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From Disruption to Design: Educator-Led Generative AI Learning Interventions in Marketing Education

La Toya Quamina[a], Rajab Ghandour[b], Felicity Hardley[c], and Ali Baig[a]

[a]Westminster Business School, University of Westminster, London, UK; [b]Liverpool Business School, Liverpool John Moores University, Liverpool, UK; [c]Centre for Academic Excellence, Global Banking School, London, UK

ABSTRACT
Generative Artificial Intelligence (GenAI) is transforming marketing practice and in turn marketing education. Yet educators lack empirical guidance on how best to implement GenAI pedagogically in the classroom. This study addresses that gap by examining how educator-led AI interventions, AI-Directed, AI-Supported, and AI-Empowered affect marketing students' motivation, engagement, satisfaction, and intentions to learn. Drawing on Agency theory and employing a between-subjects experimental design ($n = 160$), we find that AI-empowered interventions in which educators design open-ended tasks that balance structure with autonomy, significantly enhance motivation, engagement, and learning intentions. Our findings move beyond conceptual debates to offer empirically grounded, theory-informed recommendations for integrating GenAI into teaching practice. We argue for a reorientation toward theory-informed pedagogies that position GenAI as a means to foster agency not automation. Crucially, we recognize that educators play a central role in mediating GenAI's pedagogical relevance in marketing education.

Introduction

The global proliferation of Generative Artificial Intelligence (GenAI) in recent years cannot be ignored. It has significantly reshaped how we live and conduct business. Its impact has influenced sectors ranging from healthcare to commerce, transforming everyday practices and workflows (e.g., Gaur et al., 2021; Kshetri et al., 2023; Ma et al., 2023; Singh, 2024). In marketing, GenAI is already transforming practice. According to Singla et al. (2024), over 70% of marketing leaders reported using GenAI tools for content creation, customer segmentation, and campaign optimization which resulted in up to a 40% productivity increase in key marketing activities. More recently, Adobe reported that nearly 65% of senior executives are leveraging GenAI as a key contributor to driving marketing growth (Adobe, 2025). As GenAI redefines the skills required for marketing professionals, marketing education must evolve accordingly.

GenAI is no longer considered an emerging technology but rather a pedagogical imperative for preparing marketing graduates for an industry undergoing a technological transformation (Grewal et al., 2025; Schlegelmilch & Mills, 2025). GenAI refers to learning solutions trained to generate novel outputs such as text, images, or audio content based on user prompts, often by learning the structure and distribution of a given dataset (Feuerriegel et al., 2024). GenAI tools such as ChatGPT, Google Gemini, and Midjourney are already disrupting traditional marketing teaching practices by enabling new forms of activities such as campaign ideation, content creation, and strategic analysis (Guha et al., 2023; Mehmet et al., 2025). Marketing education is thus entering a period of transition. GenAI's integration is not simply about enhancing learning efficiency but cultivating creative and analytical capabilities central to the discipline. Marketing students must learn the skills required to work with GenAI in order to master core competencies that underpin marketing practices such as campaign planning, digital storytelling, creative problem solving, and strategic data literacy.

Existing research on GenAI in marketing education has predominantly focused on three streams: drivers of GenAI adoption, including perceived risk, ease of use and performance expectancy (e.g., Gulati et al., 2024; Oc et al., 2025), challenges, and benefits of GenAI integration (e.g., Jürgensmeier & Skiera, 2024; Richter et al., 2024) and its impact on learning outcomes (e.g., Allil, 2024; Pavone, 2025). Despite these insights, a critical gap persists in marketing education. There is a dearth of

CONTACT La Toya Quamina L.Quamina@westminster.ac.uk Westminster Business School, University of Westminster, 35 Marylebone Rd, London NW1 5LS, United Kingdom

empirically grounded research that explores *how* GenAI can be pedagogically integrated in classrooms to empower marketing students' learning and *under what conditions* it is most effective (Guha et al., 2023; Mehmet et al., 2025). Therefore, understanding how pedagogical models of GenAI can be used to improve students' outcomes is vital for marketing educators designing curricula.

Building on Ouyang and Jiao's (2021) paradigms of Artificial Intelligence (AI) in Education, i.e., AI-Directed (learner-as-recipient), AI-Supported (learner-as-collaborator), and AI-Empowered (learner-as-leader), we examine how educator-led AI interventions which vary in the degree of autonomy and guidance affect student outcomes within a marketing education context. Drawing on Agency Theory (Jensen & Meckling, 1976; Ross, 1973) and Self-Determination Theory (Deci & Ryan, 1985; Ryan & Deci, 2000), we investigate how educator-designed AI interventions that vary in the degree of autonomy and guidance influence student motivation, engagement, satisfaction, and learning intentions. In addition, we explore whether student characteristics, such as their attitudes toward technology and learning preferences, impact the effectiveness of the interventions. Our findings show that AI-Empowered interventions, where educators design tasks that enable students to independently navigate GenAI tools for marketing tasks, significantly enhance learning experiences. In doing so, we reframe GenAI's integration from a focus on technology adoption to one centered on pedagogical design that develops marketing student agency and competence.

By identifying the pedagogical conditions under which GenAI interventions best support student learning, we argue that the value of GenAI in marketing education depends on how educators integrate it to build student skills and competency. From social media management to full-scale marketing campaigns, GenAI is changing the way marketers do their jobs and consequently how educators must design curricula to respond to the evolving marketing landscape. The question, therefore, facing educators is not whether GenAI should be included but how. We offer marketing educators evidence-based insights for integrating GenAI in ways that are empowering and pedagogically sound.

Theoretical Background and Hypotheses Development

GenAI in Marketing Education

The emerging body of the literature on GenAI's integration into marketing education reflects a growing scholarly interest driven by rapid developments in both industry practice and pedagogical innovation. It can be broadly organized into three main streams: drivers of adoption, challenges versus benefits, and impact on teaching and learning. These streams demonstrate how GenAI is beginning to reshape educational design, instructional practice, and proficiency development within marketing curricula.

The first stream identifies drivers of GenAI adoption in marketing education (e.g., Acar, 2024; Gulati et al., 2024; Oc et al., 2025), including perceived usefulness and performance expectancy, and how it shapes students' and educators' readiness to engage with GenAI in the classroom (e.g., Acar, 2024; Slepchuk & John, 2025; Yao & Wang, 2025). Oc et al. (2025) highlight that students' adoption of GenAI tools is influenced by perceived risk and tech-savviness, suggesting that effective integration must address confidence, trust, and broader ethical considerations such as accuracy, fairness, and responsible use. Gulati et al. (2024) note that when students believe that GenAI will enhance their efficiency and academic performance, their intention to use increases. Adoption is also driven by a wider response to industry transformation. Research shows that educators are now designing assessments where students are encouraged to use GenAI tools for various in-class marketing tasks like campaign ideation and evaluation, which demonstrates a shift from ad hoc experimentation to integrated practice (e.g., Beninger et al., 2025; Guha et al., 2023). For example, Beninger et al. (2025) describe marketing classes where students used ChatGPT to develop marketing campaign concepts and then self-evaluated their outputs. The authors show that students initially viewed GenAI as highly efficient but after reflection recognized its tendency toward generic responses and misinformation, demonstrating that students' perceptions of usefulness and ease of use evolve with more understanding of GenAI's capabilities and limitations. Scholars note that the move to integrate GenAI in marketing education is driven by necessity to prepare graduates for future marketing roles (Grewal et al., 2025; Schlegelmilch & Mills, 2025; Turner-Henderson et al., 2025).

The second stream highlights the challenges and benefits of GenAI's use in marketing education. Scholars offer that GenAI enhances students' skills and confidence by facilitating idea generation, simulating creativity, and offering scaffolded feedback (e.g., Beninger et al., 2025; Guha et al., 2024; Kasneci et al., 2023). Empirical studies of classroom adoption found that integrating GenAI to support learning activities in marketing courses can enhance students' overall efficiency (e.g., Morgan et al., 2025) and enable educators to provide timely and personalized feedback to students even in resource constrained teaching environments (e.g., Jürgensmeier & Skiera, 2024). Most significantly, incorporating GenAI tools to support tasks such as predictive analytics and customer segmentation offers students the opportunity to understand complex marketing concepts through practical applications and experimentation (Grewal et al., 2025; Mehmet et al., 2025). In contrast, studies also show the negative impact of GenAI. While marketing educators acknowledge the pedagogical benefits of GenAI's integration in the classroom, persistent concerns about data privacy, plagiarism, misuse, student overreliance, as well as the potential erosion of students critical thinking and academic integrity exist (e.g., Acar, 2024; Narang et al., 2025; Richter et al., 2025). Karimova et al. (2025) suggest that marketing students hold dual perceptions regarding GenAI: while they acknowledge its utility in enhancing creativity, they also express concerns about overreliance potentially eroding their own creative skills. Slepchuk and John (2025) cautions that while incorporating AI technologies into marketing curricula may better prepare students for careers in an increasingly technology-integrated world, overreliance may also hinder learning outcomes. Echoing this concern, Acar (2024) emphasizes the need for robust frameworks and digital literacy training for thoughtful and responsible implementation of GenAI. In response, there is a current shift in higher education from prohibition and detection to designing transparency measures within assessments such as prompt logs and disclosure statements (Corbin et al., 2025).

The third emerging stream examines GenAI's impact on students' learning outcomes. Several studies identify improvements in learning engagement and creative output (e.g., Albakry et al., 2025; Alfarsi et al., 2024; Allil, 2024; Singh & Huang, 2025). For example, Singh and Huang (2025) found that integrating GenAI tools into the creative process and encouraging discussions about its capabilities and limitations enhanced students' engagement, as well as their analytical and creative capacities. Alfarsi et al. (2024) report that GenAI's integration into a media content creation class positively impacted students' engagement, motivation, and persistence in completing tasks. Similarly, Pavone (2025) found that student motivation and satisfaction were significantly enhanced when using GenAI tools, particularly among students with higher self-esteem.

