

Cultivating Critical Collaboration: GenAI as a Co-Pilot in Equity Valuation Education

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Abstract

This study explores the integration of Generative AI (GenAI) as a multi-functional pedagogical tool within an equity valuation course, demonstrating its role in bridging theoretical finance with practical application. Framed by distributed cognition, the instructor employed GenAI as a “co-pilot” to generate cases, automate financial data processing, and execute valuation models. This collaborative approach transformed students from passive calculators into active, critical analysts, enabling deeper strategic engagement by offloading routine tasks. Findings indicate that while GenAI enhances analytical efficiency and provides useful scaffolding, it remains limited in strategic thinking, qualitative assessment, and assumption development within equity valuation, highlighting the irreplaceable role of human judgment. The course cultivated critical GenAI collaboration literacy, equipping students to command, validate, and synthesise AI-generated insights, thereby preparing them for the evolving demands of the finance profession.

Keywords: Generative AI, Equity Valuation, Business Education, Pedagogical Innovation, AI Literacy

1. Introduction

Equity valuation, a cornerstone of finance education, demands that students synthesise accounting principles, financial theory, and strategic analysis to estimate a company’s intrinsic value. Traditionally, pedagogy has emphasised manual data extraction from financial statements, the application of predetermined models, and theoretical case studies. While foundational, this approach can be time-intensive and may fall short of replicating the dynamic, iterative analysis characteristic of professional practice (Wang et al., 2025).

Generative artificial intelligence (GenAI) offers a transformative means to bridge this gap. With advanced capabilities in natural language processing and data analysis, GenAI can perform valuation-relevant tasks, such as extracting key figures from reports, generating competitive analyses, explaining model nu-

ances, and drafting sections of a valuation, thereby reframing the student's role from passive executor to active, critical analyst. Yet, without deliberate instructional design, such integration risks fostering superficial learning. This raises two pivotal questions: How can generative AI be meaningfully embedded in equity valuation pedagogy to deepen learning? And what is its practical impact on the learning process?

This study adopts a pragmatic, experience-based research approach, investigating the integration of generative AI as an instructional tool within a live corporate valuation course. The methodology centres on deploying AI as a “co-pilot” for students, actively assisting them in tasks such as data extraction, financial modelling, and report drafting. The findings indicate that this guided partnership can enhance the efficiency and depth of the analytical process, allowing learners to focus on higher-order strategic interpretation rather than manual computation. Crucially, the study underscores that instructor scaffolding remains indispensable: it frames the technology's use, promotes critical engagement with AI outputs, mitigates over-reliance, and safeguards the integrity of learning objectives. Ultimately, this work contributes a practical framework for developing essential human-AI collaborative literacy, providing an evidence-based example of how to embed such competencies authentically within global business education.

2. Methodology

This study employed a mixed-methods case study design, centred on a corporate valuation course with 51 undergraduate students enrolled in a finance subject at a research-intensive university. Data were triangulated from three sources to provide a holistic evaluation of the pedagogical innovation.

First, the instructional team maintained reflective journals to document the design and implementation of AI-assisted learning activities, including the development of prompts for tasks such as financial data extraction and model application. Second, a post-course survey was administered to the entire cohort, utilising Likert-scale items to quantify perceptions and open-ended questions to capture detailed feedback on the AI-augmented learning experience. Third, semi-structured interviews were conducted with a purposive sample of five students, selected to represent a range of academic performance and different levels of familiarity with GenAI, as reflected in the survey responses. The aim was to investigate the development of their prompting strategies and their critical engagement with AI-generated outputs.

The qualitative data from reflections, open-ended responses, and inter-

views were analysed thematically to identify recurring patterns and insights. These findings were integrated with descriptive statistics from the survey to construct a comprehensive understanding of both the teaching practice and its impact on student learning.

3. Results and Discussion

3.1 Reflections and Observations from the Lecturer

Generative AI served as a versatile pedagogical instrument in the equity valuation course, bridging theory and practice by acting as a co-pilot. This approach, aligned with distributed cognition, shifted students from passive learning to active, critical analysis. The instructor used GenAI to develop real-world cases, which students then employed for tasks such as summarising reports, extracting data, and applying valuation models.

