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Framing human-AI dynamics: An epistemological perspective on generative AI practices

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Abstract

In this paper, I introduce the theorising of seven human-generative artificial intelligence (GAI) paradigms, grounded in personal epistemological beliefs. Following a conceptual, theory-building approach, I begin by outlining the construct of personal epistemological beliefs, differentiating among the source of knowledge, certainty of knowledge, organisation of knowledge, control of knowledge acquisition and speed of knowledge acquisition by drawing on Schommer (1994) and Schommer-Aikins and Easter (2008)'s multidimensional model. I contend that these epistemological dimensions offer an understanding of human-GAI engagement. I proceed by introducing the dynamic human-GAI paradigms (guarded, possibility-focused, augmented, pioneering, symbiotic, values-based and equity), outlining each and examining them against the five epistemological dimensions. Rather than fixed traits held by individuals, the paradigms are conceptualised as enacted patterns of engagement that emerge across different disciplinary, socio-technical and institutional contexts. I conclude by arguing that this understanding of human-GAI engagement, as explained through epistemological beliefs, lays the foundation for alternative approaches to teaching and assessment, student interactions, professional development, and AI governance and policy, while noting that the framework remains an exploratory heuristic requiring empirical validation.

Introduction

Much has been written about the implications of generative artificial intelligence (GAI) for higher education practices. Perspectives range from optimism to caution and trepidation (Buele & Llerena-Aguirre, 2025; Olojede, 2024). Irrespective of differing opinions, there is a clear probability that GAI may disrupt and even revolutionise established educational and work-related practices (Bozkurt et al., 2024; Nemorin et al., 2023). This is evident in different sectors, including education. Several current and future scenarios have been developed where an AI-rich learning environment is outlined. For instance, references are made to personalised learning, intelligent tutors, identification of at-risk students, learning analytics, assistance in multilingualism and so forth (Bozkurt et al., 2021; Crompton & Song, 2021).

Although AI forms part of broader interrelated fields associated with cognition, mathematics and computer science (Gadanidis, 2017; Zhai et al., 2024), it directly influences and blurs the boundaries of educational technologies. By specifically positioning GAI in the educational technologies field, it inevitably also inherits and is associated with the existing limitations and challenges of the latter. For instance, one of the key limitations is the tension between theory and practice (Strydom & Fourie-Malherbe, 2019). Also, the rapid development of emerging educational technologies challenges academics and researchers (Hannon & Al-Mahmood, 2014; Zou et al., 2025) to remain abreast of and informed about developments and implications. The field is confronted by limited theory development (Bennett & Oliver, 2011; Hoadley & Uttamchandani, 2021; Zawacki-Richter et al., 2019), variations in methodological quality or limited methodological approaches (Bennett & Oliver, 2011; Mena-Guacas et al., 2025), and a narrow scope that often falls within common-sense deductions, the exploration of the application of tools, and simple evaluative practices (Facer & Selwyn, 2021; Hannon & Al-Mahmood, 2014). The current landscape of theoretical development surrounding educational technology – and GAI in particular – suffers from what Clegg (2012) termed a “theory deficit” (p. 408). In the current educational context, these theoretical limitations, characterised by oversimplified approaches to understanding digitally related meaning-making processes, emphasise the need for a more nuanced and theoretically grounded exploration of GAI engagement across multiple dimensions.

In addition, despite the growing body of literature exploring the affordances, risks and adoption of GAI in higher education, limited attention has been paid to the epistemological traditions that explain how individuals engage with these technologies. Current discussions commonly focus on usage, policy or ethics (Garcia-López & Trujillo-Liñán, 2025; Segura Altamirano et al., 2026), but rarely focus on frameworks explaining why individuals adopt fundamentally different positions towards GAI. This paper addresses this conceptual gap by linking personal epistemological beliefs with human-GAI engagement paradigms.

This paper aims to develop a framework that explains the epistemological mechanisms underlying academics’ engagement with GAI in scholarly contexts. My theoretical approach is grounded in the examination of epistemological beliefs as a multi-dimensional construct to understand individuals’ “beliefs about knowledge and knowing” (Brownlee et al., 2009; Schwarzenegger, 2020; Tafreshi & Racine, 2015). This is important since personal epistemological beliefs offer insights into individual learning across different educational contexts. Building upon Schommer’s (1994) conceptualisation, I explore personal epistemology through five interconnected belief dimensions: source of knowledge, certainty of knowledge, organisation of knowledge, control of knowledge acquisition, and speed of knowledge acquisition. This theoretical framing underpins the seven interrelated human-GAI paradigms I examine, offering a framework for understanding GAI users’ behaviour and engagement with these technologies in relation to their epistemological beliefs. Finally, I outline the implications of this epistemologically infused understanding, arguing that it offers a more nuanced basis for rethinking teaching, assessment and institutional engagement with GAI in higher education.

Towards personal epistemologicalperspectives as sources of GAI user behaviour

There are different theoretical models associated with epistemological development. Although there are broad differences, the general connecting factor is that they are situated in a cognitive science paradigm (Tafreshi & Racine, 2015; Zdybel, 2020). To address such a “one-dimensional” perspective, an “enactivist” understanding of personal epistemology is suggested where there is an overlap between the individual and the environment. Emph-

-asis is then placed on the complex interplay between different dimensions in the process of knowledge creation, dissemination and validation (Tafreshi & Racine, 2015).

