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Artificial intelligence, job seeker, and career trajectory: How AI-based learning experiences affect commitment of fresh graduates to be an accountant?

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ABSTRACT

Integrating Artificial Intelligence (AI) into the accounting professions is reshaping traditional roles and skill requirements, prompting a reassessment of how graduates are prepared for these changes. However, a significant gap exists in understanding how AI-based learning in higher education curricula influences graduates' readiness and commitment to be accountants. Addressing this gap, this study aims to answer two pivotal questions: how do AI learning experiences affect AI self-efficacy and career commitment, and how do literacy, motivations, and competency factors mediate this relationship? This study grounds in Self-determination Theory (SDT) and Social Cognitive Career Theory (SCCT) to answer the questions and utilizes a multiple mediation model with partial least squares structural equation modeling (PLS-SEM) to analyze survey data gathered from 698 fresh graduates in accounting and finance program across the country (Indonesia). The finding confirms that AI-based learning experiences in higher education influence fresh graduates' AI self-efficacy and career commitment through the mediating role of AI literacy, competency, and motivations. This study demonstrates that AI-based learning enhances students' literacy and competencies in AI/accounting software while boosting intrinsic and extrinsic motivation to master AI skills for future career benefits. Ultimately, increased motivation, literacy, and competencies strengthen graduates' self-efficacy and confidence, supporting their commitment to a career in accounting. This study, therefore, contributes a novel insight by providing empirical considerations for higher education and the accounting industry to strengthen AI-based curricula for future workforce supply.

1. Introduction

Artificial Intelligence (AI) is reshaping the accounting field by automating routine tasks, improving efficiency, and enabling data-driven decision-making. The rapid development of AI has significantly transformed accounting and finance industries and professions, presenting opportunities and challenges within the modern workforce (Leitner-Hanetseder et al., 2021; Stancu & Duţescu, 2021). The latest Chief Financial Officer (CFO) Indicator Survey of 267 CFOs globally examined key concerns in the finance function, including financial cloud maturity, in-demand skills, data analytics capabilities, and emerging technologies. According to the survey, 57 % of CFOs seek technology skills, including AI and machine learning (ML), in future hires (Workday CFO Indicator Survey, 2022a). With finance leaders increasingly serving as strategic business partners, 40 % of CFOs prioritize data storytelling, AI, and ML expertise for new hires. However, another survey report showed that only 25 % of accounting professionals actively invest in AI training for their teams (Workday CFO Indicator Survey, 2022b). On the other side, in the AI-career relationship, the literature has explained that generative AIs influence employees' performance (Suseno et al., 2022), career resilience and competency (Kong et al., 2024), Anxiety (Kaya et al., 2022), and job burnout (Kong et al., 2021) of employees. Those studies have brought a dynamic discussion on how generative AI and its evolution have changed how accountants work and their performance.

Based on the facts above, enhancing technological capacity and digitalization is crucial for the accounting and finance workforce. In

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doing so, the role of higher education institutions as suppliers of human resources becomes increasingly important (Laupichler et al., 2022). The increasing reliance on AI in accounting underscores the need for graduates proficient in AI technologies and committed to integrating these skills into their professional practices. Despite this need, many employers report skill gaps among fresh graduates, particularly in AI-related competencies and the ability to adapt to technology-driven roles (Carlisle et al., 2023). While it is clear that AI will transform how accountants work in the future, the question of how higher education bridges the skill gaps among graduates remains uncertain.

Previous studies have observed the phenomenon of AI-based learning implementation in higher education. They discussed deeply students' perceptions (Busch et al., 2023), the use of metaverse for collaborative learning (Youssef et al., 2025), readiness (Suseno et al., 2022), and motivations (Lin et al., 2021) to use generative AI, while others analyzed the dynamics of AI adoption intention across disciplines (Li et al., 2022; Sing Chai et al., 2021). Additionally, Yilmaz and Karaoglan Yilmaz (2023) have explored AI's role in enhancing computational thinking and programming self-efficacy. Research from Kong et al. (2023) has evaluated higher education curricula that aim to improve literacy in understanding, applying, and ethically using generative AI. Those studies have provided insights into how the presence of AI is transforming learning patterns and outcomes in higher education and the impact of this learning on enhancing student competencies.

Unfortunately, research examining the AI-career relationship in higher education and student context is considerably limited. While higher education institutions have begun incorporating AI-based learning into their curricula, important questions remain about how these learning experiences prepare students to meet the demands of AI-integrated work environments. Whereas existing research has demonstrated that learning experiences in critical skills, especially those relevant to students' intended careers, can enhance their motivation and intention to pursue these professions (Bloemen-Bekx et al., 2019; Zhang et al., 2022). For instance, some studies, such as Bloemen-Bekx et al. (2019), Cieślik and van Stel (2017), Rae and Woodier-Harris (2013), and Yaghoubi Farani et al. (2017) have found a similar finding that entrepreneurial exposure, education, and learning experiences in formal education significantly enhance students' intention to be entrepreneurs. Besides, although existing research has examined the link between learning experiences and pivotal skill acquisition, there is a lack of understanding of how AI-based learning influences students' motivation, intentions, and capabilities to pursue accounting professions. Besides, the mechanisms through which AI-based learning influences students' motivation and career commitment are not yet fully understood, representing theoretical and practical gaps that this study seeks to address. Few studies have integrated multiple theoretical frameworks to solve this hypothesis. In this regard, there is a need to examine the intersection between student motivation, personal development, and career commitment, which remain overlooked. In doing so, integrating different theories would assist in studying this issue from multiple angles. Therefore, building on this reasoning, the present study introduces an unresolved hypothesis: AI-based learning experiences in higher education are expected to strengthen the self-efficacy and commitment of graduates in accounting and finance to pursue careers as accountants.

This research addresses this gap by integrating Self-Determination Theory (SDT) and Social Cognitive Career Theory (SCCT) to explore how AI-based learning experiences influence motivation, competency, and career-related behaviors (Gagné et al., 2022). The SDT focuses on how autonomy, competence, and relatedness foster the commitment of fresh graduates to be an accountant. At the same time, SCCT highlights the role of self-efficacy, outcome expectations, and goal setting in career decision-making (Cardoso et al., 2013). By combining these frameworks, this study offers a robust theoretical foundation for investigating how AI-based learning experiences influence career trajectory. The key elements of SDT (autonomy, competence, and relatedness) and SCCT (self-efficacy, outcome expectations, and goal setting) manifest in four essential factors: AI literacy, intrinsic and extrinsic motivations, and AI competency. Through this research, we believe that AI-based learning implementation fosters intrinsic and extrinsic motivations that represent the outcome expectations and goal setting by sparking curiosity and aligning students' efforts with career goals in AI-driven accounting. Besides, AI-based learning builds literacy and competency, representing competence and relatedness, helping students understand AI systems and envision themselves as skilled professionals in the evolving accounting field.

