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AI-SUPPORTED LEARNING AND HUMAN CAPITAL DEVELOPMENT THROUGH STUDENT-NEGOTIATED INTELLIGENCE

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ABSTRACT

This study examines how students work with artificial intelligence (AI) in learning, moving beyond the simple view of dependence versus control. It focuses on what students actually do when using AI and how they make decisions around it. The study is based on 18 in-depth interviews selected from more than 30 student responses. These were chosen for their clarity and detail, allowing a closer look at learning practices. The findings show that students rarely accept AI-generated content as it is. Instead, they check, adjust, and sometimes rewrite it before using it. In many cases, AI serves as a starting point rather than a final answer. This shifts cognitive effort toward evaluating, selecting, and making sense of information. To explain this, the study introduces the concept of negotiated intelligence, referring to how students regulate AI use while maintaining control over meaning. The results also highlight the role of contextual intelligence, especially when adapting content to local situations or specific audiences. These practices are linked to perceived development in critical evaluation, adaptive reasoning, and contextual understanding, which may be relevant for human capital formation in digital learning environments.

Keywords: Artificial intelligence, epistemic agency, human–AI interaction, knowledge construction, digital economy.

1. INTRODUCTION

The rapid development of artificial intelligence (AI), particularly generative AI, is transforming how knowledge is accessed, produced, and applied in learning environments. As AI tools become increasingly embedded in students' academic practices, learners are no longer passive recipients of information but active participants in AI-mediated knowledge processes. This shift raises important questions about how students interact with AI and how such interaction shapes their judgment and learning.

Existing research has largely approached AI in education from two perspectives: as a tool that enhances efficiency and personalization, or as a risk that promotes dependency and weakens critical thinking. While valuable, this binary framing oversimplifies the complex relationship between learners and AI. In practice, students do not simply rely on or reject AI; they actively evaluate, adapt, and contextualize AI-generated outputs.

Despite this, there remains limited qualitative research examining how students maintain control and judgment when working with AI, particularly in context-specific environments. To address this gap, this study explores how students engage with AI in learning and how such engagement contributes to the development of key capabilities in the digital economy.

The study addresses the following research questions:

RQ1. How do students use AI in knowledge-related tasks?

RQ2. How do they maintain control and judgment when interacting with AI?

RQ3. What shapes their trust and adaptation of AI outputs?

RQ4. How do these practices shape students' perceived cognitive and adaptive capabilities in AI-supported learning?

This study contributes by reframing AI-supported learning as a process of epistemic negotiation and introducing the concept of negotiated intelligence, highlighting how students actively maintain control over knowledge while leveraging AI for efficiency.

2. LITERATURE REVIEW

2.1. AI in Education: Benefits and Risks

The integration of artificial intelligence (AI), particularly generative AI, has significantly transformed how knowledge is accessed and constructed in education. AI enables adaptive learning, automated feedback, and personalized instruction, thereby enhancing efficiency and learner engagement [1]. These capabilities position AI as a cognitive support system that extends students' problem-solving abilities and facilitates self-directed learning.

However, these benefits are accompanied by notable risks. Research indicates that excessive reliance on AI may lead to cognitive offloading, reduced metacognitive engagement, and weaker critical thinking [2], [3]. In addition, ethical concerns such as algorithmic bias and data privacy further complicate its adoption in educational contexts [3]. Consequently, scholars emphasize that AI should complement rather than replace human judgment, maintaining critical thinking as a central learning outcome.

2.2. Beyond Dependency and Control

Much of the literature conceptualizes AI use through a binary lens of dependency versus control. This framing assumes that increased reliance on AI reduces autonomy, while controlled use reflects stronger agency. However, such a dichotomy oversimplifies the complexity of human–AI interaction.

Recent research highlights the sociotechnical nature of AI, demonstrating that AI outputs are shaped by data, design, and contextual factors, often embedding biases that require critical interpretation [4], [5]. Furthermore, users actively engage with AI through iterative prompting, evaluation, and modification, rather than passively accepting outputs [6]. These findings suggest that AI use is better understood as a dynamic and context-dependent process, rather than a fixed state of dependence or control.

