial intelligence mediated communication.

AMC: avatar mediated communication

Appendix

Appendix 1. Conceptual Domains and Guiding Research Questions for AI-Mediated Instruction

Domain	Research Question
1. Historical Evolution and Current Landscape	How has AI evolved from early instructional technologies to current applications such as AI avatars and synthetic voice in asynchronous higher education?
2. Epistemic Trust in Asynchronous AI Contexts	How do existing theoretical frameworks explain how learners develop epistemic trust in AI avatars used in asynchronous instruction?
3. Learner Identity and Demographic Intersections	How do learner characteristics—such as gender, academic background, and AI familiarity—influence trust in avatar-mediated instruction?
4. Institutional Transformation and Knowledge Management	What challenges do institutions face when shifting from viewing AI avatars as tools to adopting them as part of a cognitive instructional strategy?

Appendix 2. AI in education uses by Country resources and priorities

Country	AI in Education Focus
China	AI leadership in its educational system
Europe	Cautious due to ethical concerns and digital disparities
India	Personalized learning and skill development
North America	Fostering AI literacy
Russia	AI for assessments and inclusion

Appendix 3. Glossary of Key Terms and Definitions

Term	Definition
AI Literacy	A set of competencies enabling individuals to critically evaluate, use, and collaborate with AI, including ethical awareness and creative application (Long and Magerko (2020) in Laupichler et al., 2022).
Artificial Intelligence (AI)	The development of computer systems capable of performing tasks that require human-like cognition, such as learning and decision-making.
AI-Mediated Communication (AI-MC)	Communication in which a computational agent modifies or generates messages on behalf of a user to achieve interpersonal or instructional goals (Hancick et al., 2020 in Sahebi & Formosa, 2025).
Avatar-Mediated Communication (AMC)	A form of AI-MC in which a digital, human-like figure delivers instructional content or interacts with learners in place of a live instructor.
CASA (Computers Are Social Actors)	A theoretical model suggesting users apply human social rules and judgments to computers and digital agents (Reeves & Nass, 1996).
Epistemic Trust	The extent to which learners consider instructional sources competent, honest, and benevolent—especially important in non-human (AI) teaching agents (Hancock et al., 2011; Fricker, 2021 in Sahebi & Formosa, 2025).
Extended Social Presence	The perceived sense of social and emotional connection with others, including avatars, in digitally mediated environments (Biocca et al., 2003).
Knowledge Management (KM) 3.0 / 4.0	The evolution from static knowledge systems to dynamic, AI-integrated platforms that generate, share, and adapt knowledge in real time (Kaczorowska-Spychalska et al., 2024).
Perceived Agency	The psychological attribution of intentionality and decision-making to machines or AI, which affects user trust and engagement (Waytz et al., 2014).
Social Identity Theory (SIT)	Explains how individuals define themselves through group memberships, influencing behavior, communication, and perceptions of in-groups and out-groups (Tajfel & Turner, 1979; Teng et al., 2023).

Education 4.0	The use of innovative technologies in teaching and learning to prepare students for Industry 4.0 (Matúšová & Kollár, 2023).
Blockchain (in Education Contexts)	A distributed database structure managed by network participants, explored in education for secure record-keeping (Seenbacher & Schürtiz, 2017 in Voight et al., 2020).
DAO (Decentralized Autonomous Organizations)	Education-based DAOs promote self-directed learning, collaboration, and innovation in decentralized environments (Hirzel, 2023).
General Knowledge Model	Organizes knowledge flows into four primary areas: knowledge creation, retention, transfer, and utilization (Mukhlason et al., 2012).
ICTs (Information Communication Technologies)	Technologies that enable information sharing and communication over the internet (Sosa & Manzuoli, 2019 in Lynch et al., 2021).
Knowledge Management	The process of creating value from an organization's intangible assets (Liebowitz, 2004).
The Fabric Model of Education	Describes education as a multidimensional fabric balancing effectiveness, equity, efficiency, and responsiveness (Hirzel, 2023).

Appendix 4. Evolution of Literacies, Communication Theories, and Social Structures Shaping AI-Mediated Instruction

Era	Primary Literacies Required	Social Relationships	Communication and Social Theories
Pre-Digital (Pre-1980s)	Basic literacy (reading)	Human-to-human, face-to-face	Pre-computer mediated communications; primarily human to human unmediated.
Industrial/Post-War (1945–1980)	Traditional literacies (reading, writing, arithmetic); workplace literacy	Interpersonal, mass media-mediated	Behaviorist learning theory (Skinner, 1984)
Digital Revolution (1980s–2000)	Digital literacy; foundational KM systems emerging	Human-computer interaction; institutional knowledge storage	Technology acceptance model (TAM) (Davis, 1989); Knowledge management (KM) theory (KM) (Nonaka & Takeuchi, 1995; Nemati et al., 2002); Constructivist Learning Theory (Bruner); Situated Learning (Lave & Wenger, 1991); Computer mediated interaction (Walther et al., 1992); Instructional systems design (Gagné, 1982)
Web 2.0 Era (2000–2015)	Digital fluency; collaborative and social literacies; knowledge sharing across platforms	Peer-to-peer learning; online communities; participatory cultures	Communities of practice (Wenger, 1998); Knowledge sharing (KS) theory (Cabrera & Cabrera, 2002); Shift away from TAM (Technology Acceptance Model); Social identity theory (Tajfel & Turner, 1979); Construal level theory (CLT) (Fehrenbacher & Weisner, 2024);

			Connectivism (Siemens, 2005); Embodied cognition (Wilson, 2002)
AI Era (2015–Present)	AI literacy; data and algorithmic literacy; epistemic trust; dynamic knowledge generation via LLMs (prompt engineering)	Hybrid relationships; AI-mediated and avatar-mediated communication	**Trust-focused:** Social identity theory (Tajfel & Turner, 1979); Computer as a Social Actor (CASA) (Reeves & Nass, 1996); Epistemic trust (Hancock et al., 2011); Post-TAM (Venkatesh et al., 2012); Extended virtual identification (Mirbabaie et al., 2021); gendered trust findings (Zhang et al., 2023; Belt & Lowenthal, 2023a); Unified theory of Acceptance and use of technology (Marikyan & Papagiannidis, 2023)
			Agency-focused: Algorithmic agency in communication (Gillespie, 2014); Perceived agency in human–AI interaction (Waytz et al., 2014); AI-enhanced knowledge ecosystems in education (KM 3.0/4.0) (Ishak et al., 2020); KM as cognitive strategy (Lei et al., 2024)
			Presence-focused: Avatar-mediated communication Picard, Ishak theory (AMC) (Nowak & Fox, 2018); Avatar appearance and disclosure effects (Visser et al., 2024); Extended social presence (Biocca et al., 2003)

Projected Immersive Era (2030+)	XR literacy; ethical reasoning with autonomous systems; embodied cognition	Blended human-agent collectives; extended presence in spatial computing environments	Embodied cognition frameworks; Affective computing (Wilson, 2002); Ethical AI and human-autonomy frameworks; Human–AI co-agency theories; AI-enhanced knowledge ecosystems in education (KM 3.0/4.0) (Ishak et al., 2020); Human-AI Teaming (HAT) frameworks (Caldwell et al., 2022; Lou et al., 2025; Xu & Gao, 2023)

Note. The eras presented in this table represent dominant paradigms in communication and literacy practices, rather than strictly bounded time periods. Multiple literacies and technologies often coexist and interact across these eras.