Based on the above background, the study aims to answer two central questions: *First*, does AI-based learning in higher education influence AI self-efficacy and career commitment to be an accountant among fresh graduates in accounting and finance? *Second*, do AI literacy, intrinsic and extrinsic motivation, and AI competency mediate the relationships between AI-based learning, self-efficacy, and career commitment? These questions explore direct and indirect effects, offering a comprehensive understanding of how AI-based learning experiences shape career commitment.

The study offers two significances. *Practically*, this research gives empirical and actionable insight for higher education institutions, identifying the key factors and pathways through which AI-based learning can better prepare students for the evolving demands of the accounting profession. Hence, they can better prepare an effective AI-integrated curriculum. *Theoretically*, this study contributes to the theoretical understanding of how educational experiences influence career outcomes and offers practical recommendations for bridging the skill and motivation gaps in accounting education. Ultimately, this research aims to support the development of a workforce equipped to thrive in an AI-driven professional landscape.

This article is structured to provide a comprehensive examination of the topic. Following the introduction section, section 2 presents the study's theoretical background. Section 3 outlines the hypothesis development, establishing the theoretical framework and conceptual model. Section 4 explains the methodology, including research design, data collection, and analysis. Section 5 discusses the findings concerning the hypotheses. Section 6 explores the discussion and implications for theory, practice, and fields. Section 7 discussion and section 8 concludes with a summary of key insights, study limitations, and suggestions for future research.

2. Theoretical background

2.1. Self-determination theory (SDT)

Self-Determination Theory (SDT) is a psychological framework emphasizing the importance of intrinsic and extrinsic motivations for human development and well-being. The theory posits that people are most motivated when their basic psychological needs of autonomy, competence, and relatedness are satisfied (Hui & Tsang, 2012). Autonomy refers to the sense of control over one's actions, fostering intrinsic motivation driven by personal interest rather than external rewards. Competence involves feeling effective and capable in one's pursuits, encouraging persistence and enjoyment. Meanwhile, relatedness is the need for meaningful connections, enhancing motivation through social support and belonging (Deci & Ryan, 2012). The theory suggests that fulfilling these psychological needs leads to sustainable motivation for a particular mission, improved performance, and greater psychological well-being (Ryan et al., 2008; Tashliyev & Tirtoprojo, 2023).

SDT has been widely applied in education, the workplace, health, and parenting. In education, SDT has been used to explore the impact of autonomy-supportive teaching on student motivation and learning outcomes. For instance, Sadoughi and Hejazi (2021) found the positive effects of autonomy support on student motivation, engagement, and academic performance in foreign language classrooms. They discovered that college students who supported autonomy, where teachers offered choices and promoted personal goal settings, demonstrated higher intrinsic motivation, improved comprehension of the material, and greater persistence. Chua and Ayoko (2021) found that fostering autonomy and skill development can enhance employee engagement in the workplace. SDT has also been used to promote behaviors like exercise and healthy eating by emphasizing intrinsic motivation over external rewards (Brown et al., 2023). SDT underscores that motivation thrives when individuals feel free to choose, capable, and connected to others.

In the context of this study, SDT serves as the theoretical foundation for examining the motivational aspects of fresh graduates to be accountants. Therefore, this study contributes to the literature by extending the application of SDT in education-technology-career causality. The motivational elements are critical in mediating the relationship between students' engagement with AI-based learning and their development of AI literacy and competency. Intrinsic motivation for mastering AI reflects students' interest in understanding and engaging with AI technologies, driven by curiosity or the satisfaction of mastering a new skill during the AI-based learning implementation. On the other hand, extrinsic motivation is shaped by external incentives, such as the perceived importance of AI skills for career advancement in accounting.

AI literacy and competency constructs are closely aligned with SDT's competence dimension, reflecting an individual's ability to effectively understand and apply AI technologies. Meanwhile, AI-based learning implementation in higher education represents the relatedness element of SDT. In an educational context, relatedness is seen in how students feel supported, engaged, and connected to their environment, peers, and lecturers (Al-Jubari et al., 2019). Personalized and inclusive AI-driven learning fosters a sense of care by addressing students' unique needs, enhancing their feeling of support while also aiding professional identity formation and aligning them with their career aspirations. As students engage with AI-based learning experiences, they improve their sense of competence and strengthen their intrinsic and extrinsic motivations, leading to greater self-efficacy and enhanced skill development, representing the autonomy element of SDT. Ultimately, the high level of competence and self-efficacy will influence the strong commitment of fresh graduates to pursue a career as accountants.

In general, the connection among relatedness (AI-based learning experiences), competence (AI literacy and competency), motivations, and autonomy (self-efficacy) of SDT is adequate to explain the relationship between AI-based learning experiences in higher education and the career intentions of fresh graduates.

2.2. Social cognitive career theory (SCCT)

Social Cognitive Career Theory (SCCT) is a complementary framework for SDT. While SDT emphasizes intrinsic and extrinsic motivations rooted in fulfilling basic psychological needs, SCCT offers a structured framework to understand how external factors, self-efficacy, and cognitive processes translate motivations into actual career intentions (Segal et al., 2002). SCCT explains how individuals develop career interests, make career choices, and achieve success, focusing on the influence of cognitive processes, learning experiences, and social factors (Navarro et al., 2007). It emphasizes self-efficacy, outcome expectations, and personal goals in shaping behavior (Bandura, 2003).

At its core, SCCT highlights individuals' belief in their ability to succeed in specific tasks (self-efficacy). In career development, self-efficacy determines whether individuals pursue and persist in a profession (Schaub & Tokar, 2005). For instance, if fresh graduates feel capable in accounting, they are more likely to pursue that career. Similarly, this theory posits that outcome expectations influence career behavior. They refer to beliefs about the potential results of pursuing specific careers. SCCT also emphasizes the development of personal goals as a key element of career intentions. Individuals are motivated to set and pursue career goals, such as a student with high self-efficacy in math aiming for an engineering career (Schaub & Tokar, 2005; Segal et al., 2002).

The interaction of personal goals, outcome expectations, and self-efficacy allows students to develop their career interests. As individuals gain confidence and expect positive outcomes, their goals become more defined, influencing their career choices (Liguori et al., 2020). Learning experiences such as AI-based learning curricula play a significant role in shaping these key elements. Positive feedback also can increase confidence and influence career decisions (Bloemen-Bekx et al., 2019). In real life, SCCT is manifested in career counseling, educational interventions, and workplace development, helping individuals explore career paths, set goals, and build self-efficacy, ultimately fostering career success.

Like SDT, SCCT offers a relevant framework for understanding how students form career commitments and pursue specific career trajectories. This theory has been applied extensively in various fields to explore the relationship between students' learning experiences, cognitive beliefs, and career outcomes, including entrepreneurship (Liguori et al., 2020), teaching, tourism (Chuang & Dellmann-Jenkins, 2010), and STEM (Cardoso et al., 2013). In this study context, positive experiences in AI-based learning serve as a background contextual affordance and cognitive process shaping students' outcome expectations and personal goals for mastering AI. Specifically, when students have positive experiences, their expectations and personal goals of becoming accountants increase as they gain satisfaction from mastering AI-based skills in accounting and finance. They also develop high expectations of the future benefits of being an accountant proficient in AI and machine learning. These outcome expectations and personal goals to master AI will enhance students' motivation to improve their competencies and self-efficacy, ultimately sustaining their enthusiasm and commitment to pursuing a career in accounting.