2.3. Epistemic Agency in Learning

The concept of epistemic agency provides a more nuanced framework for understanding AI-supported learning. It refers to learners' capacity to evaluate, justify, and take responsibility for knowledge claims [7]. This perspective emphasizes active engagement in knowledge construction rather than passive consumption.

In AI-supported environments, epistemic agency becomes particularly critical. Generative AI produces outputs that appear authoritative but may lack accuracy or contextual relevance, requiring learners to engage in continuous verification and reinterpretation [2]. Rather than diminishing agency, AI intensifies the need for critical judgment and epistemic responsibility. However, empirical research remains limited in explaining how epistemic agency is enacted in real-world interactions with AI.

2.4. Human–AI Interaction

Research on human–AI interaction emphasizes human-in-the-loop systems, where AI acts as a collaborator rather than a replacement. Within this perspective, cognition is distributed across humans and technological systems [8].

AI contributes computational efficiency, while humans retain responsibility for interpretation and decision-making. This creates a process of joint sense-making, where meaning emerges through iterative interaction and feedback [9], [10]. Although cognition is distributed, epistemic authority remains with the human actor, requiring ongoing judgment and control over AI-generated outputs.

2.5. Gaps in Practice and Context

Despite theoretical advances, empirical research remains limited in capturing how individuals interact with AI at a micro level. Most studies rely on quantitative approaches focusing on perceptions such as usefulness or trust, rather than examining actual practices of verification, editing, and adaptation [1].

Additionally, context-sensitive research remains scarce, particularly in emerging economies. AI systems are often developed in Western contexts, which may not fully align with local knowledge systems, languages, or educational norms. This creates a need for localized adaptation and reinterpretation of AI-generated content, a process that remains underexplored in current research.

2.6. AI Use as Negotiation

Taken together, the literature suggests that AI-supported learning cannot be adequately explained through binary frameworks. Instead, it should be understood as a negotiated process, in which individuals balance efficiency with critical judgment and external support with epistemic control.

Through interaction with AI, learners develop key capabilities such as verification, contextual reasoning, and adaptive decision-making—competencies that are increasingly essential for knowledge work in the digital economy [11]. However, there remains a lack of qualitative research capturing how this negotiation unfolds in practice. This study addresses this gap by examining how students develop control, judgment, and knowledge practices through their interaction with AI.

3. METHODOLOGY

3.1. Research Design

This study adopts a qualitative, interpretive research design to examine how students engage with artificial intelligence (AI) in learning processes and how they negotiate control, judgment, and knowledge construction. Given the study's focus on lived experience and meaning-making, a qualitative approach is appropriate for capturing the nuanced interactions between learners and AI that are often overlooked in quantitative research [12], [13].

The study is informed by a phenomenological orientation, aiming to explore how students experience the transition from passive learners to active knowledge creators in AI-supported environments. Rather than treating AI use as a fixed behavior (e.g., adoption or dependency), this approach allows for a deeper understanding of how students interpret, evaluate, and reconstruct AI-generated knowledge in practice.

3.2. Research Context and Participants

The research was conducted in the context of a university-level entrepreneurship course in Vietnam, where students participated in a learning activity as “Edu-creators”, producing educational content (e.g., videos, visual materials) based on academic concepts.

A purposive sampling strategy was employed to select participants who had direct experience using AI tools (e.g., ChatGPT, Canva, CapCut) in their learning process. Data were initially collected from more than 30 semi-structured interview responses from undergraduate students across different groups. From this pool, 18 interviews were selected for in-depth thematic analysis based on their completeness, analytical richness, and relevance to the research focus. Responses that were incomplete, highly repetitive, or substantially overlapping were excluded to ensure analytical clarity.

The selected interviews provided sufficient variation in participants’ experience with AI, allowing the study to capture diverse patterns of engagement. This sample size aligns with qualitative research standards that prioritize analytical depth and interpretive insight over statistical generalization. Prior studies suggest that thematic saturation is typically achieved within 12–30 interviews, depending on data richness [14]. In this study, saturation was reached as no substantially new themes emerged in later stages of analysis, with key patterns—such as knowledge reconstruction, control over AI, and responsibility in content creation—recurring consistently across participants.