While the above empirical studies highlight the impact of GenAI on marketing students' learning outcomes, they predominantly emphasize enhancements in creative and analytical skills. While some studies have examined outcomes such as motivation and engagement, these typically focus on students' satisfaction with GenAI tools themselves (e.g., Pavone, 2025) rather than their broader learning experience. Limited attention has been given to how different pedagogical approaches to GenAI integration can be used to optimize learning outcomes. As Acar (2024) argues, further enquiry into GenAI integration in marketing education must evolve from debating whether to use GenAI but to determining the pedagogical conditions under which it adds the greatest educational value. Addressing this gap, the present study empirically examines how varying models of AI integration: AI-Directed, AI-Supported, and AI-Empowered influence marketing students' motivation, engagement, satisfaction, and learning intentions. Our central question shifts focus on whether AI improves learning to *how* it should be implemented. Our research builds on a growing body of work calling for more critical, theory-informed, and empirically grounded engagement with technology in marketing education.

AI Interventions: AI-Directed, AI-Supported, and AI-Empowered

AI interventions can be characterized into three paradigms as per Ouyang and Jiao's classifications (2021): AI-Directed, AI-Supported, and AI-Empowered. Each intervention varies in the degree of autonomy and guidance educators design into the learning process and offers distinct implications for teaching practice and instructional design.

AI-Directed (Learner-As-Recipient)

AI-Directed learning reflects a Behaviorist orientation (Skinner, 1958), where learning is seen as the acquisition of knowledge through specific instructions. In this model, GenAI tools are used to deliver content in tightly controlled learning environments, often through predefined prompts and fixed learning pathways. Teaching aligns with Greeno's et al. (1996) framework, where success is measured by accuracy and progression through linear sequences of content. From a pedagogical perspective, this intervention positions students as passive recipients and offers limited scope for independent reasoning or critical engagement, raising questions about its effectiveness in fostering deeper, transferable learning.

AI-Supported (Learner-As-Collaborator)

In AI-Supported learning, GenAI is used to facilitate guided learner-directed interactions based on the Social Constructivist orientation (Palincsar, 2005) that learning occurs through interactions with technology, information, and other people. In this approach, students are provided with some guidance on how to use GenAI to accomplish learning tasks. Here, AI plays a facilitative role, offering guidance and resources within a semi-structured environment. Students receive some instructions on how to use GenAI tools to complete tasks but are encouraged to explore and adapt the technology to suit their needs. While offering more autonomy than AI-Directed, AI-Supported interventions still operate within educator-defined boundaries and may not fully realize the potential of student-centered learning design.

AI Empowered (Learner-As-Leader)

AI-Empowered learning reflects an Experiential Constructive orientation (Kolb, 2014) where students take an active role in shaping and directing their learning process. In this paradigm, GenAI is viewed as a tool to augment human intelligence rather than replace it. Educators design open-ended learning opportunities that delegate autonomy to students who navigate GenAI tools independently, manage risks related to AI outputs, critically assess their outputs, and integrate them into their learning to support their own goals and strategies. The educator's role shifts from instructor to mentor, supporting students in making informed choices and reflecting critically on their use of GenAI.

Table 1 summarizes the three intervention paradigms in marketing education, highlighting the educator's evolving role, pedagogical orientation, and instructional design implications. Underpinned by Agency theory (Jensen & Meckling, 1976; Ross, 1973), we posit that an AI-Empowered intervention, which delegates greater autonomy through educator-designed structures, will have a more positive impact on students' learning outcomes compared to AI-Directed or AI-Supported interventions.

Educator-Led Design and Delegated Agency in Generative AI Learning Interventions

Agency theory (Jensen & Meckling, 1976; Ross, 1973), originally formulated to describe the relationship between principals and agents in business contexts, provides a useful lens for understanding how educators design and delegate control within AI integrated learning environments. In our adaptation, educators (principals) structure classroom interactions and distribute responsibility and autonomy to students (agents) based upon the pedagogical orientation of varying AI intervention models. As such, the key differences among the AI-Directed, AI-Supported, and AI-Empowered interventions reflect how educators' structure and allocate control and responsibility within the learning tasks. Here, educators determine how much control, decision-making authority, and task ownership are delegated to students when interacting with GenAI tools. AI-Directed intervention involves high educator control through fixed prompts and structured learning pathways. In contrast, AI-Supported intervention involves shared responsibility where the educator provides partial scaffolding and guidance. AI-Empowered intervention delegates autonomy where educators act as mentors who guide students in independently navigating, evaluating, and integrating GenAI tools into their learning strategies. This educator-led design perspective aligns with the premise of Agency theory that performance outcomes depend on how control and autonomy are distributed between principals and agents (Eisenhardt, 1989).

However, to understand the motivational processes underlying these effects, we also draw on Self-Determination theory (Deci & Ryan, 1985; Ryan & Deci, 2000) which posits that intrinsic motivation and engagement increase when students experience autonomy, competence, and relatedness. Educator design choices that encourage students to take ownership in AI collaboration tasks (as in AI-Empowered intervention) are therefore more likely to satisfy these needs more effectively than structured or directive approaches that restrict autonomy and reduce intrinsic motivation.

Higher education scholars support our above reasoning (e.g., Guoxia & Yang, 2024; Hofferber et al., 2014; Mammadov & Schroeder, 2023; Stenalt & Lassesen, 2022; Wu & Dong, 2024). For example, Reeve and Tseng (2011) found that agentic engagement, i.e., students' active contribution that shapes the flow of instruction and the learning experience enhances motivation and engagement. More recently, Fujii (2024) shows that higher perceived autonomy support (i.e., opportunities for student choice in methods, materials, and assignments) leads to better learning effectiveness and academic performance. Within marketing education, empowering students to use GenAI tools autonomously for tasks such as campaign ideation or market analysis can strengthen confidence and engagement, reflecting the synergy between educator-led design and learner motivation (Richter et al., 2024). While Agency theory helps explain how control and responsibility are structured within AI learning interventions, Self-Determination theory explains the motivational processes through which these structures influence student learning outcomes. Accordingly, we propose that AI interventions that delegate greater autonomy through educator-designed structures of control (i.e., AI-Empowered intervention) will produce superior

Table 1. GenAI interventions in marketing education.

GenAI Intervention (Ouyang & Jiao, 2021)	Educator Role	Instructional Design Characteristics	Example Classroom Task/Activity	Pedagogical Orientation	Implications for Marketing Education
AI-Directed	Instructor and controller	Educator provides predefined prompts and fixed pathways; students follow structured steps using GenAI outputs to complete narrowly defined marketing tasks.	Students are tasked with generating campaign taglines for Brand X using GenAI tools such as ChatGPT, Copy. ai, etc. They must follow a fixed set of educator-supplied prompts (e.g., Create promotional slogans emphasising sustainability) and then select the best output based on predefined criteria.	Behaviorist (Skinner, 1958)	Can develop basic familiarity with GenAI tools for marketing communication and idea generation. May be effective for introducing prompt design and message framing, though offers limited scope for deeper insight or creative problem-solving.
AI-Supported	Facilitator and guide	Educator offers partial scaffolding and sample prompts while allowing students some freedom to explore GenAI responses; reflection guided by educator.	Students are tasked with developing digital ad content for Brand X using GenAI tools such as ChatGPT or Canva Magic Write, etc. They receive example prompts and guided reflection questions but create their own follow-up queries to refine GenAI-generated ad copy or visuals for a defined target audience segment, working within a semi-structured environment.	Social-constructivist (Palincsar, 2005)	Can strengthen applied creativity and evaluative judgement in marketing communication. May help students critique and adapt GenAI outputs for brand voice, segmentation, positioning and for bridging creative and analytical skills.
AI-Empowered	Mentor and coach	Educator designs open-ended tasks that delegate autonomy to students within defined learning boundaries; students independently navigate and critique GenAI tools with reflective feedback.	Students are tasked with independently designing and justifying an integrated marketing campaign for Brand X using GenAI tools such as ChatGPT, Midjourney, etc. They determine their own prompting strategy, create campaign assets, develop performance metrics and submit a reflective report on their ethical and strategic decisions.	Constructivist (Palincsar, 2005)	Can enhance strategic and ethical competencies central to marketing practice integrating market analysis, creative concepting, and campaign evaluation. May prepare students to lead AI-augmented strategy development and produce client-ready marketing solutions.

learning outcomes relative to AI-Directed or AI-Supported interventions, as they better balance instructional structure with opportunities for autonomy and competence development. Thus:

H1a: AI integration that facilitates more agency and autonomy (AI-Empowered intervention) will have a more positive impact on students' motivations than AI-Directed or AI-Supported interventions.

H1b: AI integration that facilitates more agency and autonomy (AI-Empowered intervention) will have a more positive impact on students' engagement than AI-Directed or AI-Supported interventions.

H1c: AI integration that facilitates more agency and autonomy (AI-Empowered intervention) will have a more positive impact on students' satisfaction than AI-Directed or AI-Supported interventions.

H1d: AI integration that facilitates more agency and autonomy (AI-Empowered intervention) will have a more positive impact on students' learning intentions than AI-Directed or AI-Supported interventions.

The Moderating Impact of Attitude to Tech

While educators design the structure of AI learning interventions, students' individual characteristics also shape how effectively they engage with these designs. Attitude toward technology refers to an individual's overall disposition and feelings toward the use and integration of technology in various aspects of life (Martínez Romero et al., 2020). It encompasses dimensions such as perceived usefulness and perceived ease of use. Davis (1989) Technology Acceptance Model (TAM) underscores that perceived ease of use and usefulness are critical factors influencing technology adoption. According to TAM, individuals who view technology tools as user-friendly and beneficial are more likely to engage with them proactively and positively.