3. Hypothesis development

3.1. The implication of AI-based learning experiences on AI-literacy, motivations for mastering AI, and AI-competency

AI-based learning allows students to engage with AI technologies, fostering foundational knowledge of AI concepts, principles, and applications. Peters et al. (2023) argue that AI tools like ChatGPT-4 have gained significant attention in educational practices and learning processes. While the experiences gained from using these tools offer numerous benefits, they also present some negative impacts, particularly when ethical considerations are not prioritized. Positive experience with AI-based learning, which includes exposure to AI tools, structured curricula, and practical assignments, enhances students' ability to comprehend and evaluate AI (Kashive et al., 2021). Wu and Fan (2024) study the link between experience with AI tools for learning and their effectiveness in the learning process. The study underlines that these AI tools influence their behavior and satisfaction and enhance their cognitive ability. AI literacy, the capacity to understand, interpret, and assess AI technologies, is crucial for indicators of effective engagement with AI. In higher education, AI-based learning is key to developing this literacy by combining theoretical knowledge with hands-on activities, such as simulations and real-world applications (Tzirides et al., 2024; Zhang et al., 2023). This approach helps students connect abstract concepts with practical implementation, improving their AI literacy. For example, using AI tools to address business challenges or simulate accounting tasks enhances students' understanding of AI's potential and limitations. Sing Chai et al. (2021) and Su and Yang (2023) state that technology-integrated education boosts students' confidence and competence in using new technologies. Therefore, AI-based learning experiences in higher education are expected to positively influence students' AI literacy by equipping them with the skills to engage with AI effectively. Consequently, we posit a hypothesis as below.

H1. AI-based learning experiences in higher education increase the AI literacy of fresh graduates.

Furthermore, while AI literacy involves conceptual understanding, AI competency translates that understanding into actionable skills. The relationship between AI literacy and competency can be explained by cognitive development theories, particularly knowledge scaffolding (Hornberger et al., 2023). A strong foundational understanding (AI literacy) supports the development of practical skills (AI competency). Without a solid grasp of AI's core concepts, students may struggle to use AI tools effectively or adapt to evolving technologies. For example, understanding machine learning principles is essential for applying AI algorithms in business analytics or financial reporting. AI literacy also strengthens problem-solving and decision-making skills, key components of AI competency (Casal-Otero et al., 2023). A fresh graduate with solid AI literacy can use an AI tool and assess when and why it should be applied, thereby improving their practical competency. Some studies, such as Laupichler et al. (2022) and Temitayo et al. (2022), support the idea that literacy precedes competency. Studies in educational technology, like Kong et al. (2023), Ekamdeep Singh et al. (2024), and Ari Alamäki et al. (2023), have shown that those with higher literacy are more likely to demonstrate confidence and competence in applying AI to academic, professional, or problem-solving tasks. Therefore, we hypothesize that.

H2. The higher the artificial intelligence (AI) literacy level, the greater the AI competency of fresh graduates.

Exposure to advanced AI applications gained from AI-based learning in formal education allows students to explore AI's potential and lead to the formation of students' intrinsic motivation for mastering AI. This exposure motivates students to invest effort in learning AI to meet external motivations and achieve career goals. Positive AI-based learning experiences promoting self-paced exploration and interactivity enhance students' autonomy. For example, students who can experiment with AI tools or develop personalized projects feel more in control of their learning, boosting intrinsic and extrinsic motivation to get a better career in the future. Additionally, these experiences foster a sense of competence by enabling students to make incremental progress and master AI-related tasks (Xi-Hui Jia and Jui-Che Tu, 2024). They also enhance relatedness by offering opportunities for collaboration with peers, lecturers, and instructors. Group projects, workshops, and supportive feedback create a sense of belonging, strengthening personal goals and the expected benefits of mastering AI. Research from Wang, Zhang, and Zhang (2022) and Qawaqneh et al. (2023) have shown that well-designed, technology-enhanced learning environments boost motivation by improving technical skills and increasing enthusiasm for the subject, fostering sustained engagement with the subject. Therefore, we hypothesize that.

H3 and H4. The AI-based learning experience in higher education shapes fresh graduates' intrinsic (H3) and extrinsic (H4) motivation to master AI.

In AI learning, motivations reflect a student's passion and future expectations to explore and apply AI concepts for the fulfilment gained from the process. Motivated individuals are more likely to proactively engage with the subject, overcome challenges, and develop higher-order skills (Lin et al., 2021). Research from Qawaqneh et al. (2023) and Wang, Zhang, and Zhang (2022) found that motivations drive students to pursue knowledge and develop technical competencies. Students motivated to master AI are likelier to experiment with tools, tackle complex tasks, and explore advanced AI concepts. For example, they may participate in software-based accounting competitions or create innovative AI projects, enhancing their competency and application of AI. Intrinsic motivation also encourages resilience, as students view challenges like debugging and refining solutions as growth opportunities rather than setbacks. Studies have shown that motivated students exhibit greater creativity and success in acquiring technical skills (Bargmann et al., 2022; Lin et al., 2021; Razak, 2021). Hence, the following hypothesis is.

H5 and H6. The higher the intrinsic (H5) and extrinsic (H6) motivation for mastering AI, the greater the AI competency fresh graduates possess.

Numerous studies also indicated that AI-based learning experiences in higher education directly enhance students' AI competency (Hatane et al., 2021; Kong et al., 2021). Jonathan and Laik (2024) showed that experiential learning enhances skill retention and application. These experiences bridge the gap between education and professional expectations, preparing students for industry roles requiring AI competencies in financial forecasting, fraud detection, and automation. Students deepen their understanding of AI's functionality and potential applications by engaging with AI tools in practical settings. Simulation and utilization of AI or software in accounting class projects enhance conceptual and technical expertise, enabling students to adapt their knowledge to future challenges. This causality has been drawn from experiential learning theory, emphasizing active participation in competency development (Hsu et al., 2021). Hence, we hypothesize that.

H7. The AI-based learning experience in higher education increases the AI competency of fresh graduates.

3.2. Building fresh graduates' AI-self-efficacy through AI-based learning experiences

As students engage in hands-on AI tasks, they gain evidence of their abilities, reinforcing their belief in tackling similar challenges in the future. A solid grasp of how AI works boosts confidence, making students more likely to apply AI in real-world settings. As grounded on social cognitive career theory, the iterative nature of developing AI literacy and competency further strengthens self-efficacy (Hsu et al., 2021). Successfully learning these skills not only sharpens technical skills but also builds confidence in problem-solving. This creates a positive feedback loop, where increased literacy and competency drives further confidence and skill development. Students with higher technical competency report stronger self-efficacy. Moreover, Criollo et al. (2024) investigate how emerging technologies, such as AI-based learning tools, improve higher education. Their findings underscore that the effectiveness of these applications can enhance learning outcomes. Besides, AI literacy also provides a sense of control and preparedness, key factors in self-efficacy. Students who understand AI's capabilities and limitations are more likely to approach AI tasks confidently. Therefore, it is hypothesized that.