Personal epistemology is “an individual theory of knowledge, a set of a layperson’s beliefs concerning knowledge/knowing, often activated more or less consciously during the learning process” (Zdybel, 2020, p. 2). It can be understood as “individuals’ ways of knowing and acting arising from their capacities, earlier experiences, and ongoing negotiations with the social and brute world” (Ulyshen et al., 2015, p. 211). Personal epistemology speaks to the implications for learning and knowing, and individuals’ engagements with new knowledge (Kelly, 2021). It provides insights into individual learning in a variety of educational contexts since these beliefs serve as “filters for all other knowledge and beliefs” (Brownlee et al., 2009, p. 599).

Within the tradition of an enactivist approach, the investigation of personal epistemologies fundamentally recognises the intricate interplay between individual cognitive processes and social constructivist perspectives in shaping our understanding of experience and knowledge construction (Ulyshen et al., 2015). This theoretical stance emphasises that knowledge emerges through a dynamic interaction between personal meaning-making and socially mediated interpretative frameworks. In the specific context of GAI, users’ experiences and insights are shaped by both personal sense-making processes and broader social perspectives, creating a nuanced understanding of these technological tools.

While participating in the development of knowledge creation, individuals do not only “enact” what they have experienced in the world but also engage in the process of seeking “equilibrium” or practicality in terms of their experience (Ulyshen et al., 2015). What this implies is that they seek to understand what they have experienced (in this case, using GAI tools) by relating it to their existing knowledge structures (e.g. their own understanding). For this paper, personal epistemology and GAI engagement are conceptualised as a multi-dimensional construct that consists of interconnected epistemic dimensions (Erixon & Hansson, 2023; Ulyshen et al., 2015).

Personal epistemology is also associated with terms such as “judgement”, “reflection”, “resources” and “ideas”, with reference to “beliefs” most prevalent (Tafreshi & Racine, 2015). Perry (1968) outlined the importance of beliefs around “certainty, structure, and source of knowledge”, later referred to as “beliefs about learning”, which subsequently evolved into the conceptual term “an epistemological belief system” (Perry, 1968 as cited in Schommer-Aikins & Easter, 2006, p. 411). This includes understanding related to the “certainty of knowledge, the organization of knowledge, and the control individuals have over their own knowledge acquisition” (Schommer-Aikins & Hutter, 2002, p. 6). In 1994, Schommer (as cited in Kanadli & Akay, 2019, p.2) further developed this understanding by suggesting that epistemological beliefs relate to individuals’ perceptions about the “source, accuracy, and structure of knowledge, and speed and control of learning”. These beliefs are associated with all life phases of individuals and have a continuous impact on the way we think, make decisions, and learn (Kanadli & Akay, 2019).

Schommer called these dimensions an epistemological belief system. It suggests that personal epistemology consists of several loosely “independent belief dimensions, which implies that these dimensions do not necessarily develop or grow at the same rate” (Schommer, 2004; Schommer-Aikins & Easter, 2008, p. 922) and that they are multi-dimensional in nature (Makhathini et al., 2020). Schommer categorised epistemological beliefs into two groups: sophisticated and naïve beliefs (Kervan et al., 2021). These belief dimensions may exist simultaneously or independently (Ferguson, 2007).

According to Schommer-Aikins (2004, p. 922), epistemological beliefs influence how we “comprehend, monitor our comprehension, and interpret information”. Epistemological beliefs encompass our understanding of knowledge itself – what it is, how we obtain it, and how certain we can be about what we know. These beliefs also reflect our views on learning, such as whether learning happens rapidly or progressively, and whether our ability to learn is static or can develop.

Understanding individuals’ belief systems not only highlights their general behaviours but may also offer valuable insights into how they engage with specific technologies. For instance, when we examine epistemological beliefs, we can develop a framework for analysing their interactions with GAI tools. These belief patterns can potentially suggest whether users will approach GAI with scepticism or acceptance, how they will evaluate the information it provides, and whether they view AI-human collaboration as valuable or threatening.

Table 1. Personal epistemological dimensions by Schommer (1994) and Schommer-Aikins and Easter (2008)

Source of knowledge	This dimension investigates beliefs about where knowledge originates. It also reflects who and what are trusted as sources of knowledge.
Certainty of knowledge	This dimension outlines how individuals perceive the stability of knowledge, ranging from fixed and absolute to evolving and open to review. It represents individuals' openness to new ideas and their willingness to critique recognised knowledge.
Organisation of knowledge	This dimension indicates how individuals perceive knowledge structure as either concrete facts or as interrelated concepts. It outlines how individuals access, connect and integrate new knowledge across different areas.
Control of learning	This dimension represents beliefs about learning ability ranging from innate and fixed to evolving over time. It impacts human motivation and attitudes towards personal development and lifelong learning.
Speed of learning	This dimension outlines beliefs about how quickly learning occurs, ranging from immediate to a gradual incremental progression. It relates to individuals' perseverance with learning and their personal development approaches.

Source: Schommer (1994), Schommer-Aikins and Easter (2008), Kanadli & Akay (2019), and Zdybel (2020).

Table 2. Continuum of dimensions of Schommer's (1990) epistemological beliefs

Epistemological belief	Naïve	Sophisticated
Source of knowledge	Authority	Reason
Certainty of knowledge	Certain	Tentative
Organisation of knowledge	Simple	Complex
Control of learning	Innate	Acquired
Speed of learning	Quick	Gradual

Source: Schommer (1990) and Langcay et al. (2019, p. 38).

