AI-Supported Learning for Relational Capital Development: A Case Study in Higher Education

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Abstract: The systematic development of Relational Capital as part of Intellectual Capital is a critical element for career success. In two Austrian Master's programs in digital technology and innovation at FHWien der WKW, an innovative teaching approach integrated AI-assisted learning with individual coaching. A customized GPT model was deployed as a structured reflection tool, assisting students in assessing and strategically developing their professional networks over the course duration. While traditional lecture time was reduced to two hours, instructional resources were redirected to AI-assisted learning and to group-coaching to enhance learning outcomes.-This case study examines the use of generative AI as a dialogic tutor in a master's program on digital economy. Drawing on anonymized AI-student transcripts, coaching reflections, and structured prompts, the paper explores how AI supports strategic development of Relational Capital. Findings indicate high learner acceptance, evolving trust strategies, and improved metacognitive learning outcomes. AI shows strengths in guiding students through structured career planning exercises. However, concerns over trust and confidentiality emerged and lead students to adopt anonymization techniques to protect sensitive professional relationships. Beyond Relational Capital development, this study also highlights key pedagogical implications. AI's effectiveness depends on high-quality learning materials, and students required training in prompt engineering to navigate information overload. The role of educators shifted towards facilitating learning processes, mentorship and strategic guidance, focusing on critical engagement with AI-generated content. This case study contributes to the discourse on AI integration in higher education. It demonstrates its role not only in developing Relational Capital but also in shaping self-directed learning behaviors and pedagogical innovation.

Keywords: Relational capital, Generative AI, Dialogic tutoring, AI-Augmented learning, Prompt engineering in higher education

1. Introduction

Artificial intelligence (AI) has been integrated into higher education in various capacities over the past two decades, primarily through adaptive learning systems, intelligent tutoring, and predictive analytics (Zawacki-Richter et al., 2019; Marengo et al., 2024). These applications have traditionally focused on specific, narrowly defined tasks, such as automated grading, personalized learning pathways, and early warning systems for student retention. These tasks were reported by Salas-Pilco & Yang (2022) and Crompton & Burke (2023) for a global perspective.

However, the emergence of large language models (LLMs), such as OpenAI's GPT-4 and Google's Gemini after 2023, marks a fundamental shift in AI's role in education. These models enable general-purpose reasoning, dynamic content generation, and open-ended student interaction, fundamentally altering previous assumptions about AI in learning environments (Imran & Almusharraf, 2024). LLMs provide a general-purpose AI model that can write, analyze, explain, and generate educational materials dynamically. This shift challenges previous assumptions about how AI interacts with students and educators.

According to Open.ai (2024), LLMs require no pre-programmed task-specific training, unlike traditional AI applications that had to be developed for specific educational functions. Students and faculty can engage in natural conversations with LLMs, using AI as a thinking or sparring partner rather than just a tool for task automation. LLMs can handle complex reasoning and generate personalized instructions, thus making previous adaptive learning and tutoring AI models less necessary.

These developments suggest that findings from earlier AI research must be re-evaluated in the context of general-purpose AI models that can replace multiple previous AI applications at once.

A recurring theme in past AI research was the prohibitive cost and technical requirements associated with AI adoption in education due to the need to specifically train models (Crompton & Burke, 2023; Marengo et al., 2024). Before 2023, AI integration required institutional investment, faculty training, and dedicated infrastructure, limiting widespread adoption.

The rise of LLMs has overturned these assumptions (Open.ai, 2024). AI tools are now (almost) freely accessible through web-based applications, reducing cost barriers. Students can engage directly with AI models without needing specialized training or institutional support. AI-enhanced learning environments can now be created by individuals, not just institutions, shifting control over AI adoption from universities to students and educators themselves.

This democratization of AI raises new challenges not addressed in previous research, particularly regarding AI literacy, critical thinking, and ethical engagement with AI-generated content.