Table 1. Participant Profile

Code	Gender	Year of Study	Major	Experience with AI	Role in Task
S1	Female	Year 3	Marketing	Frequent user	Content creator
S2	Male	Year 4	Finance	Moderate user	Presenter
S3	Female	Year 3	Business	Frequent user	Content creator
S4	Female	Year 4	Marketing	Frequent user	Presenter
S5	Male	Year 3	Business	Moderate user	Content creator
S6	Female	Year 2	Marketing	Basic user	Presenter
S7	Female	Year 4	Finance	Frequent user	Content creator
S8	Male	Year 3	Business	Moderate user	Presenter
S9	Female	Year 2	Marketing	Basic user	Content creator
S10	Male	Year 4	Finance	Frequent user	Presenter
S11	Female	Year 3	Business	Moderate user	Content creator
S12	Female	Year 4	Marketing	Frequent user	Presenter
S13	Male	Year 2	Business	Basic user	Content creator
S14	Female	Year 3	Marketing	Frequent user	Presenter
S15	Male	Year 4	Finance	Moderate user	Content creator
S16	Female	Year 2	Business	Basic user	Presenter
S17	Female	Year 3	Marketing	Moderate user	Content creator
S18	Male	Year 4	Finance	Frequent user	Presenter

(Source: Authors)

3.3. Data Collection

Data were collected through semi-structured interviews, guided by a structured protocol covering four main domains:

1. Mindset transformation (perceptions of being a "good student")
2. Knowledge processing and simplification (deep learning practices)
3. Human–AI interaction (use, control, and evaluation of AI tools)
4. Identity and future orientation (entrepreneurial thinking and self-development)

This design ensured both consistency across interviews and flexibility for participants to elaborate on their experiences [15].

Each interview lasted approximately 30–60 minutes and was conducted in Vietnamese to allow participants to express their thoughts naturally. All interviews were audio-recorded and transcribed verbatim to preserve meaning and contextual nuances.

3.4. Data Analysis

The data were analyzed using reflexive thematic analysis, following Braun and Clarke [16]. This method enables the identification of patterns across qualitative data while allowing for interpretive depth.

The analysis was conducted in three stages:

(1) Open Coding

Initial codes were generated inductively from the data, focusing on key actions and experiences (e.g., verifying AI outputs, simplifying concepts, adapting content).

(2) Axial Coding

Codes were then grouped into broader categories representing recurring patterns, including:

- knowledge reconstruction
- control over AI
- contextual adjustment
- responsibility in knowledge sharing

(3) Selective Coding (Theme Development)

Finally, higher-level themes were developed to capture underlying processes in AI-supported learning. These themes emphasize how students negotiate epistemic control and meaning when interacting with AI-generated outputs.

The analysis was iterative, involving constant comparison across cases to ensure coherence and depth of interpretation.

Table 2. Thematic Analysis Structure

Themes	Axial Categories	Open Codes
Epistemic shift in learning	Traditional learning mindset	Memorizing for exams; Learning for grades
	Knowledge articulation	Explaining to others; Rewriting knowledge
	Epistemic responsibility	Feeling responsible for accuracy; Avoiding misinformation

Epistemic negotiation with AI	Verification practices	Checking AI outputs; Comparing with prior knowledge
	Selective acceptance	Filtering AI-generated content; Rejecting irrelevant answers
	Critical judgment	Evaluating correctness; Assessing logical consistency
Knowledge reconstruction	Knowledge reinterpretation	Rewriting in own words; Simplifying concepts
	Contextual illustration	Using examples; Translating theory into practice
	Perspective-taking	Thinking from the audience's perspective; Anticipating misunderstanding
Controlled dependency	Efficiency-driven use	Using AI for drafting; Saving time
	Cognitive support	Generating ideas; Structuring content
	AI literacy development	Improving prompts; Refining AI queries
Contextual intelligence	Contextual adjustment	Adapting AI outputs to Vietnam; Modifying examples
	Localization practices	Replacing foreign cases; Using local context
	Context sensitivity	Evaluating relevance; Adjusting to the audience
Uneven epistemic agency	Epistemic limitation	Feeling uncertain about knowledge; Doubting understanding
	Loss of precision	Oversimplifying content; Generalizing ideas
	Dependency tendency	Needing structured guidance; Partial reliance on AI

(Source: Authors)

4. FINDINGS

4.1. Epistemic Negotiation as a Shift in Learning Orientation

Across participants, a clear shift emerged from passive knowledge reception toward active engagement with AI-generated content. Rather than treating AI as an authoritative source, students described a process of evaluating, filtering, and adjusting information before accepting it.