The technology excelled in automating procedural tasks such as data processing, complex calculations, and the generation of analytical frameworks. This student-centred method reallocated class time towards higher-order strategic interpretation and financial analysis, enhancing both teaching efficiency and analytical depth. A critical observation confirmed AI's limitations, particularly its struggle with nuanced strategic interpretation, the development of forward-looking assumptions, and qualitative assessment, which underscored the irreplaceable need for human oversight and expertise.

The experiential model thus achieved two key goals: developing technical valuation competence and fostering a realistic understanding of AI's possibilities and constraints. Ultimately, this exercise served a dual purpose: it functioned as a powerful tool for achieving technical proficiency and, more importantly, as a practical demonstration of its own boundaries, thereby training students to command AI as a critical assistant while cultivating the sophisticated professional judgment required to validate its outputs, synthesise information, and make final investment decisions.

3.2 Survey from Students

Thirty-eight surveys were received ($\alpha=0.875$). Most students knew GenAI, although their familiarity with these tools varied across the cohort, as reflected in the survey results. About 36.8% had medium skill; 26.3% were advanced, indicating that students entered the course with different levels of prior experience using GenAI tools.

Use was common: 47.4% used it 1–2 times weekly, and another 34.2% used it over five times. Most spent 30 minutes to 2 hours weekly (65.8%),

while 26.3% spent more than 2 hours. This variation suggests that students approached GenAI as a learning support tool to different degrees during the course. Appendix 1 gives the summary of background information.

Table 1 summarises student perceptions of using GenAI as a learning tool. Overall, feedback was positive: a majority of students reported that GenAI was helpful for understanding core valuation concepts (71.1%) and for analysing the relationships between different models (73.7%). However, a significant portion also indicated drawbacks, noting that AI-generated explanations sometimes led to confusion (68.4%) or reduced clarity (60.6%). This suggests that GenAI outputs can be incomplete or lack necessary context. Consequently, GenAI is most effective as a supplemental tool rather than a stand-alone resource, highlighting the importance of guided instruction in helping students interpret and validate AI-generated outputs. And its use should be coupled with guided instruction to help students interpret, validate, and contextualise its outputs.

Table 1: Using GenAI to Learn Equity Valuation

Item	1	2	3	4	5	Mean	SD
GenAI helped me better understand core valuation concepts (e.g., DDM, FCF, WACC).	3 (7.9%)	0 (0%)	8 (21.1%)	18 (47.4%)	9 (23.7%)	3.79	1.06
GenAI was helpful in explaining complex financial terminology.	2 (5.3%)	3 (7.9%)	6 (15.8%)	18 (47.4%)	9 (23.7%)	3.76	1.06
I used GenAI to clarify topics and cases discussed in class.	2 (5.3%)	2 (5.3%)	6 (15.8%)	22 (57.9%)	6 (15.8%)	3.74	0.96
GenAI helped me understand the relationships among different valuation models.	3 (7.9%)	2 (5.3%)	5 (13.2%)	22 (57.9%)	6 (15.8%)	3.68	1.05
GenAI’s explanations sometimes confused me.	2 (5.3%)	2 (5.3%)	8 (21.1%)	19 (50.0%)	7 (18.4%)	3.71	1.00
Some concepts became less clear when I relied on GenAI for explanations.	1 (2.6%)	4 (10.5%)	10 (26.3%)	18 (47.4%)	5 (13.2%)	3.58	0.94

Note: N = 38. The survey utilises a 5-point Likert scale; 1 = Strongly Disagree, 5 = Strongly Agree.