Earlier research positioned AI as a tool that educators controlled, providing pre-programmed functions such as grading automation and predictive analytics (Gao et al., 2023). With the advent of large language models (LLMs), however, the role of AI in education has undergone a profound shift. Students can now autonomously engage with AI for research, writing, and problem-solving, without requiring educator mediation. This transition redefines AI not merely as a utility under teacher direction, but as an interactive and adaptive partner in learning processes (Guizani et al., 2025; Rupprecht, Rodenas, Stingl, 2025)

This development has significant implications for educational practice. First, there is a need to move away from traditional content delivery and instead prioritize the cultivation of critical engagement, enabling students to assess and challenge AI-generated outputs. Second, assessment strategies must evolve to evaluate students' capacity to use AI meaningfully and ethically, rather than simply reproducing content. Third, educators are tasked with developing pedagogical models where AI augments intellectual exploration and classroom dialogue, rather than serving purely administrative ends.

Crucially, LLMs should be seen as complementary rather than substitutive tools. While they can automate routine tasks and personalize learning, their effectiveness depends on thoughtful integration and the preservation of core human roles in teaching. Educators remain indispensable in fostering higher-order cognitive and ethical skills—critical thinking, creativity, and judgment—that AI cannot replicate. A balanced and responsible approach to AI in education must therefore leverage LLMs' capacities while ensuring that human oversight safeguards the quality and integrity of learning environments (Guizani et al., 2025). However, empirical studies exploring AI as a dialogic coach in knowledge-intensive domains remain scarce.

The notion of Relational Capital (RC) as a core dimension of Intellectual Capital has been central to the knowledge management discourse for decades (Edvinsson & Malone, 1997; Roos et al., 1997). Building on these foundations, scholars like Mouritsen et al. (2001) and Johanson et al. (2001) have emphasized the narrative, visual, and strategic dimensions of RC, especially in organizational contexts. However, its targeted application in higher education—and particularly its interplay with AI-driven tutoring—remains underexplored.

This paper aims to explore how generative AI tools, particularly large language models (LLMs), can support the development of Relational Capital among master's students in a digital economy program. Through a case study approach, we examine how AI was integrated into a university course as a dialogic tutor to help students identify, assess, and strategically expand their professional networks. The paper documents the pedagogical design, implementation challenges, and student perceptions over an 11-week period, offering insights into the opportunities and limitations of AI-supported RC development in higher education.

2. Method of Research

This case study examines the integration of AI-supported learning in higher education, focusing on the development of students' Relational Capital. The methodological framework is based on the principles of Intellectual Capital Reporting, as outlined by Bornemann and Reinhardt (2003) in the tradition of "Wissensbilanz made in Germany" (Bornemann et.al., 2015).

The study was conducted at FHWien der WKW, a university of applied sciences in Vienna, Austria, as part of a master's level course in digital economy offered during the winter semester of 2024. The participating students were enrolled in practice-oriented programs focused on digital technology and innovation. The AI-supported learning module was embedded into the formal curriculum and delivered in a hybrid format over 11 weeks. The primary goal was to enable students to strategically develop their individual Relational Capital, supported by AI tutoring and coaching interventions. The research unit of analysis was the student interaction with AI tools and follow-up coaching reflections, captured through transcripts, documentation, and thematic analysis.

The course design minimized traditional lecturing, reducing it to a two-hour session and reallocating time to small group coaching sessions and AI-supported self-learning. The AI agent was available to students at all times, serving as a knowledge provider and reflective partner. Its primary functions included supporting students in structuring their thoughts, formulating personal objectives for developing their RC, and offering methodological guidance and feedback.

Training of the AI system required only moderate technical expertise but benefited heavily from the availability of high-quality digital materials to ensure meaningful interactions. In autumn 2024, the technology available was a customized AI agent, a "special GPT" – which was later (2025) replaced by RAG technology.

The students were equipped with a starting prompt as outlined in table 1.