In higher education, positive disposition toward tech adoption plays a crucial role in moderating the impact of technology in educational settings (Nketiah-Amponsah et al., 2017; Stošić & Fadiya, 2017). Students with high levels of technological acceptance are more likely to engage deeply with technological tools, utilize them effectively, and thus derive greater academic benefits. For example, Teo (2011) found that students' attitudes toward technology significantly predicted their intention to use educational technologies, influencing actual usage and learning performance. Bandura's (1997) self-efficacy theory suggests that students with high self-efficacy in using technology are more confident in leveraging these tools for learning, leading to more effective use and better outcomes. Oc et al. (2025) found that students' perceived usefulness, trust, and tech-savviness significantly increased their adoption of GenAI tools, while perceived risk reduced it, highlighting the critical role of attitudinal factors in shaping AI usage and its educational impact. We argue that this confidence and proactive usage will amplify the positive effects of AI interventions. Therefore, students who are more open and positive toward technology will use GenAI tools more frequently and effectively, maximizing their learning outcomes. Hence:

H2:The effect of AI interventions on student learning outcomes is moderated by students' attitudes toward technology, such that the effect is stronger for students with more positive attitudes toward technology, particularly for learning intentions.

The Moderating Impact of Learning Styles

Previous studies suggest that individual differences have an impact on technology use (Blut & Wang, 2020; Yi et al., 2005). For example, Gefen and Straub (1997) found that males and females have different perceptions about ease of use toward e-mail systems, affecting their usage behavior. Dabholkar and Bagozzi (2002) found that personal traits like inherent novelty seeking influence the attitudes toward using a technology and intention to use it. Agarwal and Prasad (1998) suggest that individual difference variables which include personal traits, demographic variables, and situational variables account for differences attributable to personal circumstances. We argue that students' learning styles are one such individual variable.

Learning styles represent the preferential ways individuals process information, typically categorized into Visual, Auditory, and Kinesthetic preferences (Fleming & Mills, 1992). Visual learners remember details through visual context such as images, diagrams, charts, and often prefer to read or write as a method of learning. Auditory learners retain information best through listening and speaking, preferring discussions, lectures, and audio recordings. Kinesthetic learners prefer hands-on learning, engaging in physical activities rather than lectures or watching demonstrations. These learners often learn best through trial and error, physical activities and real-life experiences. Recent marketing education research highlights the importance of pedagogical approaches that cater to diverse learner needs and promote flexibility. For example, Richter et al. (2024) argue that AI integration grounded in constructivist learning enables students to engage in an active learning environment and deepen knowledge retention in ways that align with their individual learning experience. Complementing this, Beninger et al. (2025) emphasize developing interpretive flexibility as essential for marketing students to navigate GenAI outputs critically and creatively.

The moderating role of learning styles on technology has been theorized in a few studies (Cruz et al., 2014; Huang et al., 2020). Scholars suggest that students are not one dimensional and that mixed learning styles offer significant advantages over singular learning preferences in educational contexts. Mayer (2001) demonstrated that students receiving both verbal and visual instructions scored higher on tests than those receiving only one type. Similarly, Moreno and Mayer (2007) found that multimedia learning environments, catering to mixed learning styles, lead to better retention and knowledge transfer. From this perspective, we offer that mixed learning styles which encompass a combination of visual, auditory, and kinesthetic preferences allows for greater flexibility in learning, enabling students to leverage GenAI's multimodal capabilities more effectively and leading to improved learning outcomes. Thus:

> **H3**:AI interventions are moderated by learning styles, such that the effect is stronger for students with a propensity for mixed learning styles than singular Visual, Auditory, and Kinesthetic p references.

Figure 1 illustrates the conceptual model for our study.

Methodology

Research Design and Sample

We conducted a single-factor between-subjects experiment (AI interventions: AI-Directed vs AI-Supported vs AI-Empowered) to test our hypotheses. Participants were assigned to three experimental groups: AI-Directed ($n = 59$), AI-Supported ($n = 51$), and AI-Empowered ($n = 50$). The study was conducted at a Business School in Europe and participants included first year undergraduate students enrolled on a marketing degree, with similar level of academic qualification. No exclusion criteria were defined as the study was conducted once and only participants who were present in class participated. The sample $n = 160$. Participants were predominantly aged 18–24 years (91.3%), with 7.5% aged 25 years or older. Females comprised 51.2% of the sample. The ethnic composition was diverse, with 31% identifying as Asian, 28% as White, 26% as Mixed ethnicity, 9% as Black, and 6% preferring not to disclose their ethnicity.

Manipulation Checks

To check the AI interventions and respective educator-led instructions were distinct, manipulation checks were conducted using undergraduate students ($n = 125$) recruited using Prolific Academic, an online research participant platform for academic research (www.prolific.ac). Mean differences across the three interventions: AI-Directed, AI-Supported, and AI-Empowered were significant (*AI-Directed*: $M_{AiDirected} = 5.70$ SD = 1.20, $M_{AiSupported} = 4.12$ SD = 1.31, $M_{AiEmpowered} = 3.51$ SD = 1.39, $F(2,122)=30.81$, $p < .001$; *AI-*

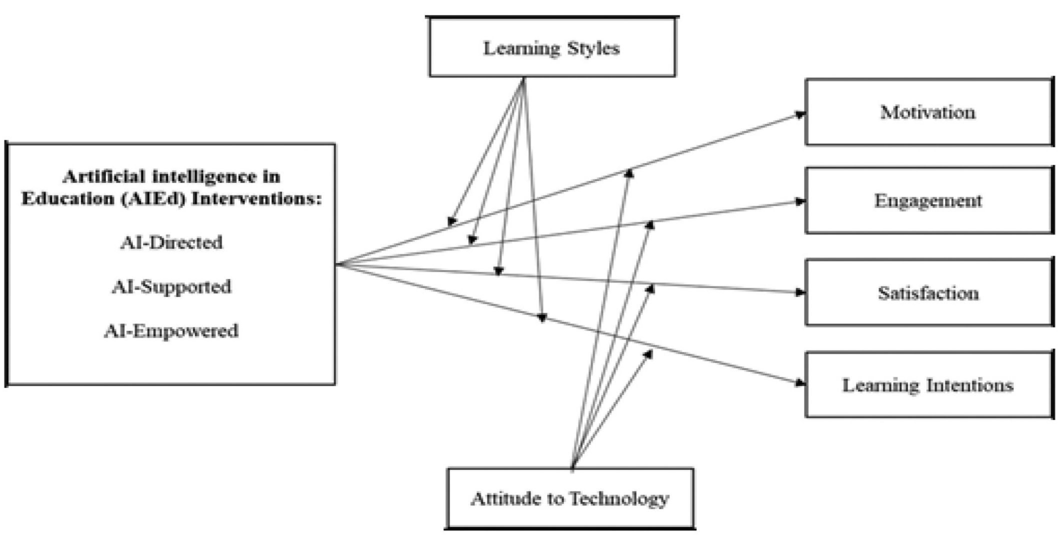

Figure 1. Conceptual framework. Source: Authors Own Work.

Empowered = $M_{AiDirected}$ = 2.93 SD = 1.72, $M_{AiSupported}$ = 3.74 SD = 1.13, $M_{AiEmpowered}$ = 5.86 SD = 1.13, $F(2,122)=53.37$, $p < .001$; *AI-Supported* = $M_{AiDirected}$ = 3.80 SD = 1.54, $M_{AiSupported}$ = 5.43 SD = 1.02, $M_{AiEmpowered}$ = 4.47 SD = 1.42, $F(2,122)=15.33$, $p < .001$). These results confirmed that the three educator-led interventions were perceived as distinct and functioned as intended.

Data Collection

Students were randomly assigned to one of the three seminar groups, each receiving a distinct AI intervention (AI-Directed vs AI-Supported vs AI-Empowered). Following the usual seminar format, students were presented with a marketing case and a set of related marketing research questions for analysis and discussion. Prior to the task, all groups viewed a short introductory video explaining what ChatGPT is, how to access it, and key reminders for its ethical and effective use. Students had been introduced to GenAI tools in earlier seminars over the semester as part of ongoing discussions on AI in marketing and digital practice, therefore, the video served as a refresher and standardized baseline of understanding across groups. Immediately afterward, participants completed short items assessing their preferred learning approach and attitudes toward technology. Participants in each group then received the same task but received different educator instructions (detailed below) regarding how they could use ChatGPT 3.5 to support their analysis. Ethical clearance was approved at the institutional level. Students were informed the research was part of pedagogic academic research and given the option to participate (11 of the 171 students present opted out, resulting in 160 completed surveys). The seminar sessions were facilitated by the regular teaching staff, who were not part of the research team. One member of the research team was present per seminar only to administer and collect the surveys. A non-AI seminar group was also included ($n = 31$); however, given the smaller and unbalanced control group relative to the AI conditions, comparisons with the non-AI seminars were not considered sufficiently robust for inclusion in the main analysis.

In the AI-Directed group, the educator retained full control over the task structure. Participants engaged with ChatGPT using predefined prompts and explicit procedural guidance designed to ensure consistent task completion. Example (Directed instruction): *Using ChatGPT, explore key macro-environmental trends likely to impact Brand X over the next 12 months in the UK. Use the following prompts to guide your analysis: 1) What are the key macro trends impacting Brand X in the UK?* Over ten educator-provided prompts were supplied.