Table 2 reports the student feedback on using GenAI in their equity valuation project, a key course assessment in the subject. Students widely perceived GenAI as a helpful tool throughout their equity valuation project, with mean

usefulness scores ranging from 3.37 to 3.76 on a 5-point scale. GenAI was rated most effective for structuring and drafting the final report (Mean = 3.76) and reliably useful for core technical tasks, such as data extraction, ratio analysis, model application, and key input estimation, where scores clustered between 3.50 and 3.58. However, its perceived utility was comparatively lower for broader, contextual tasks like company and industry background research (Mean = 3.37). This pattern indicates that GenAI serves best as a supplemental co-pilot for well-defined, quantitative analysis, while complex, nuanced interpretation still benefits from guided instruction and critical human oversight.

Table 2: GenAI’s Application in the Equity Valuation Project

Item	1	2	3	4	5	Mean	SD
Company and industry background research	1 (2.6%)	6 (15.8%)	12 (31.6%)	16 (42.1%)	3 (7.9%)	3.37	0.93
Extracting and summarizing key information from financial statements	2 (5.3%)	3 (7.9%)	10 (26.3%)	20 (52.6%)	3 (7.9%)	3.50	0.94
Performing ratio analysis and interpreting results	0 (0%)	4 (10.5%)	13 (34.2%)	16 (42.1%)	5 (13.2%)	3.58	0.85
Applying valuation models (e.g., DDM, FCF, REM)	0 (0%)	6 (15.8%)	11 (28.9%)	16 (42.1%)	5 (13.2%)	3.53	0.91
Estimating key inputs such as growth rates and terminal values	0 (0%)	5 (13.2%)	12 (31.6%)	16 (42.1%)	5 (13.2%)	3.55	0.88
Structuring and drafting the valuation report	1 (2.6%)	0 (0%)	9 (23.7%)	25 (65.8%)	3 (7.9%)	3.76	0.70
Reviewing and validating my own valuation assumptions	2 (5.3%)	2 (5.3%)	9 (23.7%)	18 (47.4%)	7 (18.4%)	3.68	1.00

Note: N = 38. The survey utilises a 5-point Likert scale; 1 = Strongly Disagree, 5 = Strongly Agree.

The survey also inquired about the primary benefits and main challenges students encountered when using GenAI. The survey results highlight a clear contrast in how students perceived GenAI. The primary benefits were practical: most students cited increased speed and efficiency, along with quick access to explanations. Conversely, the main challenges were analytical, with many reporting that outputs were often superficial and difficult to verify for reliability. Issues like factual inaccuracies and the risk of over-reliance were also commonly noted, while few found the technical process of prompting or using features to be a significant hurdle.

3.3 Semi-structured Interviews

Semi-structured interviews were conducted with five students regarding their use of GenAI in equity valuation. Thematic analysis of the transcripts revealed several prominent trends. As illustrated in Appendix 2, the findings are organised into five central themes, supported by direct student quotations.

Thematic analysis of student interviews revealed that Generative AI integration fundamentally reshapes learning approaches in equity valuation. Students developed prompt engineering as a core skill, learning to structure tasks for effective human-AI collaboration, which provided cognitive scaffolding aligned with guided learning. They also established personal critical evaluation frameworks, often using a three-stage process to verify outputs by comparing AI models, checking sources, and assessing logic. Encountering AI errors was frequently viewed as an opportunity for deeper investigation, reinforcing core competencies.

A notable learning paradox emerged: while GenAI boosted efficiency, students acknowledged it could sometimes shortcut the deeper cognitive engagement required for mastery, reflecting a tension highlighted in cognitive load theory. Ultimately, learners evolved from viewing AI as a mere tool to recognising it as a bounded strategic partner with specific capabilities and limitations. This shift underscored the need for transformed pedagogy, with students requesting instructors to act as guides and workflow designers to foster mindful, self-regulated collaboration.

4. Implications and Conclusions

This mixed-methods study demonstrates that integrating Generative AI into equity valuation education significantly enhances analytical efficiency and refocuses student effort on higher-order interpretation and strategy. However, its educational value is contingent upon the parallel development of critical GenAI literacy—the disciplined ability to command, validate, and critique GenAI outputs—rather than passive acceptance.