Table 1: Structured prompt with definition of tasks, context, methods, and format of output

Prompt	Function
Hi, I would like to work with you on Relational Capital. Could you start with an introduction and explanation for this topic and then ask 10 questions consecutive and stepwise that help me to better understand the concept?	Task
Currently, I am starting a 2-year MBA Program and would like to boost my career. My objective is to develop my own relational capital strategically to be optimally positioned in 2 years. I already have some foundations from my early professional life and jobs and education but would like to systematically develop this asset. Please be my tutor and coach. Be extensive and comprehensive in your explanations on master level. Provide sources for your hints, if applicable.	Context
In our dialogue, you will ask me about my status and descriptions, which will serve as inputs for this document.	Task
Later, we might talk about a SWOT analysis and the assessment of my Relational capital based on the 3 dimensions of quantity, quality and the current level of systematic management.	Method
Later, I will ask you to create a summary of our interaction. I wish you to create a word document which is structured according to various elements of relational capital.	Format
I wish you to drive this dialogue building on the logic of an Intellectual Capital Report.	Method
Once we have completed all the steps, I need a comprehensive and detailed report and summary,	Format
including relevant and customized hints, how to develop my Relational Capital in the next 2 years.	Method

Beyond AI-supported learning and following the recommendations of Guizani et al (2025), students participated in two circles of structured coaching sessions to provide individual support, apply AI-generated insights to real-world contexts, and critically reflect on their Relational Capital development. The focus of the first circle was on establishing a fundamental understanding of RC, reviewing existing contacts and formulating the strategic objective for the status of RC at the time of graduation. For most students, this objective meant to improve their career path. The second circle focused on identifying measures to accomplish this objective based on the status quo as well as by systematically leveraging the now clearly structured RC.

Data collection for this case study was based on transcripts of anonymized AI-student interactions, records of coaching sessions, and student reflections following a case study approach (Yin, 2018).

3. Case Study AI-Supported Learning for Relational Capital Development

Over 11 weeks, 39 students participated in two circles of 12 session each (total of 24) with about 3-4 participants per session to keep interaction as well as confidentiality high. We identified 3 general observations (high acceptance of AI as a learning assistant; confidentiality concerns; quality of AI guided learning), supported by exemplary episodes or narratives as evidence. After the quantitative overview, we will provide qualitative descriptions of these short episodes.

3.1 Quantitative Representation

Table 2 shows co-occurrences of episodes. We see the "reluctance to share personal networks" as most frequent among the cohort. Other episodes could be observed up to three times based on the data available. Less frequent episodes were eliminated here and in the qualitative description for limitations of space.

Table 2: Quantitative Insights from Transcripts

Finding	Episode #	Episode title	Similar Cases
High Acceptance of AI as a Learning Assistant	1	The AI as a Structuring Tool for Relational Capital Mapping	5
	2	AI as a Confidence Booster in Career Planning	3

Finding	Episode #	Episode title	Similar Cases
	3	Overcoming Conceptual Blocks with AI-Generated Reflection Prompts	4
Trust & Confidentiality Concerns	4	The Reluctance to Share Personal Networks	6
	5	The Fear of AI Bias and Misinterpretation	3
	6	Overcoming Initial Skepticism Through Experimentation	4
Quality of AI-Guided Learning	7	The AI as a Methodological Guide in Strategic Planning	5
	8	Refining Arguments Through Iterative AI Interaction	3
	9	AI-Generated Reflection Prompts as a Tool for Deeper Thinking	4

3.2 Qualitative Representation

While the number of student interactions is limited and far from representative, several situations reappeared in various similar forms and were condensed to episodes. For the sake of formal consistency, we grouped them to three clusters. The first cluster covers acceptance of AI as learning assistant with episodes 1-3; the second cluster covers trust and confidentiality with episodes 4-6; the third cluster covers the quality of AI guided learning with episodes 7-9.

3.3 High Acceptance of AI as a Learning Assistant

Below are three detailed qualitative episodes extracted from the transcripts, each illustrating how students interacted with the AI, how they perceived its usefulness, and how this contributed to their learning.