In the AI-Supported group, the educator designed a semi-structured learning environment that provided scaffolding and examples while allowing students some flexibility to adapt the GenAI interaction. Example (Supported instruction): *Using ChatGPT, explore key macro-environmental trends likely to impact Brand X over the next 12 months in the UK. You may create your own list of prompts, but the following example illustrates how you might proceed: What are the key macro trends impacting Brand X in the UK? After reviewing ChatGPT's response, consider whether the output is sufficiently specific and whether follow-up questions are required.*

In the AI-Empowered group, the educator delegated full autonomy to participants. Students were encouraged to independently plan, prompt, and evaluate their use of the GenAI chatbot to achieve the learning objectives. Example (Empowered instruction): *Using ChatGPT, explore key macro-environmental trends likely to impact Brand X over the next 12 months in the UK. You are free to determine how to structure your prompts, sequence your queries, and evaluate ChatGPT's responses to complete the task.*

Participants then spent time completing the marketing research activity, followed by questions reflecting on the perceived utility of GenAI in facilitating their learning experiences. Each seminar lasted 2 hr. To minimize potential biases, while ensuring confidentiality, participants completed unrelated filler questions between different sections of the questionnaire, following established guidelines in survey methodology (Podsakoff et al., 2012). All constructs were measured using scales adapted from established measures in the literature, and responses were recorded on a 7-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. Composite Reliability (CR) and Average Variance Extracted (AVE) were calculated based on standardized factor loadings obtained from exploratory factor analysis (EFA) conducted in SPSS. These values were computed manually using Microsoft Excel, following established procedures (Fornell & Larcker, 1981; Hair et al., 2014). The Average Variance Extracted (AVE) for Engagement and Motivation falls marginally below the .50 threshold; however, consistent with established guidance that Composite Reliability (CR) over the .60 threshold can compensate for slightly lower AVE, the constructs were retained (Fornell & Larcker, 1981; Hair et al., 2014). Discriminant validity was further assessed using the HTMT criterion. While most HTMT values were within acceptable thresholds,

Table 2. Constructs descriptive statistics.

Measurement Items		α	CR	AVE
Learning Intentions (Alavi, 1994)	The teaching tool used in the seminar activity today, have helped me:	.91	.90	.50
	Increase my critical thinking skills			
	Increase my ability to integrate facts (synthesise)			
	Critically analyse issues			
	Be more confident in expressing ideas			
	Learn to value other points of view			
	Learn to interrelate important topics and ideas			
	Increase my understanding of basic marketing concepts			
	Learn factual material			
	Learn to identify central issues			
	Discuss topics outside the class			
	Do additional reading			
	Do some thinking for myself			
Engagement (Alavi, 1994, akin to Classroom Experience)	I found the seminar activity a good learning experience	.84	.73	.45
	I learned more because of the seminar activity format			
	I found the seminar activity boring			
	I found the teaching tools used in the seminar activity useful			
	I found the teaching tools used in the seminar activity have contributed to the module quality			
	I found the teaching tools used in the seminar activity contributed to my learning			
	I found the teaching tools used in seminar activity fun			
Satisfaction (Ahmad et al., 2020)	I have been very satisfied with this seminar activity	.87	.84	.54
	I have enjoyed this seminar activity			
	I have been very dissatisfied with this seminar activity (r)			
	I have been happy taking this seminar activity			
	I have not enjoyed this seminar activity (r)			
Motivation (Hsiao & Su, 2021)	The teaching tools used in the seminar activity was full of challenges and it makes me want to learn new things	.87	.78	.48
	Using teaching tools like those used in the seminar activity, I can successfully complete the module content			
	I believe I can get good grades in the module using teaching tools like those used in the seminar activity			
	Using teaching tools like those used in the seminar activity, I can absorb the module knowledge and learning better			
Attitude to Technology (Edison & Geissler, 2003)	Technology is my friend	.81	.91	.55
	I enjoy learning and hearing about new technologies			
	People expect me to know about technology and I don't want to let them down			
	If I am given an assignment that requires that I learn to use new technology, I usually succeed			
	I relate well to technology			
	I am comfortable learning new technology			
	I know how to deal with technological malfunctions or problems			
	Solving a technological problem seems like a fun challenge			
	I find most technology easy to learn			
	I feel as up-to-date on technology as my peers			

(*Continued*)

Table 2. (Continued).

Measurement Items		α	CR	AVE
Learning Styles (Reid, 1987)	I prefer to learn by watching demonstrations or videos	.85	.95	.42
	I find it easy to remember information presented in graphs or charts			
	I enjoy reading and often visualise concepts in my mind			
	I benefit from using colour-coded notes or highlighters to organise information			
	I often use visual aids like diagrams or flowcharts to understand complex ideas			
	I find that seeing images or pictures helps me grasp concepts better			
	I remember faces and places more easily than names or verbal information			
	I enjoy visiting museums or art galleries to learn about new topics			
	I learn best by listening to lectures or participating in discussions			
	I remember information better when I hear it spoken aloud			
	I find it easy to follow verbal instructions without needing written guidelines			
	I enjoy listening to podcasts or audiobooks to absorb new information			
	I like to engage in conversations or debates to understand different perspectives			
	I often use verbal cues or mnemonics (e.g., rhymes or acronyms) to remember important details			
	I am good at memorising information presented in songs or rhymes			
	I find that discussions with peers help me solidify my understanding of a topic			
	I learn best when I can physically interact with objects or perform hands-on activities			
	I remember information better when I can actively participate or experiment with it			
	I enjoy activities like experiments, simulations, or role-playing to grasp concepts			
	I prefer to take breaks during study sessions to move around and re-energise			
	I like to use gestures or body movements to express ideas or concepts			
	I enjoy activities like sports, dance, or other physical pursuits			
	I find it helpful to use props or models to understand abstract concepts			
	I learn best when I can touch or manipulate objects related to the topic			
	I adapt my learning style based on the situation or subject matter			
	I feel comfortable using a combination of visual, auditory, and kinesthetic (physical activity) methods to learn.			
	I find that a blend of visual aids, discussions, and hands-on activities works best for me			
	I don't strongly lean toward one particular learning style and can adapt to various teaching methods			
	I am open to trying different learning approaches to see what works best for me			
	I believe that a balanced approach incorporating visual, auditory, and kinesthetic (physical activity) elements is most effective for my learning			

Discriminant Validity Assessment Using the HTMT Criterion

	Attitude Toward Tech	Engagement	Learning	Learning Style	Motivation	Satisfaction
Attitude TowardTech						
Engagement	0.392					
Learning	0.370	0.791				
LearningStyle	0.538	0.339	0.389			
Motivation	0.485	0.933	0.761	0.261		
Satisfaction	0.376	0.820	0.564	0.247	0.688	

Note: α = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted.

the value between engagement and motivation slightly exceeded the recommended 0.90 cutoff. This suggests a high degree of association between these constructs, which is consistent with prior research in educational contexts where engagement and motivation are closely interrelated (e.g., Fredricks et al., 2004; Howard et al., 2021; Skinner et al., 2009). Given their theoretical distinctiveness and acceptable reliability, both constructs were retained for further analysis. Table 2 presents the construct descriptives.

Analysis and Findings

Data analysis was conducted using SPSS 29. For the purpose of analysis, construct scores were computed as the mean of their respective items, with all items equally weighted. To examine the overall effect of AI intervention type on student engagement, motivation, learning intentions, and satisfaction, a multivariate analysis of variance (MANOVA) was first performed. This approach accounts for the correlations among the dependent variables and reduces the risk of inflated Type I error when testing multiple outcomes simultaneously. The MANOVA revealed a significant multivariate effect of the treatment group on the combined dependent variables, Pillai's Trace = ($p < .001$) indicating that the three intervention conditions (AI-Directed, AI-Supported, AI-Empowered) differed collectively across student engagement, motivation, learning intentions, and satisfaction (see Table 3). Follow-up one-way ANOVA was conducted to determine on which specific outcomes these differences occurred. Using one-Way ANOVA, we tested hypothesis H1. The results as presented in Figure 2 show significant differences between the AI-Directed, AI-Supported, and AI-Empowered groups on student engagement ($p < .05$), motivation ($p < .05$), learning ($p < .05$), and satisfaction ($p < .05$). Tukey HSD post hoc analysis showed that AI-Empowered achieved higher engagement compared to AI-Supported ($p < .01$) and AI-Directed ($p < .01$). Significant differences in learning were found between the AI-Empowered and the other two groups ($p < .01$). Similarly, satisfaction levels were significantly higher in AI-Empowered compared to AI-Supported ($p < .01$) and AI-Directed ($p = .01$). For motivation, significant differences were found between AI-Empowered and AI-Supported ($p < .01$) but not between AI-Empowered and AI-Directed. Thus, H1a–H1d were supported. Tables 4 and 5 present the detailed results.

To examine whether students' attitudes toward technology moderated the effect of AI intervention type on learning outcomes, a regression-based moderation analysis was conducted using Hayes' PROCESS macro (Model 1) with dummy-coded variables (AI-Empowered vs AI-Directed and AI-Supported vs AI-Directed). This approach is appropriate for testing the interaction effects using composite variable in experimental research design and provides robust estimation of moderation. While structural equation model (SEM) offers advantages for modeling latent constructs, the presented study focuses on observed variable and direct interaction effects. Additionally, given the sample size and model, Hayes PROCESS provides more suitable method. The results indicated that the interaction between intervention type and attitude toward technology was not significant for engagement, motivation, or satisfaction (all $p > .05$). However, for learning intentions, the interaction between the AI-Empowered intervention and attitude toward technology approached significance ($B = 0.309$, $p = .058$), indicating that students with more positive attitudes toward technology benefited more from the AI-Empowered intervention. No significant moderation effects were observed for the AI-Supported intervention across any outcome. Overall, the findings do not provide support for H2. However, the near-significant interaction observed for learning intentions in the AI-Empowered condition may indicate a potential relationship that warrants further investigation in the future research. Full results are presented in Table 6.