"When I have to explain something, I realize I need to understand it much more deeply than just reading it." (S6)

"I don't just take what AI gives me. I usually check again or adjust it based on what I learned." (S12)

"Sometimes AI gives general answers, so I need to filter and make it more accurate." (S9)

These accounts reflect a transformation in epistemic orientation. Understanding is no longer defined by exposure to information, but by the ability to interrogate, validate, and reconstruct it. The need to explain knowledge introduces reflexivity, forcing learners to confront gaps in their own understanding.

Importantly, the act of "checking" AI outputs represents more than skepticism. It signals the emergence of an internal evaluative framework in which AI-generated content is treated as provisional input rather than epistemic authority. Learners actively position themselves as decision-makers, mediating between algorithmic outputs and personal knowledge.

These findings indicate that AI-supported learning operates through epistemic negotiation, where learners continuously regulate the acceptance, rejection, and transformation of knowledge.

4.2. Knowledge Reconstruction as Cognitive Reconfiguration

Participants consistently described transforming knowledge through processes of simplification and reinterpretation. This process extends beyond summarization and involves active restructuring of meaning.

"I had to break down complex concepts and explain them in a simpler way so others could understand." (S3)

"Sometimes I imagine I'm explaining to someone who knows nothing." (S14)

"The hardest part is choosing what to keep and what to remove without losing the meaning." (S8)

These responses illustrate that simplification requires selective abstraction and reorganization. Learners must identify core concepts, eliminate redundancy, and restructure information in ways that preserve meaning while enhancing accessibility.

At the same time, perspective-taking plays a critical role. By anticipating the needs of an uninformed audience, learners translate knowledge into more relatable and cognitively accessible forms. This process involves both reduction and expansion—reducing complexity while expanding clarity.

Participants also linked this process to a deeper understanding:

"Before, I just memorized definitions. Now I actually understand why things work that way." (S5)

This indicates that reconstruction is not a loss of information, but a reconfiguration of knowledge, where meaning emerges through reinterpretation rather than accumulation.

This suggests that learning through content creation involves cognitive reconfiguration, in which understanding is produced through the selective restructuring and translation of knowledge.

4.3. Human Control in AI-Augmented Cognition

Participants consistently framed AI as a supportive but subordinate tool, emphasizing that control over content remained with the learner.

"AI helps me with ideas and wording, but I decide what to keep." (S10)

"I always check if the information is correct before using it." (S7)

"AI cannot understand real situations like I do, so I need to change examples." (S2)

These statements reveal a clear asymmetry in human–AI interaction. While AI contributes to idea generation and structural support, it lacks the capacity to interpret meaning within specific contexts. As a result, learners assume responsibility for evaluating relevance, accuracy, and applicability.

Rather than reducing cognitive effort, AI redistributes it. Lower-level generative tasks are delegated to AI, while higher-order processes such as evaluation, interpretation, and contextualization remain human-driven. This division of labor reinforces the importance of human oversight.

At the same time, participants demonstrate awareness of AI limitations, particularly in terms of generalization and lack of contextual sensitivity. This awareness further strengthens their role as active regulators rather than passive users.

This suggests that AI-supported learning is characterized by asymmetrical cognition, in which human actors retain interpretive authority while leveraging AI for generative efficiency.

4.4. Contextual Intelligence as a Mediating Mechanism

A key process observed is the A prominent pattern across participants is the need to adapt AI-generated content to specific contexts, particularly local or cultural environments.

"Some examples from AI don't fit the situation in Vietnam, so I need to change them." (S15)

"AI gives global ideas, but I have to make them relevant to my audience." (S1)

"I need to adjust the content so people can relate to it." (S4)

These responses indicate that AI-generated knowledge often operates at a level of abstraction that lacks contextual specificity. Learners must therefore engage in processes of localization, modifying content to align with real-world conditions and audience expectations.