3.3.1 *Episode 1: The AI as a structuring tool for relational capital mapping*

During one of the coaching sessions, a student expressed frustration over how to systematically assess their personal and professional networks. Initially, they struggled with identifying which contacts were relevant to their career goals and how to categorize these relationships effectively. When prompted by AI, the student received a structured framework suggesting that relationships could be grouped by strength, reciprocity, and strategic importance. Encouraged by this clarity, the students used the AI to refine their own knowledge balance, realizing that some professional contacts were underutilized resources. In the coaching follow-up, the student reflected on how the AI's prompts helped them transition from intuitive networking to a structured, data-driven approach. They emphasized that without the AI's guidance, they would not have thought of quantifying their Relational Capital systematically.

3.3.2 *Episode 2: AI as a confidence booster in career planning*

Another student, preparing for a transition into a managerial role after graduation, initially doubted whether their existing network provided sufficient leverage for future career opportunities. They approached AI with broad, unspecific career questions, expecting only generic responses. However, through a series of iterative refinements, the AI prompted the student to analyze which network contacts had decision-making power in their desired industry. Through multiple interactions, the student gained confidence in reaching out to contacts they had previously undervalued, particularly former professors and internship supervisors. In the final coaching session, they reflected on how AI had subtly changed their approach from passive observation to proactive engagement, demonstrating that AI's role extended beyond answering queries to shaping strategic behavior.

3.3.3 *Episode 3: Overcoming conceptual blocks with AI-generated reflection prompts*

A student with a background in engineering had difficulty understanding the abstract concept of Relational Capital. In earlier discussions, they saw networking as transactional rather than strategic and struggled to define what "capital" meant beyond financial assets. In frustration, they asked the AI to explain why relationships should be considered a form of capital. The AI responded with a metaphor comparing a well-maintained professional network to a diversified investment portfolio, which immediately resonated with the student's technical mindset. This analogy shifted their perspective, allowing them to recognize the long-term value of trust and credibility in professional settings. In the subsequent coaching session, they actively engaged in discussing the nuances of social capital and even began advising their peers on optimizing their own networks, demonstrating that the AI was not only accepted but had transformed their conceptual understanding of the topic.

3.4 Trust and Confidentiality Concerns

Below are three episodes illustrating how students dealt with issues of trust and confidentiality when interacting with AI. These episodes highlight different strategies students employed to protect sensitive information while still benefiting from AI-assisted learning.

3.4.1 Episode 4: The reluctance to share personal networks

One student, preparing a Relational Capital analysis for career planning, expressed hesitation about entering specific names or organizational affiliations when interacting with the AI. Initially, they provided only vague descriptions, such as "a senior colleague" or "a mentor in a consulting firm," fearing that the AI might store or misuse their data. However, after a coaching session where strategies for anonymization were discussed, the student adopted a coded labeling system, referring to contacts by functional role rather than name (e.g., "Industry Mentor A" or "Former Manager B"). This allowed them to work through relationship evaluations systematically without disclosing personally identifiable information. In later reflections, they stated that this strategy enabled them to fully engage with the AI while feeling in control of their data, demonstrating that trust concerns could be mitigated through structured anonymization.

3.4.2 Episode 5: The fear of AI bias and misinterpretation

Another student, who had previously used AI tools in a corporate setting, expressed skepticism about how the AI would interpret sensitive career dilemmas. In one case, they sought advice on navigating office politics and securing internal promotions, but they worried that the AI's responses might be too generic or reinforce biases present in its training data. To test this, they posed the same question in multiple rephrasings, checking for consistency and potential biases in the AI's advice. This experiment revealed that the AI provided strategic guidance but lacked nuanced, situational awareness, reinforcing the student's belief that critical judgment must accompany AI use. During the coaching debrief, they reflected that while AI was helpful for structuring their thought process, they would never fully rely on it for confidential career decisions. Instead, they saw it as a neutral, external perspective that supplemented—but did not replace—human mentorship.