H8 and H9. AI literacy (H8) and AI competency (H9) shape the AI self-efficacy of fresh graduates.

Extrinsic and intrinsic motivations also play a crucial role in shaping an individual's belief in their ability to succeed with AI technologies (AI self-efficacy). Motivation provides clear goals that guide learners in mastering AI and pushing themselves to learn AI-powered tools, reinforcing their belief in their ability to succeed (Qawaqneh et al., 2023; Yilmaz & Karaoglan Yilmaz, 2023). They also foster a positive mindset, helping learners feel more confident as they achieve success through personal curiosity. These two forms of motivation complement each other. Extrinsic motivation ensures goal-oriented progress, while intrinsic motivation nurtures long-term interest and sustained effort, even without external rewards. Together, they help learners overcome challenges, persist through difficulties, and internalize their achievements, all essential for building self-efficacy. In line with self-determination theory, extrinsic and intrinsic motivation contribute to skill acquisition and the confidence to apply those skills. Therefore, we hypothesize that.

H10. and H11. Intrinsic (H10) and extrinsic (H11) motivations for mastering AI of fresh graduates shape their AI efficacy.

3.3. AI competency and self-efficacy enhance career commitment to Be an accountant

Since AI technologies become more prevalent in accounting, individuals with strong AI skills and confidence in using these tools are better equipped to meet industry demands, enhancing their commitment to a career in accounting (Dogar & Scorte, 2023; Musyaffi et al., 2023). These skills align with the profession's evolving needs, making students with high AI competencies feel prepared for success. When technical expertise is considered valuable to career goals, students are more likely to commit to their profession (Zhang & Zhang, 2022). A graduate skilled in AI-powered accounting practices may see a career in accounting as achievable and rewarding. On the other hand, high self-efficacy leads students to approach AI challenges positively, viewing them as growth opportunities rather than obstacles. This confidence reduces uncertainty and strengthens career commitment. The relationship between AI competency, AI self-efficacy, and career commitment generally reflects the integration of technical skills, personal confidence, and professional goals. Together, AI competency and AI self-efficacy form a robust foundation for career commitment. AI competency provides essential skills, while self-efficacy fosters the mindset to apply them effectively. It helps students thrive in an AI-driven accounting environment. Social cognitive career theory supports this relationship, suggesting that perceived competence and confidence strongly influence career intentions (Schaub & Tokar, 2005). Therefore, we hypothesize that.

H12. The higher the fresh graduates' AI competency level, the greater their career commitment to being accountants.

H13. The higher the fresh graduates' AI self-efficacy level, the greater their career commitment to being accountants.

3.4. The mediating role of AI literacy, motivations, and competency

By merging the SDT and SCCT, this study explains how AI-based learning experiences in higher education affect fresh graduates' career trajectories as accountants. This effect is not solely direct but includes complex indirect relationships. As mentioned, AI literacy, motivations, and competency are why positive learning experiences strongly influence fresh graduates' self-efficacy and commitment to being an accountant. Learning enhances students' knowledge, understanding, and skills, reflecting AI literacy and competency. The more positive the experiences, the higher the students' motivations for mastering AI. Higher motivation and competency will boost students' confidence and commitment to be an accountant in the future. Therefore, we posit the hypothesis as below.

H14 and H15. AI literacy, motivations, and competency generally mediate the relationship between AI-based learning experiences and fresh graduates' self-efficacy (H14) and career commitment (H15). These three factors increase the coefficient value of direct effect.

4. Methodology

4.1. Sampling technique and procedure

This study collects primary data through a self-reported online and offline survey. A purposive sampling strategy was employed to select participants relevant to the research objective regarding the impact of AI-based learning experiences in formal education on fresh graduate job seekers' career commitment to being accountants. This sampling technique was chosen to ensure that the survey targeted relevant respondents, Hence, the inclusion criteria specifically targeted fresh graduate job seekers in accounting and finance programs in the first year after graduation. Google Forms were used to streamline online survey administration. This platform was chosen for its efficiency, familiarity, and broad reach. A screening question was included in the questionnaires to ensure that this research reached the relevant, targeted sample; these questions include "What is your nationality? Are you a fresh graduate from an Indonesian university? Have you used AI-based learning tools?" The respondents were requested to answer (Yes or No) to proceed to the following section.

The survey was conducted in Indonesia within 48 days and involved 698 accounting students from 20 provinces. The geographic diversity of participants ensures the presence of a representative sample of fresh graduate job seekers nationwide. Meanwhile, offline surveys were conducted at several leading universities with surveyors who distributed questionnaires in person. The surveyors were provided with training and a thorough understanding of each question to ensure they mastered the questionnaire's content and could explain it to respondents, ensuring accurate responses aligned with the definitions of each construct.

Several measures were implemented to minimize potential biases in the survey. First, the survey was randomly and indiscriminately distributed via various online and social media platforms, including e-mail, WhatsApp, Facebook, Instagram, TikTok, and LinkedIn. Thus, this study leverages social media platforms for their effectiveness in terms of time, resources, and ability to access a broader and more diverse population representing Indonesian graduates. In addition, these tools also ensure a high response rate since the majority of the fresh graduates in Indonesia are more familiar with and use one of the chosen platforms. Second, the survey advised participants to use initials instead of full names to protect participant privacy and encourage unbiased and accurate responses. Participants were assured data confidentiality and anonymity, with only the research team accessing individual responses. Third, the survey questions were formulated and structured to align with the study's variable definition. Lastly, we prepared a consent statement to secure participants' permission and explained that the survey was solely for research purposes. They were also encouraged to seek clarification for any ambiguities while completing the questionnaire.

Following the recommendation from Hair et al. (2018). The study aimed for a sample size of 10 times the number of indicators in the measurement model, requiring at least 310 respondents for the 40-item survey. With a final sample size of 698, the study exceeded this requirement, providing robust data for analysis using partial least squares structural equation modeling (PLS-SEM).

Since many respondents preferred to answer in Bahasa Indonesia, the questionnaires were translated into this language. After completion, the responses were translated back into English. The translation process followed Brislin's (1970) methodology and was carried out with the help of two bilingual, native-speaking language experts.

4.2. Sample characteristics

An analysis of the participant profile, as shown in Table 1, provides valuable insights into the demographic characteristics of the study sample. The distribution of GPAs reveals that 93.7 % of participants

Table 1
Profile of fresh graduate job seekers.