The moderating impact of learning styles on AI interventions was tested using a two-way ANOVA. The results showed that learning styles (visual, auditory, kinesthetic, and mixed) did not significantly moderate the impact of AI interventions on satisfaction, engagement, motivation, and learning intentions ($p > .05$ for all variables). Specifically, the interaction effects were not significant, suggesting that the type of learning style did not influence the effectiveness of the AI interventions. Thus, H3 was rejected.

Discussion

The statistical analysis confirms our hypotheses that an AI-Empowered instructional intervention designed to balance educator guidance with student autonomy positively impacts on students' motivation (H1a), engagement (H1b), satisfaction (H1c), and learning intentions (H1d) more than AI-Directed and AI-Supported interventions. ANOVA results show significant differences, with the AI-Empowered group consistently outperforming the others. These findings suggest that when educators deliberately structure learning to delegate appropriate control to students, ownership, and flexibility enhance students' learning experience and outcomes. Moreover, the post hoc Tukey analysis further

Table 3. Statistical findings MANOVA.

Effect		Value	F	Hypothesis Df	Error Df	Sig.
Intercept	Pillai's Trace	.978	1724.875[b]	4.000	154.000	<.001
	Wilks' Lambda	.022	1724.875[b]	4.000	154.000	<.001
	Hotelling's Trace	44.802	1724.875[b]	4.000	154.000	<.001
	Roy's Largest Root	44.802	1724.875[b]	4.000	154.000	<.001
TREATMENT_GROUP	Pillai's Trace	.259	5.755	8.000	310.000	<.001
	Wilks' Lambda	.754	5.852[b]	8.000	308.000	<.001
	Hotelling's Trace	.311	5.947	8.000	306.000	<.001
	Roy's Largest Root	.245	9.499[c]	4.000	155.000	<.001

a. Design: Intercept + TREATMENT_GROUP
b. Exact statistic
c. The statistic is an upper bound on F that yields a lower bound on the significance level.

elucidates where the AI-Empowered intervention excels. Significant differences in engagement and satisfaction between empowered and the other two groups highlight the value of educator facilitated autonomy. Rather than replacing the instructor's role, effective AI integration depends on how educators design learning environments that support exploration, reflection, and self-directed inquiry.

The results also reveal that the AI-Supported and AI-Directed interventions did not differ significantly across the outcome variables. The absence of significant differences between the two suggests that introducing moderate levels of instructor scaffolding through AI-Supported approaches may not be sufficient to produce measurable improvements in student outcomes relative to more directive AI-Directed intervention. However, this does not preclude their pedagogical value within a broader curriculum sequence. AI-Directed interventions with predefined prompts and fixed pathways appear to limit students' intrinsic motivation and engagement. This interpretation aligns with Self-Determination theory (Deci & Ryan, 1985), which argues that excessive control can undermine intrinsic motivation. While AI-Supported interventions introduce some flexibility, they still operate within educator-defined parameters. The level of instructor guidance may not provide sufficient autonomy for meaningful agentic engagement to emerge, resulting in learning outcomes that resemble those observed in the instructor-led AI-Directed intervention. Taken together, these findings suggest that the pedagogical value of AI comes from the intentional task design which strategically

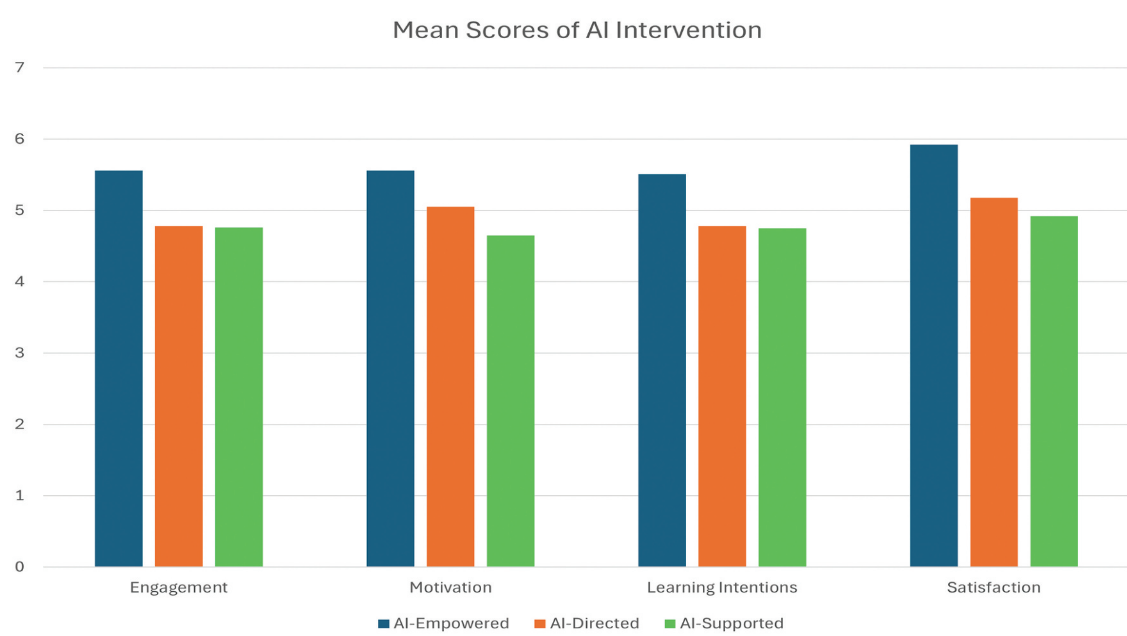

Figure 2. Mean scores of GenAI interventions.

Table 4. Statistical findings between groups one-way ANOVA.

Construct	Df	Mean Square	F	*p*-value	Significance
Engagement	2	10.706	13.064	<.001*	Yes
Between Groups	157	.820			
Within Groups	159				
Total					
Motivation	2	10.349	7.192	.001*	Yes
Between Groups	157	1.439			
Within Groups	159				
Total					
Learning	2	9.465	13.244	<.001*	Yes
Between Groups	157	.715			
Within Groups	159				
Total					
Satisfaction	2	13.431	11.905	<.001*	Yes
Between Groups	157	1.128			
Within Groups	159				
Total					

Table 5. Post hoc Tukey HSD analysis (H1).

						95% Confidence Interval	
Variable	Treatment Group (I)	Treatment Group (J)	Mean Difference (I-J)	Std Erro	Sig	Lower Bound	Upper Bound
Engagement	Empowered	Supported	.79821*	.18017	<.001	.3719	1.2245
		Directed	.78121*	.17401	<.001	.3695	1.1930
	Supported	Empowered	−.79821*	.18017	<.001	−1.2245	−.3719
		Directed	−.01700	.17309	.995	−.4265	.3926
	Directed	Empowered	−.78121*	.17401	<.001	−1.1930	−.3695
		Supported	.01700	.17309	.995	−.3926	.4265
Motivation	Empowered	Supported	.90314*	.23873	<.001	.3383	1.4680
		Directed	.50915	.23058	.073	−.0364	1.0547
	Supported	Empowered	−.90314*	.23873	<.001	−1.4680	−.3383
		Directed	−.39398	.22935	.202	−.9367	.1487
	Directed	Empowered	−.50915	.23058	.073	−1.0547	.0364
		Supported	.39398	.22935	.202	−.1487	.9367
Learning	Empowered	Supported	.75686*	.16825	<.001	.3588	1.1550
		Directed	.72853*	.16250	<.001	.3440	1.1130
	Supported	Empowered	−.75686*	.16825	<.001	−1.1550	−.3588
		Directed	−.02833	.16164	.983	−.4108	.3541
	Directed	Empowered	−.72853*	.16250	<.001	−1.1130	−.3440
		Supported	.02833	.16164	.983	−.3541	.4108
Satisfaction	Empowered	Supported	.99059*	.21139	<.001	.4904	1.4908
		Directed	.73695*	.20417	.001	.2538	1.2201
	Supported	Empowered	−.99059*	.21139	<.001	−1.4908	−.4904
		Directed	−.25364	.20309	.426	−.7342	.2269
	Directed	Empowered	−.73695*	.20417	.001	−1.2201	−.2538
		Supported	.25364	.20309	.426	−.2269	.7342

transfers control from educator to student, aligning with Roll and Winne (2015) and Zacharia et al. (2015), who emphasize the importance of structured autonomy for meaningful learning. We offer that over-structuring AI tasks may constrain students' sense of competence and agency, reducing deep engagement.

The results did not provide statistical support for a moderating effect of attitudes toward technology on engagement, motivation, satisfaction, or learning intentions (H2). Although the interaction effect for learning intentions approached significance, this finding should be interpreted with caution and warrants further investigation in future research. It is possible that students with more positive attitudes toward technology may be more receptive to AI-Empowered learning environments, particularly when these environments encourage autonomous exploration and experimentation with GenAI tools. Such a possibility

Table 6. Moderation effects of attitude toward technology (process model 1).