3.4.3 Episode 6: Overcoming initial skepticism through experimentation

At the beginning of the course, a student voiced strong reservations about engaging with AI in a personal learning process, fearing that every input might be recorded, analyzed, or later repurposed without their consent. This led them to avoid deep engagement with the AI assistant in early sessions, opting instead to rely solely on coaching and peer discussions. However, after observing how peers successfully used anonymization techniques and how the AI never required personal data to generate meaningful responses, they gradually began incorporating AI interactions into their workflow. By the final coaching session, they admitted that their initial reluctance had been based more on assumption than experience and acknowledged that structured, anonymized use of AI could be both effective and secure. Their case underscores how exposure and controlled experimentation helped them transition from distrust to a pragmatic, strategic engagement with AI.

3.5 Quality of AI-Guided Learning

Below are three episodes illustrating how students interacted with AI for structured learning. These episodes highlight different ways the AI contributed to methodological guidance, structured reflection, and deeper learning outcomes.

3.5.1 Episode 7: The AI as a methodological guide in strategic planning

A student working on their RC assessment struggled to identify the criteria for evaluating the strength of professional relationships. Initially, they relied on intuition, listing contacts without clear differentiation. When engaging with AI, they received a structured response suggesting a three-dimensional model: frequency of interaction, level of trust, and strategic importance. This structured approach led the student to reclassify their relationships, moving from a flat list to a multi-tiered network analysis. In the subsequent coaching session, they expressed surprise at how the AI helped them see overlooked patterns in their network. They noted that, without this structured approach, they would have continued making career decisions based on gut feeling rather than a strategic analysis of their RC.

3.5.2 Episode 8: Refining arguments through iterative AI interaction

Another student, preparing a written reflection on the role of weak ties in professional networking, found their arguments lacking depth and coherence. They approached AI with open-ended prompts, asking for counterarguments and alternative perspectives. Through multiple iterations, the AI challenged their assumptions, introducing granular distinctions between bonding and bridging social capital (Granovetter, 1973). Encouraged by this, the students reformulated their arguments, integrating new theoretical perspectives and citing empirical studies suggested by the AI. During the coaching review, they described this process as like having an academic sparring partner, helping them strengthen their reasoning before finalizing their paper. This case illustrates that AI did not merely provide information but actively contributed to the refinement of argumentation.

3.5.3 Episode 9: AI-generated reflection prompts as a tool for deeper thinking

A student unfamiliar with the concept of Relational Capital initially struggled to see its relevance to their own career development. When engaging with the AI, they received a set of structured reflection prompts, such as:

- "Which professional relationships have played an unexpected role in shaping your career path?"
- "How do you maintain and invest in weak ties, and what has been the outcome?"
- "If you had to quantify the value of your network, which factors would you include?"

At first, they dismissed these questions as overly abstract. However, after attempting to answer them within the AI chat, they realized that these structured prompts forced them to articulate tacit knowledge about their professional interactions. In the coaching debrief, they admitted that, without AI-generated reflection prompts, they would have remained unaware of the latent potential in their existing networks. This episode demonstrates that AI-supported reflection exercises can trigger deeper self-awareness and more structured career planning.

4. Findings and Discussion

This case study investigated how AI-supported learning environments influence students' development of Relational Capital in a Master's level higher education module. Based on anonymized transcripts, coaching records, and student reflections, three core patterns emerged.