This adaptation is not purely corrective but interpretive. Learners evaluate not only whether information is accurate, but whether it is meaningful and relatable. In doing so, they act as intermediaries who translate generalized outputs into situated knowledge.

The emphasis on audience relevance further suggests that knowledge is not evaluated solely in terms of correctness, but also in terms of communicability and resonance.

This suggests that contextual intelligence functions as a mediating mechanism in AI-supported learning, enabling the transformation of generalized knowledge into contextually meaningful understanding.

4.5. Uneven Epistemic Agency and Conditional Dependence

Despite widespread engagement in epistemic negotiation, participants exhibited varying levels of control when interacting with AI.

"I compare different sources before deciding what is correct." (S2)

"If I'm not sure, I tend to rely on AI more because it's faster." (S17)

"Sometimes I don't know if the answer is right or wrong, so I just use it." (S16)

These contrasting responses illustrate a spectrum of epistemic agency. Some learners demonstrate strong evaluative capacity, triangulating information and exercising independent judgment. Others display conditional dependence, particularly in situations of uncertainty.

This variation appears closely linked to prior knowledge and confidence. Learners with stronger foundations are better able to critically assess AI outputs, while those with weaker knowledge bases are more likely to defer to AI.

Additionally, the process of simplifying knowledge introduces tension:

"I'm afraid I might miss important details when making it simpler." (S18)

This reveals an inherent tension between accessibility and accuracy, as efforts to make

knowledge more communicable may come at the cost of conceptual precision.
Epistemic agency thus emerges as a contingent capacity, shaped by learners' prior knowledge, confidence, and task demands, rather than a stable or uniformly distributed capability.

To synthesize these patterns, Figure 1 presents the overall process through which students engage with AI-supported learning.

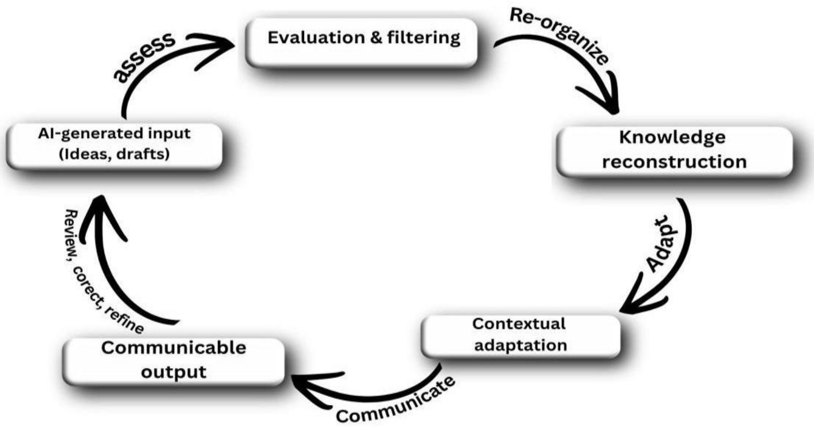

Figure 1. Process of Epistemic Negotiation in AI-Supported Learning (*Source: Authors' compilation*)

As shown in Figure 1, AI-generated content functions as an initial input rather than a final source of knowledge. The central process involves evaluation and filtering, followed by knowledge reconstruction and contextual adaptation. These stages reflect how students actively transform AI-generated outputs into meaningful and communicable knowledge.

The directional arrows indicate that this process is not strictly linear. The feedback loop from communicable output back to evaluation highlights the iterative nature of learning, where students continuously review, refine, and adjust their understanding. This recursive process reinforces the role of learners as active regulators rather than passive recipients of AI-generated information. These processes correspond directly to the patterns identified in Sections 4.1 to 4.4, including epistemic negotiation, knowledge reconstruction, and contextual adaptation.

5. DISCUSSION

5.1. AI Use as Epistemic Negotiation and Learning Transformation

This study moves beyond the dominant binary framing of AI use as either beneficial or detrimental by showing that students engage with AI through an ongoing process of epistemic negotiation. Rather than passively relying on AI, learners actively evaluate, filter, and adapt AI-generated outputs based on their own judgment and contextual understanding.