DV	B (Emp vs Dir × Att)	SE	T	p	95% CI (LL, UL)	ΔR^2 (Emp)	B (Supp vs Dir × Att)	SE	t	p	95% CI (LL, UL)	ΔR^2 (Supp)
Engagement	0.065	0.175	0.369	0.713	[−0.282, 0.411]	0.001	−0.217	0.271	−0.800	0.425	[−0.753, 0.319]	0.004
Motivation	−0.078	0.225	−0.346	0.730	[−0.522, 0.366]	0.001	0.122	0.332	0.367	0.714	[−0.534, 0.778]	0.001
Learning	0.309	0.162	1.913	0.058	[−0.010, 0.629]	0.019	−0.016	0.253	−0.064	0.949	[−0.517, 0.484]	0.000
Satisfaction	−0.044	0.207	−0.211	0.833	[−0.452, 0.365]	0.0002	0.270	0.313	0.863	0.389	[−0.348, 0.888]	0.004

is consistent with perspectives from the Technology Acceptance Model (Davis, 1989) and self-efficacy theory (Bandura, 1997), which suggest that perceptions of usefulness, ease of use, and confidence in using technology may influence learners' engagement with digital tools. However, the current findings do not provide sufficient empirical support for this interpretation. The absence of significant moderation effects across all outcomes suggests that attitudes toward technology alone may not be a decisive factor in shaping students' learning experiences with AI-Empowered interventions. Future research should examine whether technological attitudes interact with other learner- or context-related factors, such as digital literacy, prior experience with AI tools, self-regulated learning skills, or instructional design features. Such research may help clarify the conditions under which attitudes toward technology influence learning outcomes in AI-integrated educational environments.

Furthermore, our hypothesis regarding the moderating impact of learning styles was not confirmed (H3). This is consistent with critiques of the learning-styles framework in previous studies (Al-Azawei et al., 2017; Dinh & Vo, 2022; Granić & Marangunić, 2019; Kirschner, 2017) that question the predictive power of learning styles in educational outcomes.

Our findings indicate that the benefits of AI interventions appear consistent across learning styles, likely due to the multimodal affordances of GenAI, i.e., combining text, image, and interactive dialog which naturally accommodate diverse learning preferences (Heilala et al., 2025). This versatility may explain the absence of significant learning-style effects, suggesting that flexible, well-designed instruction can effectively support varied student needs without relying on fixed learner styles.

Taken together, our findings suggest that GenAI should be understood as an extension of experiential and student-centered pedagogies rather than a disruptive replacement. Consistent with Peña et al. (2025a, 2025b) we argue that irrespective of the teaching innovation employed, the unifying mechanism underpinning effective GenAI integration remains educator-facilitated agency and reflective practice.

Theoretical Contributions, Implications, and Areas For Further Research

Theoretical Contributions

Our research makes two notable contributions to marketing education literature. First, our study is one of the first empirical, design-based inquiries into how educators' use of AI shapes student learning outcomes within marketing education. Much of the existing literature has largely been conceptual offering narrative insights into the benefits and challenges of AI integration in educational contexts (e.g., Acar, 2024; Guha et al., 2023; Narang et al., 2025; Schlegelmilch & Mills, 2025). We advance this discussion by 1) providing direct empirical evidence that AI integration in marketing classrooms can influence students' motivation, engagement, satisfaction, and learning intentions 2) demonstrating that the success of GenAI in the classroom has less to do with the technology or tools itself and more to do with how marketing educators design and delegate control within AI integrated learning activities. In so doing, our findings position the educator as the central agent of pedagogical transformation in AI integrated marketing education.

Second, we extend Ouyang and Jiao's (2021) AI in Education paradigms by empirically examining its differential impact in marketing education. Our findings reconceptualize these paradigms as educator-led strategies that vary based on levels of control and responsibility. In AI-Directed interventions, the educator is in full control using defined structured prompts. In AI-Supported interventions, however, the educator introduces partial scaffolding and shares guidance, while in AI-Empowered interventions, the educator gives students more autonomy within clear learning boundaries. Importantly, the interventions reflect varying levels of delegated agency from educators to students,

Table 7. Curriculum implications of educator-led GenAI interventions for marketing education.

AI Intervention	Core Competencies Developed	Industry Relevance	Curriculum Implications
AI-Directed	Basic AI literacy, prompt formulation, procedural task completion	Aligns with early-stage marketing functions such as social content scheduling or automated copy generation.	Can serve as an introductory framework for integrating AI into early modules like Principles of Marketing. Helps students gain initial confidence and technical competence before engaging in more independent AI use.
AI-Supported	Analytical reasoning, evaluative judgement, applied creativity	Mirrors mid-level professional skills such as campaign testing, message refinement, and customer insight analysis.	Can function as a developmental bridge in the curriculum, blending educator scaffolding with student initiative. Suitable for modules like Marketing Analytics or Creative Strategy where guided autonomy is encouraged.
AI-Empowered	Strategic thinking, creative leadership, ethical decision-making, adaptive problem-solving	Reflects advanced professional roles in brand management, digital strategy, and campaign leadership.	Can be adapted across all course levels depending on task complexity. In early modules like Digital Marketing Fundamentals, empowerment may focus on guided experimentation. In advanced modules like Strategic Marketing or Marketing Consultancy Projects, it may emphasise full autonomy and strategic integration. Represents the ideal pedagogical model for developing critical, AI literate marketing graduates.

demonstrating how intentional instructional design can impact performance in AI integrated learning environments. Our work aligns with recent calls from marketing education scholars to reimagine marketing curricula that promotes adaptability and critical thinking in AI integrated settings (Acar, 2024; Schlegelmilch & Mills, 2025; Yao & Wang, 2025). Our findings are also consistent with and complement emerging work emphasizing constructivist educator-facilitated approaches to GenAI integration (Allil, 2024; Beninger et al., 2025; Luo, 2024; Richter et al., 2025). Our work contributes to emerging theory on digital pedagogy and marketing education by advancing theoretical understanding of the underlying pedagogical conditions through which educator-led design fosters effective and meaningful AI integrated learning in marketing education.

Implications for Marketing Education

We provide pragmatic insights for marketing educators on how to integrate GenAI into their teaching practices to enhance student learning outcomes. Our findings show that AI-Empowered interventions when structured by educators to balance guidance with student autonomy increases motivation, engagement, satisfaction, and learning intentions more effectively than AI-Directed or AI-Supported interventions. We offer that the educator's role in designing, scaffolding, and designing control is central to realizing AI's pedagogical value in marketing education.

Table 7 summarizes how each AI intervention can be embedded within marketing curricula to cultivate progressively advanced competencies from foundational AI literacy to strategic and autonomous practice. While the AI-Empowered intervention demonstrated the strongest effect on student outcomes, this does not necessarily imply that earlier intervention types should be bypassed in curriculum design. Rather, AI-Directed and AI-Supported interventions may serve as important developmental stages, helping students build foundational AI literacy, confidence, and technical competence before engaging more autonomously with GenAI tools. A sequential approach from AI-Directed to AI-Supported and ultimately AI-Empowered interventions may provide an effective pathway for developing students' capabilities over time, particularly for those with limited prior experience with GenAI. The value of the AI-Directed and AI-Supported interventions lie less in their immediate impact on learning outcomes and more in enabling students to effectively transition toward AI-Empowered learning environments. To implement AI-Empowered interventions effectively, marketing educators require both technical and pedagogical design competencies. Training should focus on helping educators design learning activities that empower students to take the lead, explore ideas, and learn in flexible, self-directed ways. At an institutional level, universities should approach AI integration as a curriculum design effort rather than a technology roll-out, investing in infrastructure, faculty training, and collaborative course design to ensure it is impactful. By foregrounding educator-facilitated design, marketing education can move beyond automation to foster deeper, industry-relevant learning that cultivates adaptable and critically engaged marketers.

Limitations and Areas for Further Research

Despite the theoretical contributions and managerial implications of this research, we acknowledge its limitations, which offer avenues for future investigation. The modest sample size in the current study may limit statistical power, particularly for detecting interaction effects such as those involving learning styles. Future studies could replicate our model with larger and more diverse samples, across various disciplines (e.g., life sciences, arts, and humanities) and cultural contexts to enhance generalizability, providing more comprehensive understanding of GenAI's impact as a classroom tool. Additionally, because our data were collected from a single European university and limited to students who attended the seminar, the findings reflect a specific institutional and cohort context. Institutional environment, course design and student demographics may influence how AI-enabled interventions are experienced. Replication across multiple institutions and delivery modes would help address this limitation and strengthen external validity. While our study focused on the immediate effects of AI interventions on student learning outcomes, longitudinal research is imperative to explore their sustained impact. Future work could employ repeated-measures or mixed-effects modeling to capture within-subject variation over time, providing a more nuanced understanding of how engagement and motivation evolve throughout the learning process, including how students' responses may change as they become more familiar with GenAI tools. Such studies could also investigate GenAI's long-term effects on learning retention, career readiness, and overall educational attainment, providing deeper insights into its evolving role in marketing education. Moreover, to mitigate potential bias from self-reported measures of student motivation, satisfaction, engagement, and learning intentions, future research should integrate objective measures, such as behavioral observations, performance metrics, or physiological indicators. In addition, procedural approaches such as reverse-coded items, time separation of measures, or triangulation with behavioral data could further reduce common method bias and enhance validity. This approach will provide more robust evaluation of AI interventions by capturing both subjective experiences and objective data.

Additionally, future research could incorporate structural equation modeling (SEM) to examine potential mediation pathways and latent constructs implied by the theoretical framework. SEM would enable a more fine-grained analysis of how different AI interventions influence engagement, motivation, learning intentions and satisfaction through underlying mechanisms, offering deeper theoretical insight. Beyond this, studies should also explore how student differences such as prior familiarity with GenAI tools, digital literacy, and cognitive load as well as educator-related factors, including teaching style, relationships with students, and attitudes toward AI, can influence the effectiveness of interventions. Finally, exploring the ethical implications of GenAI's usage and students' perceptions of AI's fallibility remains crucial. Can traditional learning methods, which often cultivate independent and creative thinking associated with privileged backgrounds and secondary education systems, surpass GenAI's potential as a learning companion? This question is particularly relevant for leveling the educational playing field for students from under-resourced backgrounds, warranting continued investigation.