Methodology and conceptual framework development

This paper adopts a conceptual, theory-building methodology rather than an empirical or systematic review design. This approach is consistent with established guidance on the design of conceptual contributions (Jaakkola, 2020; MacInnis, 2011). It follows a typology approach (Jaakkola, 2020) where existing theoretical resources from literature are synthesised and reorganised into a new classificatory framework. Literature was identified through a purposive search strategy that aligns appropriately to conceptual work focusing on theoretical attention (Jaakkola, 2020). Searches were conducted in Scopus, Web of Science and Google Scholar using term combinations across different domains, namely personal epistemology, GAI in higher education, human-GAI interaction, AI ethics, governance and equity. This was supplemented by a psychological motivational account of human-GAI relationships (Strydom, in press) in the *Encyclopedia of Cyberpsychology*. Publications from 2020 to 2025 were covered. Sources were included where they offered an essential theoretical account of these domains. Alternatively, as in the case of GAI literature, well-developed empirical studies of human engagement with technology, or foundational literature within each domain (e.g. Schommer, 1990) were accepted. The limitation of this purposive design choice is acknowledged as due to a single author selection of literature that is shaped by the author's disciplinary context. The framework should therefore not be viewed as an exhaustive account of the literature but rather as one account thereof.

The process of analysis progressed through three iterative stages. Firstly, each body of literature was read with emphasis placed on recurring assumptions about knowledge, learning and human agency in the AI-rich context. These assumptions were coded into descriptive categories via continuous comparison between sources. These constructs were informed in part by a psychological motivational account of human-GAI interactions (Strydom, in press). Secondly, these categories were cross-referenced to Schommer's (1990) five epistemological dimensions, to allow for categories to be reinterpreted through an epistemic lens. Conceptually similar orientations were consolidated, while conceptually divergent ones were differentiated. This developed into an initial set of epistemically informed paradigms. Finally, the paradigms were iteratively refined against source literature to check for coherence and distinctiveness. This resulted in the seven epistemologically informed paradigms presented in Table 4.

An introduction to the dynamic human-GAI engagement paradigms

Personal epistemological beliefs (Schommer, 1994; Schommer-Aikins, 2004) offer valuable theoretical insights into how people understand knowledge and learning. However, as GAI technologies rapidly evolve and gain widespread adoption, it will be helpful to connect these theoretical views to practical investigations of how these beliefs manifest in actual academic settings.

By examining the emerging patterns and attitudes towards GAI within academia, this section works toward a more holistic understanding of GAI's impact that extends beyond theoretical frameworks, user guides and knowledge of the affordances of these technologies. This integrated approach acknowledges human actions and perceptions as critical components of our analysis and recognises that the significance of these technologies cannot be fully appreciated without considering how people respond to and conceptualise them in practice.

This section explores paradigms based on literature synthesis and conceptual abstraction as outlined in the methodology. Although these proposed paradigms have not been empirically validated, they are grounded in theoretical perspectives and suggest a heuristic framework for examining the relationship between individuals' epistemological beliefs and their interactions with GAI technologies.

For each paradigm, I outline its characteristics, supported by some practical examples, and explore how these differ across Schommer's epistemological dimensions. The paradigms are not fixed classifications, but a flexible, enacted framework where individuals can move between paradigms depending on the context they face or adopt a hybrid position aligning with more than one paradigm at once. Figure 1 visually represents the seven human-GAI engagement paradigms.

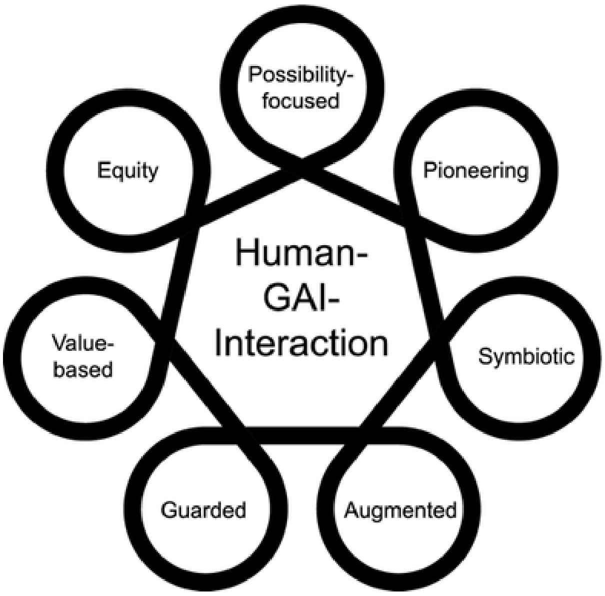

Figure 1. Flexible human-GAI engagement paradigms

Possibility-focused paradigm (Optimist)

The possibility-focused paradigm reflects an optimistic epistemological position on the legitimacy and organisation of knowledge in AI-rich environments. Those who align themselves with this paradigm acknowledge GAI's capabilities to synthesise, organise and identify patterns across large bodies of literature (Lu et al., 2024; Wagner et al., 2026). These capabilities are viewed as an extension of how knowledge is created and not only as a vehicle to process knowledge.