At the same time, the findings reveal a fundamental shift in learning processes—from knowledge acquisition toward knowledge reconstruction and validation. Students do not merely simplify information; they reinterpret concepts, reorganize knowledge structures, and translate abstract ideas into accessible forms. In doing so, learning becomes inherently relational, requiring attention not only to correctness but also to clarity and communicability.

Importantly, AI does not reduce cognitive effort but redistributes it. Students shift from generating information to evaluating and refining it, emphasizing higher-order processes such as judgment and synthesis. This extends existing perspectives on human-centered AI [9] and distributed cognition [8], suggesting that while cognition is partially distributed, epistemic authority remains with the human actor.

5.2. Negotiated Intelligence as a Mechanism of Human–AI Interaction

Building on these findings, this study conceptualizes *negotiated intelligence* as a dynamic mechanism through which students regulate their interaction with AI systems. Learners engage in continuous processes of evaluation, filtering, and reconstruction of AI-generated outputs in context-specific ways.

This mechanism can be understood through three interrelated dimensions: evaluative judgment, adaptive reconstruction, and contextual alignment. Together, these dimensions explain how students maintain epistemic control while leveraging AI for efficiency.

In this sense, negotiated intelligence extends existing frameworks such as epistemic agency [7] by emphasizing not only responsibility for knowledge claims, but also the continuous regulation of algorithmically generated information. This highlights that effective AI-supported learning is not determined by access to technology, but by the learner's capacity to regulate its use.

Rather than directly measuring human capital outcomes, this study focuses on how students perceive the development of key capabilities through their interaction with AI, including critical evaluation, adaptive reasoning, and contextual interpretation. These capabilities can be understood as indicative of emerging forms of human capital in AI-supported learning contexts.

Building on the empirical process illustrated in Figure 1, this study develops a conceptual framework linking AI-supported learning practices to capability formation. While Figure 1 describes how students engage in epistemic negotiation, Figure 2 explains the mechanism through which these practices give rise to negotiated intelligence and its associated capabilities.