Author contributions

CRediT: **La Toya Quamina:** Conceptualization, Data curation, Investigation, Methodology, Project administration, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing; **Rajab Ghandour:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing; **Felicity Hardley:** Conceptualization, Investigation, Methodology, Writing – original draft; **Ali Baig:** Investigation, Writing – original draft.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

During the preparation of this manuscript, ChatGPT (OpenAI) was used to support language refinement and improve clarity. All intellectual content, including the conceptual framework, research design, and data analysis were developed solely by the authors, who take full responsibility for the final content.

Data Availability Statement

We make sure that all data and materials support our published claims and comply with field standards.

Ethics Statement

This study was conducted in line with the ethical guidelines approved by the University of Westminster Ethics Committee (reference number ETH2324-0449). Students participated as part of their scheduled class activities, engaging in regular learning experiences. However, the data collection (anonymous survey) was conducted independently of core coursework at the end of the class activity and was entirely voluntary. Informed consent was obtained from students interested in participating after they were briefed on the study's objectives and their right to withdraw at any time without any repercussions. Since the survey was optional, no financial compensation was provided, and participation had no bearing on their academic performance or assessment. All data was anonymized, securely stored, and managed in compliance with data protection regulations. The study posed minimal risk and every precaution was taken to ensure students' safety and protection from harm.

References

Acar, O. A. (2024). Commentary: Reimagining marketing education in the age of generative AI. *International Journal of Research in Marketing*, *41*(3), 489–495. https://doi.org/10.1016/j.ijresmar.2024.06.004

Adobe. (2025). *2025 AI & digital trends report*. [online] Available at: Retrieved November 6, 2025, from https://business.adobe.com/resources/digital-trends-report.html?utm_source=chatgpt.com#driving-growth-through-ai

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, *9*(2), 204–215. https://doi.org/10.1287/isre.9.2.204

Ahmad, A., Zeshan, F., Khan, M. S., Marriam, R., Ali, A., & Samreen, A. (2020). The impact of gamification on learning outcomes of computer science majors. *ACM Transactions on Computing Education (TOCE)*, *20*(2), 1–25. https://doi.org/10.1145/3383456

Al-Azawei, A., Parslow, P., & Lundqvist, K. (2017). Investigating the effect of learning styles in a blended e-learning system: An extension of the technology acceptance model (TAM). *Australasian Journal of Educational Technology*, *33*(2). https://doi.org/10.14742/ajet.2741

Alavi, M. (1994). Computer-mediated collaborative learning: An empirical evaluation. *MIS Quarterly*, *18*(2), 159–174. https://doi.org/10.2307/249763

Albakry, N. S., Hashim, M. E. A., Harun, M. F., & Puandi, M. F. (2025). The role of artificial intelligence in creative design for advertising and digital content in educational contexts. *Semarak International Journal of Creative Art and Design*, *4*(1), 12–23. https://doi.org/10.37934/sijcad.4.1.1223

Alfarsi, G., Al-Rahmi, W. M., Tawafak, R. M., Alyoussef, I. Y., Alshimai, A., & Aldaijy, A. (2024). Using artificial intelligence to influence student engagement in media content creation. *International Journal of Interactive Mobile Technologies*, *18*(24), 38–50. https://doi.org/10.3991/ijim.v18i24.51911

Allil, K. (2024). Integrating AI-driven marketing analytics techniques into the classroom: Pedagogical strategies for enhancing student engagement and future business success. *Journal of Marketing Analytics*, *12*(2), 142–168. https://doi.org/10.1057/s41270-023-00281-z

Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freeman.

Beninger, S., Reppel, A., Stanton, J., & Watson, G. (2025). Facilitating generative AI literacy in the face of evolving technology: Interventions in marketing classrooms. *Journal of Marketing Education*, *47*(2), 112–125. https://doi.org/10.1177/02734753251316569

Blut, M., & Wang, C. (2020). Technology readiness: A meta-analysis of conceptualizations of the construct and its impact on technology usage. *Journal of the Academy of Marketing Science*, *48*(4), 649–669. https://doi.org/10.1007/s11747-019-00680-8

Corbin, T., Dawson, P., & Liu, D. (2025). Talk is cheap: Why structural assessment changes are needed for a time of GenAI. *Assessment and Evaluation in Higher Education*, *50*(7), 1–11. https://doi.org/10.1080/02602938.2025.2503964

Cruz, Y., Boughzala, I., & Assar, S. (2014). Technology acceptance and actual use with mobile learning: First stage for studying the influence of learning styles on the behavioral intention. In *ECIS, 2014 proceedings - 22nd European conference on information systems*.

Dabholkar, P. A., & Bagozzi, R. P. (2002). An attitudinal model of technology-based self-service: Moderating effects of consumer traits and situational factors. *Journal of the Academy of Marketing Science*, *30*(3), 184–201. https://doi.org/10.1177/0092070302303001

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Springer.

Dinh, T. C., & Vo, S. M. (2022). Factors affecting students' perspectives on the usefulness of learning online. *International Journal of Emerging Technologies in Learning*, *17*(15), 123–141. https://doi.org/10.3991/ijet.v17i15.33243

Edison, S. W., & Geissler, G. L. (2003). Measuring attitudes towards general technology: Antecedents, hypotheses and scale development. *Journal of Targeting, Measurement and Analysis for Marketing*, *12*(2), 137–156. https://doi.org/10.1057/palgrave.jt.5740104

Eisenhardt, K. M. (1989). Agency theory: An assessment and review. *Academy of Management Review*, *14*(1), 57–74. https://doi.org/10.2307/258191

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, *66*(1), 1–16. https://doi.org/10.1007/s12599-023-00834-7

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, *74*(1), 59–109. https://doi.org/10.3102/00346543074001059

Fujii, A. (2024). Exploring autonomy support and learning preference in higher education: Introducing a flexible and personalized learning environment with technology. *Discover Education*, *3*(1), 26. https://doi.org/10.1007/s44217-024-00111-z

Fleming, N. D., & Mills, C. (1992). Not another inventory, rather a catalyst for reflection. *To Improve the Academy*, *11*(1), 137–144. https://doi.org/10.1002/j.2334-4822.1992.tb00213.x

Gaur, L., Afaq, A., Singh, G., & Dwivedi, Y. K. (2021). Role of artificial intelligence and robotics to foster the touchless travel during a pandemic: A review and research agenda. *International Journal of Contemporary Hospitality Management*, *33*(11), 4079–4098. https://doi.org/10.1108/IJCHM-11-2020-1246

Gefen, D., & Straub, D. W. (1997). Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS Quarterly*, *21*(4), 389–400. https://doi.org/10.2307/249720

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology*, *50*(6), 2572–2593. https://doi.org/10.1111/bjet.12864

Greeno, J. G., Collins, A. M., & Resnick, L. B. (1996). Cognition and learning. In D. C. Berliner & R. C. Calfee (Eds.), *Handbook of educational psychology* (pp. 15–46). Macmillan Library Reference USA; Prentice Hall International.

Grewal, D., Guha, A., Beccacece Satornino, C., & Becker, M. (2025). The future of marketing and marketing education. *Journal of Marketing Education*, *47*(1), 61–77. https://doi.org/10.1177/02734753241269838

Guha, A., Grewal, D., & Atlas, S. (2023). Generative AI and marketing education: What the future holds. *Journal of Marketing Education*, *46*(1), 6–17. https://doi.org/10.1177/02734753231215436

Gulati, A., Saini, H., Singh, S., & Kumar, V. (2024). Enhancing learning potential: Investigating marketing students' behavioral intentions to adopt ChatGPT. *Marketing Education Review*, *3*(3), 1–34. https://doi.org/10.1080/10528008.2023.2300139

Guoxia, W. A. N. G., & Yang, Z. H. A. O. (2024). A meta-analysis on teacher autonomy support and student academic achievement: The mediating effect of psychological need satisfaction, academic motivation, and academic engagement. *Frontiers of Education in China*, *19*(4). https://doi.org/10.3868/s110-010-024-0022-3

Hair, J. F. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage.

Heilala, V., Araya, R., & Hämäläinen, R. (2025, March). Beyond text-to-text: An overview of multimodal and generative artificial intelligence for education using topic modeling. In *Proceedings of the 40th ACM/SIGAPP symposium on applied computing* (pp. 54–63). https://dl.acm.org/doi/abs/10.1145/3672608.3707764

Hofferber, N., Eckes, A., & Wilde, M. (2014). Effects of autonomy supportive vs. controlling teachers' behavior on students' achievement. *European Journal of Educational Research*, *3*(4), 177–184. https://doi.org/10.12973/eu-jer.3.4.177

Hsiao, P. W., & Su, C. H. (2021). A study on the impact of STEAM education for sustainable development courses and its effects on student motivation and learning. *Sustainability*, *13*(7), 3772. https://doi.org/10.3390/su13073772

Huang, C. L., Luo, Y. F., Yang, S. C., Lu, C. M., & Chen, A. S. (2020). Influence of students' learning style, sense of presence, and cognitive load on learning outcomes in an immersive virtual reality learning environment. *Journal of Educational Computing Research*, *58*(3), 596–615. https://doi.org/10.1177/0735633119867422

Howard, J. L., Bureau, J. S., Guay, F., Chong, J. X. Y., & Ryan, R. M. (2021). Student motivation and associated outcomes: A meta-analysis from self-determination theory. *Perspectives on Psychological Science*, *16*(6), 1300–1323. https://doi.org/10.1177/1745691620966789

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. In *Corporate governance* (pp. 77–132). Gower.