However, tensions between processing knowledge and discovering knowledge become more evident in questions related to the epistemic contributions of authorship. For instance, GAI's positioning becomes contested when it generates hypotheses, structures scientific arguments, or identifies multidisciplinary connections (Reddy & Shojaee, 2024) that researchers might not have found on their own. Therefore, the boundary of where legitimate knowledge creation is situated becomes blurry and contested.

However, rather than viewing this as a threat, those aligned with this paradigm see the uncertainties as sites of productivity provided that the source of knowledge is appropriately distributed between human and machine, while humans retain the final interpretive judgement over what GAI produces (Lloyd, 2025). Optimism in this paradigm is rooted in who can participate in knowledge discovery without reducing what is viewed as legitimate knowledge.

Pioneering paradigm (Dreamer)

The pioneering paradigm is less of an alignment with the possibilities and optimism highlighted by GAI's capabilities and more of a reflection of a willingness among its supporters to view GAI as a participant, rather than a means of knowledge creation. Proponents of this paradigm engage actively with the more philosophical dimensions of GAI's presence in academic work, grappling with the possibility that if innovation and creativity can be attributed to human-machine interaction and co-production, then the origin of knowledge becomes an open matter rather than something resolved through microlevel analysis (Matta, 2026; Peschl, 2024). For example, Coeckelbergh's work on the effect of GAI on belief revision offers an evolving example of ideas about the pioneering nature of GAI in our engagements with knowledge and learning. His work suggests that when individuals engage with machine-generated outputs, the consequences could be more than just adding new knowledge to what we already know. It may potentially also impact the underlying ways in which we accept something as the truth, how we choose to trust fluent and confident-sounding responses and how much authority we allow for machine-generated outputs in comparison to peer-reviewed sources (Coeckelbergh, 2025). This work, however, is still mainly theoretical with limited empirical evidence.

Also, associated with a pioneering orientation is the use of generative tools to accelerate peer review and manuscript turnaround. This is evident in reviewers claiming that AI provides the opportunity for quicker analysis to have more time for criticality (Ebadi et al., 2025). Despite these pioneering capabilities, questions about the trade-off between speed and academic rigour remain (Feetham-Walker, 2025).

Augmented paradigm (Enhancer)

Those aligned with this paradigm view GAI as an embedded tool that becomes part of the reasoning processes of individuals by changing the organisation of knowledge rather than just adding to existing knowledge bases. Recent philosophical work extends on the work of Clark and Chalmers (1998), who posited that tools such as calculators and notebooks became integrated into human cognition by retrieving and storing information humans already possess. It is argued that GAI provides an alternative view since it not only stores or calculates existing content but can generate novel outputs that are not directly aligned with the application of Clark and Chalmers' criteria, a distinction Clark (2025) made after an extended consideration of GAI.

This resulted in some scholars arguing for the notion of an "amplified mind" instead of an "extended mind" whereby individuals no longer only access stored information but actively contribute to the dynamic cognitive space produced by an active, unpredictable partner (Matta, 2026). Such a view does not diminish human agency but rather reorganises it, whereby individuals take on an active role in evaluating, selecting and directing generative processes rather than only storing content or information (Samuel, 2026). Those aligned to this paradigm differ in deciding on how much interpretive agency they retain once GAI participates in the reasoning process.

Symbiotic paradigm (Collaborator)

The symbiotic orientation is viewed more as a relational than a transactional orientation. A relational lens views human-machine engagement as an exchange-oriented relationship thinking of the mutual benefit (Hopwood, 2016) while a posthumanist relational ontology, such as the symbiotic paradigm, views the boundaries between human and machine cognition as permeable rather than accommodating. Human and machine are entangled (Bavdaz, 2018) rather than just exchanging where knowledge is understood and co-created via the relationship itself, rather than created by either and then negotiated. Those associating with this paradigm are comfortable with a blurry boundary where a clear distinction between human and machine contribution is not required.

This also implies that these proponents organise knowledge more broadly in, for instance, the new materialist accounts of entangled, intra-active learning where learning entities (i.e. human and non-human) are mutually transformed within the engagement process (Quimno et al., 2013). Questions about who contributed what become less important than attending to the value of the mutually entangled relationship.

Although both the augmented and symbiotic paradigms position GAI as an extension of human capabilities, they differ in the positioning of human agency and knowledge creation. The augmented paradigm views the individual as the interpretive agent of cognition while GAI amplifies reasoning, while the symbiotic paradigm views agency as distributed across the human-machine relationship. It implies that the latter views knowledge as co-constructed rather than individually retained and supplemented. Wu et al. (2025) illustrated this relational orientation in practice by introducing a conceptual framework of shared epistemic agency that argues that effective learning depends on humans critically engaging with GAI outputs rather than handing epistemic authority to the system. The symbiotic nature of the relationship becomes evident when each party continuously adapts to the other while sustained interaction can impact learners' epistemic positions over time.

Guarded paradigm (Guardian)

In contrast to the optimistic views pertaining to GAI, many align with a more cautious perspective. Those associated with the guarded paradigm are oriented towards an interrogation of who is making knowledge claims, on what grounds the claims are made, and what the reliability of these claims is before accepting it. Such a positioning echo-

-es what Bielik and Krell (2025) term *epistemic vigilance*, which foregrounds the scrutiny of a claim's source, its grounds and potential biases as conditions for critical engagement. Such an orientation is often encouraged due to the fluent and convincing nature of GAI outputs that are often incorrectly viewed as valid and correct (Kumar et al., 2026). For instance, Ferrario et al. (2024) challenge the claim that AI systems should be granted epistemic expertise over human experts. They are of the opinion that real expertise requires an understanding and research-related capabilities that AI systems do not possess.