Profile	*n*	%	Profile	*n*	%
Gender			Education institution		
Female	567	81.2	Private	614	88
Male	131	18.8	Public	84	12
Generation			**Family background in accounting**		
Gen Y (1981–1996)	6	0.9	Yes	206	29.5
Gen Z (1997–2012)	692	99.1	No	492	70.5
Grade point average (GPA)			**Accounting/finance program taken**		
1.00–2.00	4	0.6	Bachelor	671	96.1
2.01–3.00	40	5.7	Vocational	27	3.9
3.01–3.50	351	50.3			
3.51–4.00	303	43.4			
Total	698	100	**Total**	698	100

Note: **Frequency (*n*); Percentage (%).**

have a GPA above 3.00, indicating a sample skewed toward academically high-achieving students, who may be more engaged and motivated, potentially influencing their views on AI. Additionally, 99.1 % of participants are from Generation Z, with minimal representation from Generation Y, highlighting the digital nativity and likely higher technological fluency of the sample, which may foster a more favorable attitude toward AI. The sample also shows a notable gender imbalance, with 81.2 % female and 18.8 % male participants. Most participants (96.1 %) are enrolled in bachelor accounting programs, while only 3.9 % are in vocational accounting programs. Furthermore, 88 % of participants come from private institutions, with 12 % from public ones. Lastly, 29.5 % of participants have a family background in accounting, while 70.5 % do not. Table 2

4.3. Survey measures

A questionnaire was developed to capture fresh graduate job seekers' perspectives on the impact of AI-based learning experiences in formal education toward their future career commitment. The questionnaire represented all constructs in the conceptual model (Fig. 1 and Table 4). The questionnaire included demographic questions (e.g., gender, age, marital status, education, and work experience) and measures for various constructs relevant to the study. All constructs were measured using a five-point Likert scale, from "strongly disagree" (1) to "strongly agree" (5).

AI-based learning experience in higher education refers to using AI technologies to personalize, enhance, and support learning, improving engagement and outcomes. This construct is developed through a scale comprising four items adapted from Su and Yang (2023) and Wood et al. (2021). These measurements were used to capture an accurate representation of formal AI coursework. Thus, the self-reported questions for AI-based learning experience were focused on the view of the participants of the AI coursework provided in the accounting program. AI literacy, defined as to which a student can understand AI, was measured with five items adapted from Li et al. (2022) and Sing Chai et al. (2021). Intrinsic motivation and Extrinsic motivation for mastering AI, referring to personal goals and external reasons for learning AI, were assessed with five and seven items, respectively, adapted from Lin et al. (2021), Nordhaug (1989) and Wang, Zhang, and Zhang (2022).

Meanwhile, self-efficacy was measured with seven items adapted from Almaiah et al. (2022) and Kwak et al. (2022). AI perceived competency is an individual's perception of their ability to use and engage with AI technologies in accounting effectively. This construct is measured by four items of scale adapted from Temitayo et al. (2022). Lastly, the construct of career commitment is measured by a scale comprising eight items adapted from Bargmann et al. (2022) and Hatane et al. (2021). All items used to calculate the variables and model are presented in Table 3.

To ensure clarity, three researchers in human resource management took part in a pre-test to evaluate the appropriateness of the measurement items before distributing the questionnaire, thereby ensuring *content validity*. The survey was pretested with 20 respondents following the protocol method outlined by Hunt et al. (1982), where respondents vocalized their thoughts as they completed the study. This pretest, as recommended by Sekaran and Bougie (2016), helped identify and correct potential ambiguities. Based on pretest feedback, a pilot study was conducted with 45 respondents, as suggested by Cooper and Schindler (2011). After obtaining promising results, the main data collection proceeded with a larger sample. Table 4

Table 2
Common Method Bias using Measured Latent Marker Variable (MLMV).

Relationship	Without marker		With marker		Significant difference?
	Beta	p-value	Beta	p-value	
AI-based learning experience → Ai-literacy	0.636	0.000	0.634	0.000	No
AI-based learning experience → Intrinsic motivation for mastering AI	0.342	0.000	0.345	0.000	No
AI-based learning experience → Extrinsic motivation for mastering AI	0.327	0.000	0.330	0.000	No
AI-based learning experience → AI-competency	0.131	0.004	0.131	0.006	No
AI-literacy → AI-competency	0.270	0.000	0.276	0.000	No
Intrinsic motivation for mastering AI → AI-competency	0.193	0.002	0.187	0.003	No
Extrinsic motivation for mastering AI → AI-competency	0.168	0.001	0.165	0.001	No
AI-literacy → AI-self efficacy	0.201	0.000	0.210	0.000	No
Intrinsic motivation for mastering AI → AI-self efficacy	0.110	0.027	0.109	0.026	No
Extrinsic motivation for mastering AI → AI-self efficacy	0.507	0.000	0.582	0.000	No
AI-competency → AI-self efficacy	0.201	0.000	0.201	0.000	No
AI-competency → Career commitment to be an accountant	0.210	0.000	0.204	0.000	No
AI-self efficacy → Career commitment to be an accountant	0.300	0.000	0.286	0.000	No

4.4. Data analysis technique and procedures

Partial least squares-structural equation modeling (PLS-SEM) was used to assess the proposed relationships, utilizing Smart PLS software. This method was chosen for its suitability for non-normally distributed data, such as the female-dominant sample in this study. PLS-SEM is particularly effective for complex models and formatively measured constructs (Ali et al., 2018; Kurniawan et al., 2025). Its flexibility with data assumptions and techniques makes it ideal for theory development and understanding complex relationships among constructs (Hair et al., 2011). With 40 items across seven constructs and a sample size of 698, the method's statistical power supports robust analysis (Henseler et al., 2016). PLS-SEM is suitable for exploratory and confirmatory research, measuring how independent constructs influence dependent ones (Akter et al., 2017). In addition, since PLS-SEM can simultaneously analyze multiple relationships and accommodate both direct and indirect links between variables and is widely used in educational research, this statistical technique is most suitable for the proposed model.

In general, the PLS-SEM analysis includes evaluating the measurement model for validity and reliability of the survey instrument before testing hypotheses through the structural model (Sedera et al., 2024). Specifically, the PLS-SEM analysis followed a three-stage process, starting with identifying common-method bias (CMB). This is achieved through the collinearity test by calculating the Variance Inflation Factors (VIF) and Measured Latent Market Variable (MLMV) test. The second stage of analysis is the measurement model. This phase assessed the reliability and validity of the constructs through several statistical tests (Henseler et al., 2009). Convergent validity was examined by evaluating indicator loadings and the Average Variance Extracted (AVE), while discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio. Reliability was confirmed through Cronbach's alpha (CA) and Composite Reliability (CR) scores (Hair et al., 2018).