Jürgensmeier, L., & Skiera, B. (2024). Generative AI for scalable feedback to multimodal exercises. *International Journal of Research in Marketing*, *41*(3), 468–488. https://doi.org/10.1016/j.ijresmar.2024.05.005

Karimova, G. Z., Kim, Y. D., & Shirkhanbeik, A. (2025). Poietic symbiosis or algorithmic subjugation: Generative AI technology in marketing communications education. *Education and Information Technologies*, *30*(2), 2185–2209. https://doi.org/10.1007/s10639-024-12877-8

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., . . . Kuhn, J. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning & Individual Differences*, *3*(102274), 1041–6080. https://doi.org/10.1016/j.lindif.2023.102274

Kirschner, P. A. (2017). Stop propagating the learning styles myth. *Computers and Education*, *106*, 166–171. https://doi.org/10.1016/j.compedu.2016.12.006

Kolb, D. A. (2014). *Experiential learning: Experience as the source of learning and development*. FT Press.

Kshetri, N., Hughes, L., Louise Slade, E., Jeyaraj, A., Kumar Kar, A., Koohang, A., & Wright, R. (2023). So what if ChatGPT wrote it?" multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71* (102642). https://doi.org/10.1016/j.ijinfomgt.2023.102642

Luo, J. (2024). How does GenAI affect trust in teacher-student relationships? Insights from students' assessment experiences. *Teaching in Higher Education*, *29*(5), 567–580. https://doi.org/10.1080/13562517.2024.2341005

Ma, Y. M., Dai, X., & Deng, Z. (2023). Using machine learning to investigate consumers' emotions: The spillover effect of AI defeating people on consumers' attitudes toward AI companies. *Internet Research*, *34*(5), 1679–1713. https://doi.org/10.1108/INTR-02-2022-0113

Mammadov, S., & Schroeder, K. (2023). A meta-analytic review of the relationships between autonomy support and positive learning outcomes. *Contemporary Educational Psychology*, *75*, 102235. https://doi.org/10.1016/j.cedpsych.2023.102235

Martínez Romero, S. J., Ordóñez Camacho, X. G., Guillén-Gamez, F. D., & Bravo Agapito, J. (2020). Attitudes toward technology among distance education students: Validation of an explanatory model. *Online Learning*, *24*(2), 59–75.

Mayer, R. E. (2001). *Multimedia learning*. Cambridge University Press.

Mehmet, M., Papakosmas, M., Kyriazis, E., & Nikidehaghani, M. (2025). Re-imagining marketing education for career readiness in the GenAI era. *Journal of Marketing Education*, *47*(2), 170–190. https://doi.org/10.1177/02734753251326457

Moreno, R., & Mayer, R. E. (2007, June 22). Interactive multimodal learning environments. *Educational Psychology Review*, *19*(3), 309–326. https://doi.org/10.1007/s10648-007-9047-2

Morgan, H., Russell, L. T. M., & Jocic, M. (2025). Student perspectives on generative AI integration in advertising education. *Journal of Advertising Education*. https://doi.org/10.1177/10980482251376947

Narang, U., Sachdev, V., & Liu, R. (2025). When AI wears many hats: The role of generative artificial intelligence in marketing education. *Journal of Public Policy & Marketing*, *44*(3), 473–489. https://doi.org/10.1177/07439156251328237

Nketiah-Amponsah, E., Asamoah, M. K., Allassani, W., & Aziale, L. K. (2017). Examining students' experience with the use of some selected ICT devices and applications for learning and their effect on academic performance. *Journal of Computers in Education*, *4*(4), 441–460. https://doi.org/10.1007/s40692-017-0089-2

Oc, Y., Gonsalves, C., & Quamina, L. (2025). Generative AI in higher education assessments: Examining the impact of risk and tech-savviness on students' adoption. *Journal of Marketing Education*, *47*(2), 138–155. https://doi.org/10.1177/02734753241302459

Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence*, *2*(100020). https://doi.org/10.1016/j.caeai.2021.100020

Palincsar, A. S. (2005). Social constructivist perspectives on teaching and learning. In H. Daniels (Ed.), *An introduction to* Vygotsky (Vol. 2, pp. 285–314). Routledge.

Pavone, G. (2025). Generative AI in the learning process: Threat or tool? Understanding the role of self-esteem and academic anxiety in shaping student motivations. *Journal of Marketing Education*, 02734753251346857. https://doi.org/10.1177/0273475325134685

Peña, P., Riley, J., & Davis, N. (2025a). Marketing meets the machine: Practical applications and innovative pedagogical insights from the frontlines of AI adoption. *Marketing Education Review*, *35*(4), 269–270. https://doi.org/10.1080/10528008.2025.2518396

Peña, P., Riley, J., & Davis, N. (2025b). Beyond the "AI" powered slide deck: Exploring emerging tools that engage, empower, and elevate student learning. *Marketing Education Review*, *35*(4), 289–290. https://doi.org/10.1080/10528008.2025.2518407

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, *63*(1), 539–569. https://doi.org/10.1146/annurev-psych-120710-100452

Reeve, J., & Tseng, C. M. (2011). Agency as a fourth aspect of students' engagement during learning activities. *Contemporary Educational Psychology*, *36*(4), 257–267. https://doi.org/10.1016/j.cedpsych.2011.05.002

Reid, J. M. (1987). The learning style preferences of ESL student. *Tesol Quarterly*, *21*(1), 87–111. https://doi.org/10.2307/3586356

Richter, S., Giroux, M., Piven, I., Sima, H., & Dodd, P. (2024). A constructivist approach to integrating ai in marketing education: Bridging theory and practice. *Journal of Marketing Education*, *47*(2), 94–111. https://doi.org/10.1177/02734753241288876

Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *Journal of Learning Analytics*, *2*(1), 7–12. https://doi.org/10.18608/jla.2015.21.2

Ross, S. A. (1973). The economic theory of agency: The principal's problem. *The American Economic Review*, *63*, 134–139. https://doi.org/10.2307/1817064

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *The American Psychologist*, *55*(1), 68. https://doi.org/10.1037/0003-066X.55.1.68

Schlegelmilch, B. B., & Mills, A. J. (2025). Artificial intelligence and the future of marketing education. *Journal of Marketing Education*, *47*(2), 91–93. https://doi.org/10.1177/02734753251336956

Singla, A., Xing, Z., Agarwal, V., & Chui, M. (2024). *The state of AI in early 2024: Gen AI adoption spikes and starts to generate value, McKinsey & company*. Retrieved November 6, 2025, from https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-2024

Singh, P., & Huang, L. (2025). AI meets brainstorming: Enhancing creativity and collaboration in marketing education. *Marketing Education Review*, *35*(4), 1–9. https://doi.org/10.1080/10528008.2025.2501790

Singh, P. (2024). Transforming healthcare through ai: Enhancing patient outcomes and bridging accessibility gaps. *The Journal of Artificial Intelligence Research*, *4*(1), 220–232. https://doi.org/10.2139/ssrn.5115767

Skinner, B. F. (1958). Reinforcement today. *The American Psychologist*, *13*(3), 94–99. https://doi.org/10.1037/h0049039

Skinner, E. A., Kindermann, T. A., & Furrer, C. J. (2009). A motivational perspective on engagement and disaffection: Conceptualization and assessment of children's behavioral and emotional participation in academic activities. *Journal of Educational Psychology*, *101*(3), 765–781.

Slepchuk, A. N., & John, J. (2025). Exploring perceptions of AI in the marketing classroom: A stimuli-organism-response framework. *Marketing Education Review*, *35*(4), 1–9. https://doi.org/10.1080/10528008.2025.2478869

Stenalt, M. H., & Lassesen, B. (2022). Does student agency benefit student learning? A systematic review of higher education research. *Assessment and Evaluation in Higher Education*, *47*(5), 653–669. https://doi.org/10.1080/02602938.2021.1967874

Stošić, L., & Fadiya, S. (2017). The attitudes of students towards the use of ICT during their studies. *Russian Psychological Journal*, *14*(1), 135–148. https://doi.org/10.21702/rpj.2017.1.9

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers and Education*, *57*(4), 2432–2440. https://doi.org/10.1016/j.compedu.2011.06.008

Turner-Henderson, T., Bryant, M., Riley, J., Watson, A., & Nicewicz Scott, K. (2025). Strategic AI integration in marketing education: Elevating personal branding and career readiness. *Marketing Education Review*, 1–14. https://doi.org/10.1080/10528008.2025.2551972

Wu, D., & Dong, X. (2024). Autonomy support, peer relations, and teacher-student interactions: Implications for psychological well-being in language learning. *Frontiers in Psychology*, *15*, 1358776. https://doi.org/10.3389/fpsyg.2024.1358776

Yi, Y., Wu, Z., & Tung, L. L. (2005). How individual differences influence technology usage behavior? Toward an integrated framework. *Journal of Computer Information Systems*, *46*(2), 52–63. https://doi.org/10.1080/08874417.2006.11645883

Yao, Y., & Wang, Z. (2025). The integration of artificial intelligence in marketing education within the context of education for sustainable development (ESD). In C. Chrimes, R. Boardman, T. C. Melewar, & C. Dennis (Eds.), *Future priorities for design, branding, marketing and retail: The era of technology and sustainability* (1st ed., p. 193). Emerald Publishing Limited. https://doi.org/10.1108/978-1-83608-806-620251010

Zacharia, Z. C., Manoli, C., Xenofontos, N., De Jong, T., Pedaste, M., van Riesen, S. A., Kamp, E. T., Mäeots, M., Siiman, L., & Tsourlidaki, E. (2015). Identifying potential types of guidance for supporting student inquiry when using virtual and remote labs in science: A literature review. *Educational Technology Research and Development*, *63*(2), 257–302. https://doi.org/10.1007/s11423-015-9370-0