Another main consideration in the academic community is the accuracy of the detection of LLM (large language model) usage. It is clear from the literature that the current detection tools lack accuracy and reliability and show a preference for classifying outputs as human-created rather than produced by an AI technology (Weber-Wulff et al., 2023). Subsequently, many issues arose in terms of ethical concerns and academic integrity. The adoption of these technologies disrupted the conventional copyright and academic integrity frameworks since questions about authorship, ownership and originality became more prominent and complex (Wajdan Rafay Bukhari & Ullah Hassan, 2023). Williamson et al. (2023) similarly cautions against techno-solutionist narratives by drawing attention to the knowledge production risks linked to depending on these technologies.

Individuals who associate with a guarded paradigm do not discard the use of GAI nor its outputs, but choose to follow a slower, more deliberate verification process by checking AI-generated outputs against the trusted knowledge of humans or other verified sources. This orientation is more conservative than the others and is not rooted in technological resistance, but is rather a disposition that argues for a slower uptake to properly validate knowledge claims and outputs (Lyu et al., 2025).

Values-based paradigm (Defender)

This paradigm prioritises a values-based approach by emphasising the ethical use of AI technologies and the moral implications linked to academic practices (Nemorin, 2024). This orientation not only looks at the reliability or validity of machine-generated outputs but is also directly focusing on the ethics of knowledge creation (Lloyd, 2025). Those associated with this paradigm are likely to further develop literacies and competencies that supplement their understanding of the ethical principles of fairness, transparency and accountability (Hosseini et al., 2023). Apart from the functional considerations when engaging with AI, others also explore broader philosophical aspects such as whether AI may be held accountable for contributions to research (Yildiz, 2023).

Furthermore, others interrogate the long-term societal implications of AI by arguing that the ethical use of AI is critical for preserving democratic processes. In this case, it is contended that such ethical considerations should be acknowledged in the development and implementation of AI technologies. This also includes considerations about privacy and the protection of personal data to prevent the exploitative use of data (Kooli, 2023; Popenici, 2023). According to Battaly (2008), those inclined towards a values-based orientation do not only ask if claims are true, but also, more importantly, how we arrived at these claims responsibly (Battaly, 2008; Hagendorff, 2022). Ethical scrutiny remains at the centre of this paradigm where transparency of GAI use, and processes of accurate content acquisition are essential when engaging with GAI tools (Sun et al., 2024).

Equity paradigm (Advocate)

In the equity paradigm, issues of power, ideology and equity are foregrounded, with opposing positions visible. There are those who argue that when employed properly, AI may create many benefits to mankind such as linguistic diversity (Pradhan & Dey, 2025). These believers will argue for advancements in democratising education and knowledge. Those associated with this paradigm also recognise that tools such as GAI could potentially expand access to knowledge that was otherwise confined by institutional or financial barriers. This is particularly relevant to those who were historically excluded from these structures and knowledge pathways (Ballantyne et al., 2025).

The opposite is also true. Even in the advanced era of AI technologies, there are still glaring issues of digital inequality that are influenced by multi-dimensional factors (Kuhn et al., 2023). Throughout the history of technology, it has always been linked to specific cultures, biases, genders, beliefs and the values of those societies t-

-hat create it. In particular, the role and positioning of investors and venture capital as economic and political actors in the educational sector are highlighted as issues of concern. Often, narratives about social impact are used as a means of attracting further investment (Komljenovic et al., 2023). In addition, GAI systems that are predominantly trained on English-language, data-rich Western academic sources risk reproducing rather than correcting current hierarchies of whose knowledge counts (Kay et al., 2024; Olaniyan et al., 2026). This raises awareness of the political nature of technology and its inability to be neutral (Popenici, 2023). Equity-orientated individuals recognise the power relations within technology and acknowledge that technology is not neutral by considering whose voices and knowledge count (Pedroni, 2026).

Table 3. Summary of paradigms of human-GAI interaction

Optimist	Possibility-focused paradigm	Benefits and transformative potential of human-GAI interaction across various fields are emphasised
Dreamer	Pioneering paradigm	Space for dreaming and innovation, moving beyond conventional boundaries
Collaborator	Symbiotic paradigm	Acknowledging AI's equal status with humans by acting as collaborator
Enhancer	Augmented paradigm	Enhancing human capabilities by complementing traditional methods without replacing them
Guardian	Guarded paradigm	Attention to AI's impact on the academic project and broader society
Defender	Values-based paradigm	Prioritising ethical and values-based use of AI technologies and associated moral obligations
Advocate	Equity paradigm	Foregrounding issues of democratisation of knowledge but also power and equity concerns

The dynamics of personal epistemological dimensions and human-GAI interaction

To articulate the interrelated nature of personal epistemological beliefs and the paradigms of human-GAI engagement, I propose an exploratory framework in Table 4. Each of the paradigms presents an orientation towards the nature of knowledge and knowledge acquisition in the context of AI interaction. As mentioned previously, personal epistemological beliefs are situated along a continuum and, therefore, rather than depicting rigid classifications, the framework highlights the varying degrees of inclination towards the different paradigms based on the evolving nature of different situational factors. I also attempt to present the interconnected paradigms in order ranging from initial naive orientations to more sophisticated belief systems (Kervan et al., 2021). The intersections offered in the table serve as suggestions on how to interpret individuals' behaviour and attitude towards GAI usage. The guarded paradigm, therefore, represents the naivest orientation towards GAI engagement in this framework, and the equity paradigm the most sophisticated orientation. The five intervening paradigms reflect varying combinations of naive and sophisticated beliefs across the five dimensions below.