Once the measurement model was validated, the structural model was analyzed to assess the hypothesized relationships. This involved

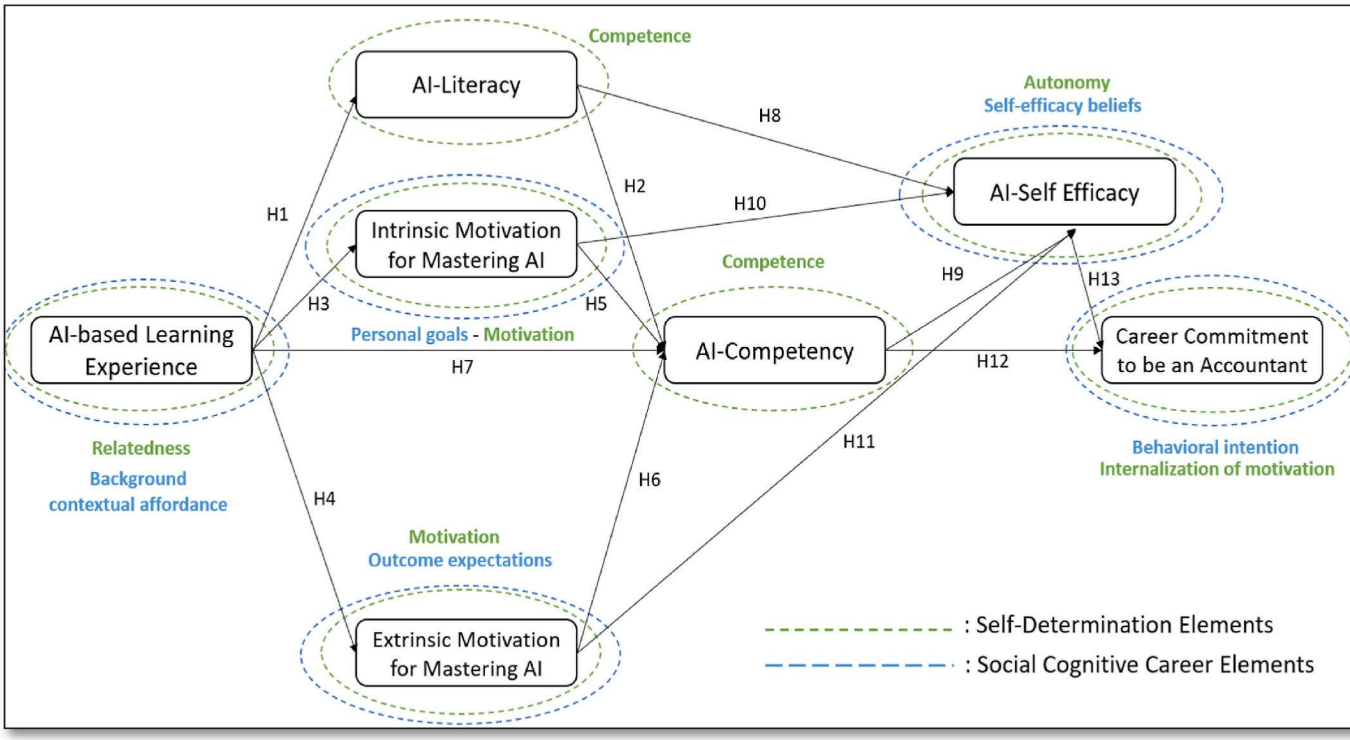

Fig. 1. Research framework and hypotheses.

evaluating (1) model fit test using the Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI) evaluation, (2) explanatory power (R^2) to measure the proportion of variance explained by the independent variables, (3) predictive relevance through blindfolding test to evaluate the Stone-Geisser's Q^2 values for endogenous constructs, and (4) path analysis using bootstrapping with a sub-sample of 5000 to test the hypothesized relationships.

5. Findings

5.1. Preliminary assessment (common method bias)

We confirmed the normality of our data by analyzing kurtosis and skewness, with values ranging from −2 to +2, well within the acceptable range of −3 to +3. To address common-method bias, we conducted a measured latent marker variable test recommended by Chin et al. (2013, pp. 231–239). This method provided an extra layer of scrutiny. A construct unrelated to the main study variables, "*Job replacement anxiety*", was used as a marker variable. Path coefficients were then compared across two models: one with the marker variable and one without. The comparison, presented in Table 2, showed no significant distortions, supporting the conclusion that common method bias was not present in the dataset. Additionally, we assessed collinearity using the variance inflation factor, with all values remaining below the critical threshold of five, ensuring the data's robustness, as seen in Table 3 (Hair Jr. et al., 2017).

5.2. Measurement model assessment

To ensure the measurement model's validity and reliability, we assessed convergent validity, discriminant validity, and reliability. Convergent validity was evaluated through AVE values, all exceeding the 0.5 threshold (Hair, Hollingsworth, et al., 2017), as shown in Table 3, confirming strong validity. Discriminant validity was assessed using the HTMT ratio (Henseler et al., 2018). As shown in Table 4, the HTMT values were below 0.90, supporting discriminant validity. Henseler et al. (2016) proposed that the HTMT ratio provides a more accurate assessment of discriminant validity in the reflective PLS-SEM approach. Finally, composite reliability for each construct met acceptable standards (Table 3), ensuring internal consistency. Overall, the measurement model demonstrates robust validity and reliability, confirming its integrity for the study.

5.3. Structural model assessment

The first assessment of structural model measurement is the model fit test. The model fit test revealed an SRMR value below 0.08 and an NFI value approaching 0.90 in the saturated model (Table 5), indicating a reasonable model fit (Hair et al., 2018). Secondly, we have assessed the proportion of variance explained by the independent variables by using R^2. The adjusted R^2 values were 0.199 for AI competency, 0.603 for AI self-efficacy, and 0.194 for career commitment, confirming the model's reliability. To check for collinearity, we reviewed the VIF of all constructs, ensuring that all values fell within the recommended range (less than 3), as shown in Table 3 (Henseler et al., 2016). Thirdly, to assess the predictive accuracy of our model, we used Stone-Geisser's Q^2 measure with the blindfolding method. According to Chin and Dibbern (2010), Q^2 value greater than 0.05 indicates strong predictive validity. Our results showed Q^2 values of 0.144 for AI competence, 0.404 for AI self-efficacy, and 0.139 for career commitment, confirming the robustness and relevance of our findings.

To conclude the hypotheses, we examined structural path coefficients, and the results are shown in Table 6 and Fig. 2. The results show all construct relationships' direct, indirect, and total effects. The total effect is the outcome used to conclude the sum of the direct and total indirect effects. In the total impact, the result has shown that AI-based learning in higher education experienced by fresh graduates strongly and positively increases their AI-literacy (β: 0.636, *p*: 0.000), intrinsic (β: 0.342, *p*: 0.000) and extrinsic (β: 0.327, *p*: 0.000) motivation for mastering AI, and AI-competency (β: 0.162, *p*: 0.000). The high AI-literacy (β: 0.270, 0.215 *p*: 0.000, 0.000) and intrinsic (β: 0.193, 0.149 *p*: 0.002, 0.004) and extrinsic (β: 0.168, 0.541 *p*: 0.010, 0.000)

Table 3
Conceptualization, operationalization, and the results of measurement model.