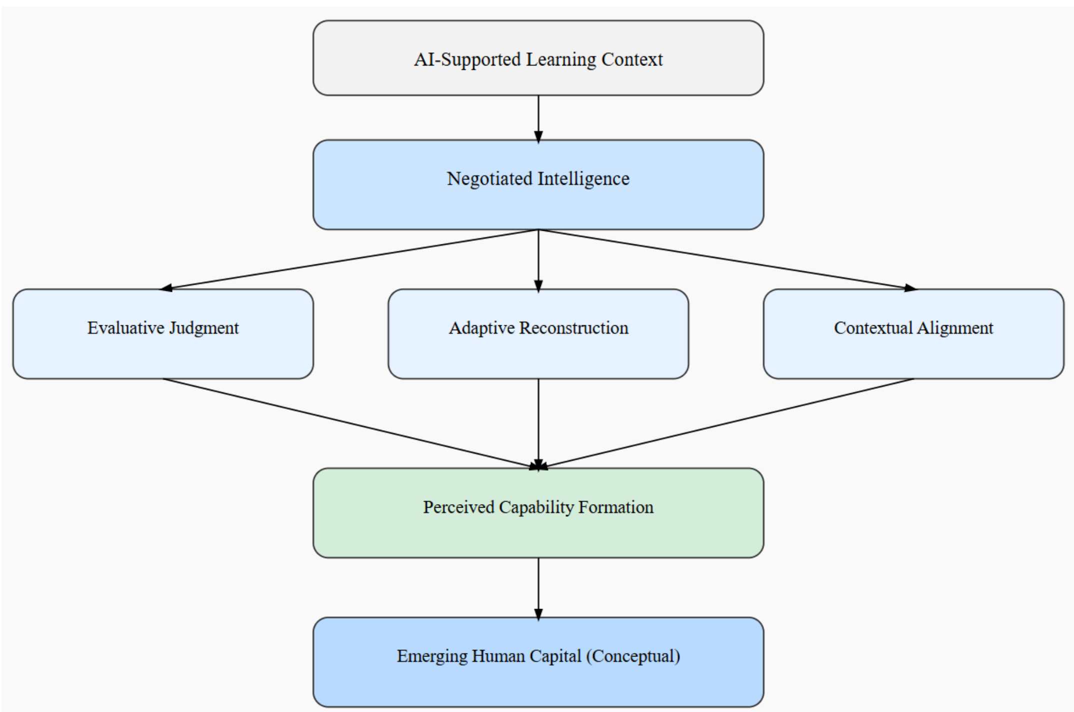

Figure 2. Conceptual Framework of Negotiated Intelligence and Capability Formation
(*Source: Authors' compilation*)

As illustrated in Figure 2, negotiated intelligence emerges through repeated engagement with AI-supported learning tasks. It consists of three interrelated dimensions: evaluative judgment, adaptive reconstruction, and contextual alignment.

Evaluative judgment refers to the ability to assess the accuracy and relevance of AI-generated outputs. Adaptive reconstruction captures the process of modifying and rearticulating knowledge into understandable forms. Contextual alignment reflects the ability to adapt content to specific audiences and local conditions.

Together, these dimensions contribute to the development of perceived cognitive and adaptive capabilities. These capabilities are interpreted as indicative of emerging forms of human capital in the digital economy, rather than as directly measured outcomes.

5.3. Contextual Intelligence and the Limits of AI Generalization

A key contribution of this study is the identification of contextual intelligence as a central component of AI-supported learning. Students frequently encounter limitations in AI-generated outputs, particularly in terms of contextual relevance, and must actively adapt content to align with local realities.

This points out that AI-generated knowledge is not inherently transferable across contexts. Instead, it requires human interpretation and modification to become meaningful. Students therefore act as contextual mediators, bridging the gap between globally generated AI outputs and locally situated knowledge practices.

This finding extends current discussions on AI limitations by shifting the focus from accuracy to contextual validity. It also reinforces the importance of human expertise in AI-supported environments-not for generating information, but for interpreting and situating it appropriately.

5.4. Uneven Epistemic Agency, Implications, and Limitations

While the findings highlight the development of negotiated intelligence, they also reveal uneven patterns of epistemic agency among students. Not all participants demonstrate the same level of control or confidence when interacting with AI.

This variation can be attributed to several factors. Limited prior knowledge constrains students' ability to evaluate AI-generated outputs, while uncertainty in distinguishing accurate from misleading information increases reliance on AI. Additionally, the cognitive demands of simplifying complex concepts may lead to overgeneralization or partial dependency.

These findings suggest that epistemic control is contingent upon individual capabilities and learning conditions. As a result, AI-supported learning environments may both empower and constrain learners, depending on their level of preparedness.

From a practical perspective, this highlights the importance of developing students' critical and reflective capacities, rather than focusing solely on technological access or efficiency.

However, several limitations should be acknowledged. This study does not directly measure human capital outcomes such as productivity or performance. Instead, it captures students' perceived development of cognitive and adaptive capabilities. The findings should therefore be interpreted as indicative of capability formation rather than definitive evidence of measurable human capital development.

Future research may extend this work by examining the relationship between negotiated intelligence and broader educational or labor market outcomes using quantitative or mixed-method approaches.

6. CONCLUSION

This study demonstrates that students' engagement with AI-supported learning cannot be adequately understood through simplistic notions of dependency or control. Instead, learners actively negotiate their interaction with AI, balancing efficiency with critical judgment and maintaining authority over knowledge construction. The results indicate that AI reconfigures cognitive engagement rather than diminishing it. Students shift from generating information to evaluating, refining, and contextualizing it, thereby strengthening epistemic agency. In this process, AI functions not as a replacement for human thinking but as a catalyst that reshapes how thinking occurs. Importantly, the study highlights the role of contextual intelligence, as learners adapt AI-generated outputs to local and situational realities. This underscores the continued importance of human judgment in AI-mediated environments.

Overall, the study contributes to the understanding of learning in the digital era by proposing that effective AI use involves negotiated intelligence—a process through which individuals actively maintain control, responsibility, and meaning in knowledge production. These capabilities are essential for developing human capital in the digital economy.

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