The paradigms presented in Table 4 are best explained not as fixed traits evident in individuals, but rather as patterns of engagement that emerge depending on the type of engagement with GAI in the academic context. Such a perspective aligns with an enactivist view of cognition that views thinking as the continuous connection between an individual and their environment, rather than an established cognitive property (Varela et al., 1991). Based on such a view, epistemological beliefs are not simply held but are enacted through different interactions with GAI, disciplinary traditions, institutional cultures and educational practices. For example, an academic may enact a guarded stance towards the use of GAI in high-stakes assessments where institutional accountability and the validity of assessments are highly valued. An augmented stance, however, could be enacted in the research context where GAI is viewed as a vehicle in augmenting some tasks in the research process. Such an approach speaks to an enactivist understanding rooted in participatory sense-making where meaning is created through the coupling itself rather than pre-existing mechanisms (De Jaegher & Di Paolo, 2007). The paradigms should therefore be interpreted as a reflection of varying degrees of inclinations an individual enacts across different socio-technical contexts and not as a typology that assign individuals to a single, static position.

By reading across the table, the contrast between the guarded and equity paradigms is the clearest illustration of the continuum. The guarded paradigm privileges external authority, fixed certainty and human-paced learning, while the equity paradigm embraces relativist, inclusion-oriented views of knowledge alongside democratised access to AI tools. The possibility-focused paradigm and the symbiotic paradigm occupy more balanced positions across most dimensions, reflecting a blend of naive and sophisticated orientations rather than a consistent alignment with either pole.

Guarded paradigm: Epistemological beliefs

Those aligned with the guarded paradigm will prefer conventional authoritative sources of knowledge such as human experts instead of AI-generated knowledge. This may imply preferring reputable peer-reviewed academic sources and established sources of knowledge where, if needed, AI is only used in limited capacities where appropriate (Cooper, 2023; Hannigan et al., 2024). In the latter, AI will probably be used as a source of organisation or summary of knowledge while human knowledge remains superior (Yusuf et al., 2024).

In relation to the organisation of knowledge, those aligned with the guarded paradigm are likely to prefer established structures that are fixed and with clear boundaries, while AI will be considered to clarify or strengthen existing knowledge. Human learning is rooted in critical thinking and human effort that cannot be outsourced to AI (Cooper, 2023; Gustilo et al., 2024; Yusuf et al., 2024).

In terms of the control of knowledge acquisition, humans are viewed as the active actors in their own learning processes where AI is positioned as a tool that is subject to human control and oversight. Inevitably, outputs produced by AI are still in need of human interpretation and evaluation (Gulumbe et al., 2024; Hannigan et al., 2024). Rapid AI insights are not acknowledged in this paradigm, but rather the gradual process of learning that prioritises deep understanding and consideration (Gustilo et al., 2024; Hannigan et al., 2024).

Possibility-focused paradigm: Epistemological beliefs

The possibility-focused paradigm is viewed as transitional since those aligned with this school of thought started to recognise and value the importance of different sources of knowledge, inclusive of AI (Zawacki-Richter et al., 2019). This developmental shift is illustrated by the work of Schommer-Aikins where it is argued that individuals often move from dualism to multiplicity in thinking about different learning environments (Schommer, 1990; Schommer-Aikins, 2004; Schommer-Aikins et al., 2003). Advocates of the possibility-focused paradigm may encourage the inclusion of AI to provide additional insights that should underlie the value of reflective and critical thinking. AI is potentially viewed as a powerful tool for developing existing knowledge by synthesising information from diverse sources originating from various fields and levels of educational systems (Holmes et al., n.d.; Luckin et al., 2016).

With reference to the certainty of knowledge, this paradigm recognises foundational knowledge combined with the alternative avenues of knowledge afforded by AI. An appreciation for both simple and integrated forms of knowledge is evident in this paradigm. It implies that AI could, for instance, be used to simplify complex and multi-