Construct conceptualization	Item operationalization	Convergent validity			Reliability	
		Factor loading	Variance inflation factor	Average variance extracted	Cronbach's alpha	Composite reliability
AI-based learning experience (AIBC): using AI technologies to personalize and enhance learning engagement and outcomes.	AIBC1: Does your Accounting program teach the operation of AI/accounting software systems (e. g., Accurate, Zahir, MYOB, SAP Accounting, and others)?	0.826	1.987	0.746	0.886	0.922
	AIBC2: Does your program provide practical learning experiences to train you in using AI accounting software/systems?	0.870	2.539			
	AIBC3: Is the learning on using AI accounting software/systems in your program adequately comprehensive?	0.877	2.685			
	AIBC4: Does the curriculum of your accounting program offer courses included in the information system-based courses from the IAESB 2018?	0.881	2.477			
AI-literacy (AIL): AI literacy is the ability to understand, use, and critically assess AI.	AIL1: I understand the functions and features available in accounting software/AI (e.g., ZAHIR, Accurate, SMACC, XERO, ERP, and others).	0.895	3.142	0.776	0.904	0.933
	AIL2: I can operate one of the accounting AI systems widely available online.	0.874	2.884			
	AIL3: I know how to acquire accounting software/AI.	0.889	2.735			
	AIL4: I am familiar with and knowledgeable about various brands of accounting software/AI (e.g., ZAHIR, Accurate, SMACC, XERO, ERP, and others).	0.866	2.455			
Intrinsic motivation for mastering AI (IMAI): personal goals that motivate an individual to learn AI.	IMAI1: I learn AI-related skills in accounting in greater depth to enhance my personal development.	0.856	2.585	0.715	0.889	0.926
	IMAI2: I learn AI-related skills in greater depth to provide significant benefits in my professional career.	0.855	2.563			
	IMAI3: I learn AI-related skills in greater depth to enrich my skill set.	0.904	3.397			
	IMAI4: Studying AI-related skills in the field of accounting is highly engaging.	0.740	1.719			
	IMAI5: Studying AI-related skills in accounting presents an exciting challenge for me.	0.864	2.647			
Extrinsic motivation for mastering AI (EMAI): External reasons motivate an individual to learn AI.	EMAI1: Studying AI skills will enhance my competitiveness in the job market.	0.776	2.250	0.698	0.928	0.942
	EMAI2: Studying AI skills will help me secure my employment in the future.	0.841	2.932			
	EMAI3: Studying AI skills will help me attain a higher salary in the future.	0.848	2.742			
	EMAI4: My opinion will receive more attention from my colleagues in the future if I master AI.	0.849	2.822			
	EMAI5: Generally, studying AI skills is highly beneficial for achieving my career goals.	0.854	3.209			
AI-competency (AIC): the ability to effectively understand, apply, and manage AI.	AIC1: Are you capable of operating AI/ accounting software (e.g., ZAHIR, MYOB, SAP Accounting, Accurate, etc.)?	0.832	2.109	0.747	0.887	0.922
	AIC2: Are you capable of operating AI for digital taxation (e.g., digital tax reporting software)	0.891	2.793			
	AIC3: Are you capable of operating a spreadsheet for finance? (e.g., Microsoft Excel, Google Sheets, or LibreOffice)?	0.881	2.914			
	AIC4: Are you capable of operating data visualization software?	0.853	2.616			
AI-Self-efficacy (AISE): The belief an individual has to work with AI.	AISE1: It will be easy for me to master the use of AI in my future work as an accountant.	0.844	3.537	0.676	0.931	0.943
	AISE2: I can leverage AI to make my work as an accountant much more effective in the future.	0.876	4.995			
	AISE3: It will be easy for me to learn any AI in the field of accounting that emerges in the future.	0.872	4.427			
	AISE4: I can master skills related to AI.	0.846	3.193			
	AISE5: I am not apprehensive about learning AI-related skills in accounting.	0.838	3.084			
Career commitment to be an accountant (CCIA): the level of dedication and intent an individual has to pursue the accounting profession.	CCIA1: I will keep choosing a career as an accountant despite the proliferation of accounting software/AI.	0.814	2.531	0.732	0.947	0.956
	CCIA2: I will work diligently to become an accountant.	0.879	3.971			

(*continued on next page*)

Table 3 (*continued*)

Construct conceptualization	Item operationalization	Convergent validity			Reliability	
		Factor loading	Variance inflation factor	Average variance extracted	Cronbach's alpha	Composite reliability
	CCIA3: My career as a professional accountant will provide me with personal fulfilment.	0.890	3.974			
	CCIA4: I aspire to become an accountant for a reputable company or public accounting firm.	0.876	3.464			
	CCIA5: I am deeply excited to begin my career as an accountant.	0.871	3.157			

Table 4
HTMT results.

	AI-based learning experience	AI-competency	AI-literacy	AI-Self efficacy	Career commitment to be an accountant	Extrinsic motivation for mastering AI
AI-based learning experience						
AI-competency	0.181					
AI-literacy	0.709	0.349				
AI-Self efficacy	0.375	0.528	0.485			
Career commitment to be an accountant	0.175	0.387	0.187	0.424		
Extrinsic motivation for mastering AI	0.359	0.404	0.382	0.772	0.441	
Intrinsic motivation for mastering AI	0.38	0.421	0.409	0.686	0.477	0.837

Table 5
Model fit, explanatory power, and predictive relevance test result.

Model Fit Test	Saturated model	Estimated model
Standard root mean square (SRMR)	0.049	0.146
Normed fit index (NFI)	0.862	0.841
Explanatory power and predictive relevance	**R^2**	**Stone-Geisser's Q^2**
AI-competency	0.199	0.144
AI-literacy	0.404	0.311
AI-Self efficacy	0.603	0.404
Career commitment to be an accountant	0.194	0.139
Extrinsic motivation for mastering AI	0.107	0.074
Intrinsic motivation for mastering AI	0.117	0.082

motivations for mastering AI resulted from AI-based learning are significantly and positively influence AI-competency and AI-Self efficacy of fresh graduates. The accumulated AI competencies derived from AI-based learning, in turn, have been strongly and positively associated with the development of fresh graduates' AI self-efficacy (β: 0.201, *p*: 0.000) and career commitment of fresh graduates to be an accountant (β: 0.270, *p*: 0.000). Lastly, the AI-self efficacy itself is strongly associated with career commitment of fresh graduates (β: 0.300, *p*: 0.000). Therefore, we can conclude that all hypotheses (H_1 - H_{13}) are supported.

The results of the total indirect effect in Table 6 reflect the essential mediating role embedded in AI literacy, intrinsic and extrinsic motivations for mastering AI, and AI competency in the relationship between AI-based learning experiences, AI self-efficacy, and career commitment. Several construct relationships show higher total effect coefficients due to the accumulation of direct and indirect effects. Specifically, AIBC has a significant negative association with AIC in the direct relationship (β: −0.131, *p*: 0.004) but a positive association with the total effect (β: 0.162, *p*: 0.000) when accounting for the contributions of the three intervening variables (AIL, IMAI, and EMAI). This pattern is also found in the relationships of AIL → AISE, EMAI → AISE, and IMAI → AISE, where total effect coefficients exceed direct effects due to the mediating role of AIC.

In response to the core research question, Table 6 shows that AI-based learning experiences in higher education positively and significantly impact AI self-efficacy and career commitment among fresh graduates. Such experiences enhance AI competency, literacy, and motivation, influencing their AI self-efficacy and career commitment. These effects are indicated by the significant total indirect effects in the relationships AIBC → AISE (β: 0.338, *p*: 0.000) and AIBC → CCIA (β: 0.135, *p*: 0.000). Therefore, the hypothesis of H14 and H15 are supported.