From a pedagogical perspective, the findings suggest several implications for course design. First, instructors may integrate structured human-AI collaboration tasks into finance education, requiring students not only to generate AI-assisted outputs but also to critically evaluate their validity. Second, assessment practices can emphasise transparent reasoning processes by encouraging students to explain how AI-generated results were interpreted, validated, or revised. Such approaches help ensure that GenAI enhances learning efficiency without replacing essential analytical thinking.

At a broader level, universities may consider developing guidelines for responsible GenAI integration in business education. These may include promoting AI literacy among students, clarifying expectations regarding AI-assisted academic work, and supporting faculty in designing effective human–AI collaborative learning activities.

The findings necessitate a pedagogical transformation. Instruction must evolve beyond introducing GenAI as a simple tool to explicitly cultivate competencies in prompt engineering, output verification, and assumption defence. This requires redesigning assessments to include tasks that mandate structured reasoning and justification without GenAI assistance.

Theoretically, this study contributes by operationalising critical digital literacy into a teachable framework of professional skills for finance. It provides empirical evidence for the dual effect of cognitive offloading: while GenAI saves time on computation and data collection for finance education, it can inadvertently reduce the cognitive engagement necessary for deep conceptual understanding unless activities are deliberately designed to counteract this. The central pedagogical challenge thus becomes balancing efficiency with effortful thinking to achieve durable learning.

In summary, this work responds to the global imperative for AI-ready graduates. By demonstrating how GenAI can function as a structured “co-pilot” in finance learning, the study provides a practical example of how AI tools can be integrated into specialised business education while preserving the central role of human judgment and critical thinking.

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Ethical Declaration Statement

The project has been approved by the Research and Innovation Office of The Hong Kong Polytechnic University (Reference Number: HSEARS20251118002).

Generative AI Policy

The authors used GPT and DeepSeek during the preparation of this work to instruct students to use GenAI, design and prepare initial survey and interview questions, and proofread the draft. After utilising the tool/service, the au-

thors thoroughly reviewed and edited the content as necessary and assumed full responsibility for the publication's content.

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Appendix 1: Summary of Background Information and GenAI Usage

Item / Category	Frequency	Percentage (%)
A1. Prior experience with GenAI		
1 = No prior experience	3	7.9
2 = Beginner	9	23.7
3 = Intermediate	14	36.8
4 = Proficient	10	26.3
Total (Valid)	36	94.7
Missing	2	5.3
A2. Frequency of use during the course		
1 = Less than once per week	2	5.3
2 = 1–2 times per week	18	47.4
3 = 3–5 times per week	3	7.9
4 = More than 5 times per week	13	34.2
Total (Valid)	36	94.7
Missing	2	5.3
A3. Weekly time spent using GenAI		
1 = Less than 30 minutes	2	5.3
2 = 30 minutes–1 hour	13	34.2
3 = 1–2 hours	12	31.6
4 = More than 2 hours	10	26.3
Total (Valid)	37	97.4
Missing	1	2.6

Appendix 2: Key Findings and Supporting Quotes from Interviews

Theme	Key Finding	Illustrative Evidence
Professionalization of prompt engineering	Students evolved from basic queries to structured, role-specific prompt design.	S1: “Now I specify the task context and requirements more concretely.”
Autonomous critical evaluation	Students developed multi-source verification strategies for AI outputs.	S2: “I ask several different AIs simultaneously. If they arrive at consistent conclusions based on different logic, the credibility is higher.”
Efficiency vs. cognitive reliance	GenAI boosted efficiency but raised concerns about over-reliance and shallow processing.	S2: “I became more reliant on the AI’s logical framework, and my own ability to independently conceive and write a complete report actually declined somewhat.”
Evolving understanding of GenAI	Student perceptions shifted from a generic tool to a nuanced understanding of its specific capabilities and limits.	S5: “I originally thought AI could only answer simple questions, but the new generation of models performs like a ‘high-EQ teacher’...”
Structured pedagogical appeal	Students requested systematic training in prompting and demonstrations of complete human-AI workflows.	S2: “I suggest using a full tutorial session to demonstrate a complete AI workflow from start to finish, rather than explaining it in fragments.”