Table 4. Nexus of personal epistemology and human-GAI interaction paradigms

Paradigm	Source of knowledge	Certainty of knowledge	Organisation of knowledge	Control of knowledge acquisition	Speed of knowledge acquisition
	External authority to empirical evidence & reason	Fixed to evolving	Simple to integrated	Fixed at birth to improvable	Quick to adaptive
Guarded	Prioritises conventional or external knowledge authorities over AI-generated content	Leans to a fixed, absolute view and remain cautious of AI-generated knowledge	Prefers established structures that are more concrete	Emphasises independent, human-led learning and critical thinking in learning	Prefers gradual, human-paced learning over rapid AI-generated information
Possibility-focused	Appreciates diverse sources of knowledge, including AI, but combined with human judgement	Balanced view of knowledge certainty by accepting both fixed and evolving dimensions of knowledge	Acknowledges both simple and complex structures of knowledge	Views learning as a combination of innate ability and individual effort and views AI as an enhancer of learning	Open to both slow, gradual learning processes and fast learning from AI
Augmented	Rooted in personal experience and verified sources with AI viewed as an enhancer	Attached to established knowledge but is inclined towards relativism	Recognises complexity of knowledge but seeks simplification through AI use	Emphasises human-led learning with the support of AI	AI is used to accelerate learning, but maintaining depth of understanding is essential
Pioneering	Open to external and constructivist approaches to knowledge construction	Embraces the evolving and dynamic nature of knowledge	Views knowledge as complex and integrated	Lifelong learner who embraces AI as co-agent of learning	Embraces rapid change and adaptation due to the advancements in AI
Symbiotic	Co-constructed with a combination of external sources, human construction and AI-generated information	Relativist considerations combined with context sensitivity	Acknowledges the interrelated nature of simple and integrated knowledge structures	Collaborative learning opportunity between human and AI	Balances quick AI insights with gradual and in-depth human understanding
Values-based	Open to all sources of knowledge but through a values-based and ethical lens	Relativist view with an ethical foundation	Recognises the complexity of knowledge, specifically in relation to ethical considerations	Emphasises responsible learning that is ethical in nature	Prioritises thorough ethical reflections over quick knowledge acquisition
Equity	A balanced view with emphasis on inclusion of marginalised and AI voices	Relativist view that embraces diverse voices and uncertainty with inclusion as main force	Acknowledges both access to knowledge and its complexity	Argues for democratised access to learning opportunities, including AI tools	Balances quick knowledge access with deliberation and thoughtful engagement

Note. The row beneath each dimension heading indicates the naive pole and the sophisticated pole of that epistemological dimension, adapted from Schommer (1994). The paradigm rows below indicate where each paradigm tends to fall along that continuum.

-dimensional constructs by offering more accessible clarifications and summaries (Markowitz, 2024; Shyr et al., 2024). Learning is viewed as a combination of innate ability and AI as an enhancer of learning. It implies a level of collaboration between human and technology where existing expertise is combined with AI to further increase human potential (Luckin et al., 2016). The speed of knowledge acquisition could be either gradual or fast, depending on the context. For instance, AI could be used for initial conceptualisations and explanations, while time is then used to gradually explore and critically analyse the outputs of the technologies.

Augmented paradigm: Epistemological beliefs

The augmented paradigm acknowledges the integration of individual experience and expertise with AI-enabled opportunities. This paradigm represents an intermediate epistemological shift from dualistic to relativist thinking (Schommer-Aikins, 2004). In relation to the source of knowledge, existing knowledge is prominent with AI viewed as an enhancer of knowledge (Alvarado, 2023; Simon et al., 2024). Individuals may use AI to enhance or supplement their individual expertise without replacing the primary knowledge source. There is a tendency towards relativism in relation to the certainty of knowledge, but individuals continue to be attached to established knowledge (Hofer & Pintrich, 1997). The augmented paradigm views knowledge as mostly complex but seeks simplification using AI technologies. The latter could be used as a tool to simplify complexities and make it more accessible (Binns, 2018; Kitchin, 2014). Knowledge acquisition is human controlled while AI is used as a supportive and deliberate tool. It is the user who will direct and outline goals, expectations and critical evaluation of AI outputs (Seeber et al., 2020; Shneiderman, 2020). The technology is used to accelerate learning via the collection of information and ideation, but a deep level of comprehension remains critical.

Pioneering paradigm: Epistemological beliefs

The pioneering paradigm represents a more sophisticated approach to epistemology by viewing knowledge as contextual and dynamic. Those aligned with this paradigm are often comfortable with uncertainty and flexibility. They acknowledge external and individual sources of knowledge whereby AI is viewed as an important source of external knowledge. This paradigm emphasises the collaboration between human awareness and AI capabilities (Bozkurt, 2023; Sundberg & Holmström, 2024). AI is often used as a sounding board for anthropogenic ideas and conceptualisations. It is within this paradigm that the evolving nature of knowledge is embraced by accepting the dynamics between humans and the technology. Individuals view knowledge as complex and acknowledge the contributions that AI provides in terms of unveiling the hidden networks not often visible via conventional approaches of inquiry (Bozkurt, 2023; Sundberg & Holmström, 2024). Those aligned with the pioneering paradigm associate themselves with lifelong learning and recognise AI as an active partner in knowledge acquisition (Ahn, 2024). Individuals associated with this paradigm continually explore the possibilities afforded by the technologies for the purpose of their own learning. The rapid pace of development and learning afforded by AI is embraced in this paradigm by acknowledging all the avenues of new explorations and ideas previously not possible (Sundberg & Holmström, 2024).

Symbiotic paradigm: Epistemological beliefs

The symbiotic paradigm views knowledge as a co-construction between humans and AI by accepting relativism and subsequent complexity. This paradigm speaks to the later works of Schommer-Aikins where the interconnected nature of epistemological dimensions and the value of shared knowledge construction are suggested (Schommer-Aikins, 2004; Schommer-Aikins et al., 2003). In this paradigm the sources of knowledge comprise external, individual and AI-generated outputs whereby the interconnected nature of knowledge construction is highlighted (Atchley et al., 2024; Punziano, 2025). AI may be used as a tool to synthesise or expand on the diverse knowledge sources. Knowledge is furthermore viewed as relativist by proposing that certainty is not always expected but may further evolve based on contextual factors or the iterative processes involved in AI prompt crafting (Punziano, 2025; Sundberg & Holmström, 2024). It is the dynamic interplay between human and technology that contributes to the dynamic nature of knowledge. AI could contribute to the simplification of complexities, but similarly, point to hidde-

-n intricacies in seemingly simple assumptions (Atchley et al., 2024). Learning is viewed as a collaboration between human and technology where both benefit in the knowledge acquisition process (Bozkurt, 2023). Neither human nor technology is in control, but rather a symbiotic relationship is developed between the two entities where AI is elevated to a collaborative partner. This paradigm appreciates the affordances of rapid AI-generated outputs but balances it with the importance of human understanding and application.