1. **High Acceptance of AI as a Learning Assistant:** Students broadly appreciated the AI agent as a competent and non-judgmental reflection partner. It supported structuring thoughts, identifying patterns in personal networks, and formulating strategic objectives for relational development. Especially valuable were AI-generated prompts that encouraged iterative clarification and reflection. Students with technical backgrounds responded particularly well to the structured logic and metaphoric framing (e.g. comparing RC to investment portfolios).
2. **Trust and Confidentiality Considerations:** A recurrent theme was students' hesitation to share sensitive network information with the AI. In response, several adopted anonymization strategies (e.g. using role-based labels). Trust was negotiated pragmatically—students accepted varying levels of disclosure depending on whether they used paid or free AI services. Those with prior exposure to AI systems often tested for bias or inconsistencies before deeper engagement.
3. **Enhanced Methodological Quality Through AI Interaction:** AI-supported learning contributed substantially to the clarity and structure of student reasoning. Students used AI not only to receive feedback but to challenge their own assumptions and refine arguments. This iterative process deepened their understanding of RC as a strategic asset. Students reported shifts from intuitive to model-based decision-making in career planning and network analysis.

These findings reflect the thematic clusters explored through Episodes 1–9 (see Table 1). While not generalizable beyond this cohort, the patterns offer insight into the role of generative AI in supporting metacognitive learning processes.

The integration of generative AI into this course module reconfigures the relationship between learners, educators, and educational technology. Rather than replacing traditional instruction, AI functioned as a dynamic, dialogic support structure—shaping both the content and process of learning.

4.1 From Tool to Partner: Rethinking AI's Role

Students treated AI not as a static source of information, but as an adaptive partner in sensemaking. This echoes recent scholarship (e.g. Guizani et al., 2025) calling for a shift from automation to augmentation in AI pedagogy. The observed improvements in conceptual clarity and strategic planning suggest that AI can catalyze deeper levels of engagement—particularly when aligned with domain-specific prompts and supported through human coaching.

4.2 Navigating Trust Without Overengineering Ethics

While data privacy concerns were present, they were rarely framed in terms of abstract ethical dilemmas. Instead, students employed situational solutions—choosing subscription models, pseudonyms, or compartmentalized inputs. These pragmatic adaptations suggest that AI trust can emerge organically within well-scaffolded learning environments. Regulatory structures and institutional policies remain relevant but need not be the focal point of pedagogical design.

However, trust appears to be a general prerequisite for students to share information about their personal networks, regardless of whether the thinking partner is an AI chatbot or a human teacher.

4.3 Designing for Productive AI-Learner Interaction

The effectiveness of AI-supported learning in this case depended on three interrelated factors:

- Quality of Prompting: Students who invested in iterative dialogue with the AI saw greater cognitive benefit. Prompt engineering emerged as a new skill for academic reflection.
- Contextual Embedding: The AI performed best when supported by a well-designed course structure, including pre-curated learning materials and live coaching.
- Shifting Educator Roles: Faculty transitioned from delivering content to enabling intellectual autonomy. Coaching sessions focused less on factual correction and more on epistemic framing, strategic thinking, and emotional validation.

This case supports a hybrid pedagogy model (Schmid et al, 2021) where AI mediates individual reflection, and human educators support integration and judgment. For such models to succeed at scale, both students and educators must develop new literacies—technical, strategic, and relational.

5. Limitations and Future Research

This study draws on a small cohort of students within a specific course design and cultural context of students of the digital economy. The focus on developing RC was both, an educational goal to raise awareness for the importance on early career building as well as to leverage students' capabilities to systematically leverage RC with AI over time. Future research should explore how these dynamics unfold in more diverse settings, and how AI-supported learning can be sustained over longer educational trajectories. Of particular interest are the longitudinal effects on professional behavior and decision-making once students leave the formal learning context.

Ethics Declaration: Ethical clearance was not required for the research.

Statement on the use of AI: Artificial intelligence tools were employed to support various stages of the research process. Automated transcription software was used to convert audio recordings of coaching sessions into text. OpenAI's ChatGPT-4.0 was utilized to summarize these transcripts, identify thematic episodes, and extract frequency data for analytical purposes (see Table 2). Additionally, ChatGPT-4.0 and DeepL Write © were employed to enhance the consistency, clarity, and readability of the manuscript, as English is not the authors' first language. All content was subsequently reviewed and validated by the authors to ensure it accurately reflects the research findings and interpretations. The authors affirm full responsibility for the interpretation and validation of all AI-assisted outputs.

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