Values-based paradigm: Epistemological beliefs

Ethical reasoning is at the forefront of the values-based paradigm. The development of knowledge is viewed through an ethical lens as impacted by values and context (Kamali et al., 2024). Those who align with this paradigm tend to critically evaluate AI-generated outputs in terms of social responsibility and inclusivity (García-López & Trujillo-Liñán, 2025). Diverse sources of knowledge are recognised, but this recognition always includes an ethical perspective (Kamali et al., 2024; Punziano, 2025). Criticality remains essential in this paradigm. The complexity of knowledge organisation is underlined by an assumption that seemingly simple outputs produced by AI may have far-reaching ethical implications. However, AI may also be used to point to potential ethical or values-based dilemmas produced in human-created outputs. This paradigm suggests a responsible approach to learning that is values-based when engaging with AI tools (Jobin et al., 2019). In relation to the speed of learning, individuals tend to prioritise the ethical scrutiny of knowledge created by AI-generated outputs by not automatically embracing quick knowledge acquisition (Barelli et al., 2025).

Equity paradigm: Epistemological beliefs

The equity paradigm primarily represents an equitable and inclusive epistemological view. This paradigm is rooted in the belief that epistemology is not neutral but is embedded in power structures and social justice issues (Knox, 2020; Toyokawa et al., 2023). A balanced view of the sources of knowledge is displayed, but clear emphasis is placed on the integration of diverse knowledge sources and perspectives that include marginalised voices (Williamson & Eynon, 2020). It recognises the different and diverse knowledge sources with a critical view of how AI may contribute to new and integrated knowledge production. This paradigm goes from the assumption that knowledge remains contextual and that all diverse voices should be included and recognised as equal in the process of knowledge creation. Although knowledge is viewed as multi-dimensional, accessibility to a wider and more diverse user audience is prioritised within this paradigm (Melo-López et al., 2025; Oyetade & Zuva, 2025). Equal access to learning, which includes AI literacies, tools and user support, is of importance in this paradigm. Although this paradigm highlights the potential benefits associated with AI-enabled tools and approaches, it also raises awareness of the potential limitations and inequalities due to these rapid technological developments.

Conclusion

Understanding how humans position themselves in relation to GAI offers more than theoretical value. It also points to practical considerations that could inform educational practice. This understanding may practically inform how we teach and assess in the era of GAI, how we approach student interactions, and the strategies students are encouraged to adopt in learning and in broader societal contexts. It also suggests professional development needs that extend beyond AI literacy training, while opening pathways for empirical research into human-GAI interaction. The lenses offered here could similarly inform AI governance frameworks and educational policy where they are engaged with in multidisciplinary and professional contexts.

The epistemological understanding of the seven paradigms is not intended to be viewed as what individuals know or believe about GAI in fixed terms but should rather be viewed as a heuristic map of how individuals enact knowledge and learning within different human-GAI assemblages. Such a positioning of the framework also has implications for how the framework should inform practice. Since the paradigms are enacted rather than possessed as fixed traits, the processes to shift how individuals engage with GAI cannot focus on belief alone. Efforts should also consider the broader socio-technical environment, such as assessment design, pedagogical approaches, institutional policy and disciplinary norms that foreground one paradigm rather than another as the sensible response to a given context (Pérez-Verdugo & Barandiaran, 2023). Viewing the paradigms in such a way, the framework explains how epistemological engagement is continuously enacted and subsequently also always open to pedagogical and institutional influence.

Building on this conceptual contribution, the framework's value extends beyond theory into more direct implications for practice in higher education. For instance, guarded orientations are not simply resistance to innovation or technology but represent a coherent epistemological positioning that requires targeted staff development opportunities to build trust and acknowledge the limitations of GAI. In contrast, those aligned with the pioneering or possibility-focused paradigms could be encouraged to experiment with alternative approaches to assessment rather than adopting formats that acknowledge only polished products as evidence of learning. The values-based and equity orientations refer to institutional application where teams could potentially use the framework as a diagnostic tool to inform differentiated professional development. The framework offers academic developers or disciplinary teams a diagnostic vocabulary for differentiating and matching activities in assessment, curriculum development and policy to the epistemological position highlighted by each paradigm.

While this conceptual framework offers a novel lens for understanding human-GAI interaction, it remains exploratory and untested. As the framework has not been tested against empirical data, it cannot yet establish whether the seven paradigms correspond to stable, observable patterns of engagement, how prevalent each paradigm is among students or staff, how individuals move between paradigms over time, or whether the socio-technical interventions implied by the framework would produce the outcomes suggested.

This paper is not intended to provide a complete examination of the various theoretical frameworks underpinning human-GAI interaction. Rather, it serves as an investigative study that hopefully acts as a stimulus for additional research and wider dialogue about the rationale and implications of the different ways humans can approach GAI in educational contexts. As AI continues to evolve, so must our conceptual frameworks and understanding. Recognising our epistemological stance may allow for intentional shifts and reflections rather than reactive responses.

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