Although Baron and Kenny's (1986) mediation method is commonly used, we chose not to apply it in this study. This approach has been widely debated, especially when multiple mediators are involved, as in our study (Zhao et al., 2010). We employed the bootstrapping procedure with 5000 resamples, following Preacher and Hayes (2008). Our primary aim was to examine the mediating role of psychological empowerment and organizational commitment in the link between brand authenticity and prosocial service behavior. The results showed significant mediating effects: psychological empowerment (β: 0.187, t: 5.512, $p < 0.001$) and organizational commitment (β: 0.035, t: 2.144, $p < 0.05$) both mediated the relationship, supporting H2 and H3. Additionally, both variables mediated the relationship (β: 0.039, t: 2.799, $p < 0.01$), supporting H4. While the indirect effect of brand authenticity on prosocial behavior was significant (β: 0.261, t: 6.278, $p < 0.001$), the direct effect was not (β: −0.045, t: 1.325, p: 0.185 > 0.05), suggesting full mediation, in line with Zhao et al. (2010).

The study also utilized the Importance-Performance Map Analysis (IPMA) to assess predictors' relative significance and effectiveness on outcomes. IPMA visually represents predictor variables, with the x-axis indicating their importance (scaled from 0 to 1) and the y-axis reflecting their performance (ranging from 1 to 100) in predicting the outcome (Hair et al., 2018). Higher values on both axes denote greater importance and performance, highlighting the predictors most effectively influencing the target outcome (Hair et al., 2018; Sarstedt et al., 2011).

As displayed in Fig. 3, the performance of all variables spanned from 60.949 to 75.868, indicating that AI-based learning experiences, motivations, AI literacy, AI competency, and AI self-efficacy are all essential elements for establishing a career commitment to be an accountant. Noteworthily, AI self-efficacy and competency demonstrate the most substantial overall impact on the career commitment of fresh graduates (0.300 and 0.270), exceeding the importance of other variables, such as

Table 6
Structural Model Assessment of main and mediating effects.

Relationship	Path Coefficient	Standard deviation	*t*-value	*p*-value	BCCI 95 %	Outcome/Hypothesis Testing
Direct Effect						
AIBC → AIL	0.636	0.028	22.99	0.000**	0.589, 0.679	**Significant**
AIL → AIC	0.270	0.049	5.534	0.000**	0.187, 0.349	**Significant**
AIBC → IMAI	0.342	0.041	8.327	0.000**	0.274, 0.406	**Significant**
IMAI → AIC	0.193	0.063	3.081	0.002**	0.089, 0.295	**Significant**
AIBC → EMAI	0.327	0.039	8.446	0.000**	0.263, 0.389	**Significant**
EMAI → AIC	0.168	0.065	2.578	0.010*	0.059, 0.274	**Significant**
AIBC → AIC	−0.131	0.046	2.842	0.004**	−0.207, −0.054	**Significant**
AIL → AISE	0.161	0.033	4.832	0.000**	0.105, 0.215	**Significant**
EMAI → AISE	0.507	0.049	10.262	0.000**	0.423, 0.584	**Significant**
IMAI → AISE	0.110	0.050	2.208	0.027*	0.030, 0.188	**Significant**
AIC → AISE	0.201	0.034	5.985	0.000**	0.148, 0.257	**Significant**
AIC → CCIA	0.210	0.045	4.700	0.000**	0.136, 0.282	**Significant**
AISE → CCIA	0.300	0.041	7.252	0.000**	0.229, 0.365	**Significant**
Total Indirect (Mediating) Effect						
H14. AIBC → AISE	0.338	0.034	9.877	0.000**	0.280, 0.394	**Supported**
H15. AIBC → CCIA	0.135	0.021	6.436	0.000**	0.100, 0.170	**Supported**
AIL → AISE	0.054	0.013	4.233	0.000**	0.036, 0.079	**Significant**
EMAI → AISE	0.034	0.015	2.316	0.021*	0.013, 0.061	**Significant**
IMAI → AISE	0.039	0.014	2.774	0.006**	0.019, 0.066	**Significant**
AIC → CCIA	0.060	0.013	4.812	0.000**	0.042, 0.083	**Significant**
AIBC → AIC	0.293	0.034	8.541	0.000**	0.234, 0.349	**Significant**
AIL → CCIA	0.121	0.019	6.511	0.000**	0.091, 0.153	**Significant**
EMAI → CCIA	0.197	0.032	6.198	0.000**	0.146, 0.250	**Significant**
IMAI → CCIA	0.085	0.025	3.396	0.001**	0.046, 0.127	**Significant**

Relationship	Path Coefficient	Standard deviation	*t*-value	*p*-value	BCCI 95 %	Outcome/Hypothesis Testing
Total Effect = Direct Effect + Total Indirect Effect						
H1. AIBC → AIL	0.636	0.028	22.99	0.000**	0.589, 0.679	**Supported**
H2. AIL → AIC	0.270	0.049	5.534	0.000**	0.187, 0.349	**Supported**
H3. AIBC → IMAI	0.342	0.041	8.327	0.000**	0.274, 0.406	**Supported**
H4. AIBC → EMAI	0.327	0.039	8.446	0.000**	0.263, 0.389	**Supported**
H5. IMAI → AIC	0.193	0.063	3.081	0.002**	0.089, 0.295	**Supported**
H6. EMAI → AIC	0.168	0.065	2.578	0.010**	0.059, 0.274	**Supported**
H7. AIBC → AIC	0.162	0.041	3.983	0.000**	0.091, 0.225	**Supported**
H8. AIL → AISE	0.215	0.034	6.381	0.000**	0.161, 0.270	**Supported**
H9. AIC → AISE	0.201	0.034	5.985	0.000**	0.148, 0.257	**Supported**
H10. IMAI → AISE	0.149	0.051	2.904	0.004**	0.065, 0.228	**Supported**
H11. EMAI → AISE	0.541	0.052	10.499	0.000**	0.454, 0.621	**Supported**
H12. AIC → CCIA	0.270	0.041	6.577	0.000**	0.202, 0.335	**Supported**
H13. AISE → CCIA	0.300	0.041	7.252	0.000**	0.229, 0.365	**Supported**
H14. AIBC → AISE	0.338	0.034	9.877	0.000**	0.280, 0.394	**Supported**
H15. AIBC → CCIA	0.135	0.021	6.436	0.000**	0.100, 0.170	**Supported**
AIL → CCIA	0.121	0.019	6.511	0.000**	0.091, 0.153	**Significant**
EMAI →CCIA	0.197	0.032	6.198	0.000**	0.146, 0.250	**Significant**
IMAI → CCIA	0.085	0.025	3.396	0.001**	0.046, 0.127	**Significant**

Note 1: AIBC = AI-based learning experience; AIL = AI-literacy; AIC = AI-competency; AISE = AI-self efficacy; IMAI = Intrinsic motivation for mastering AI; EMAI = extrinsic motivation for mastering AI; CCIA = career commitment to be an accountant. **Note 2**: BCCI = Bias-corrected confidence interval. **Note 3**: *p < 0.05 **p < 0.01.

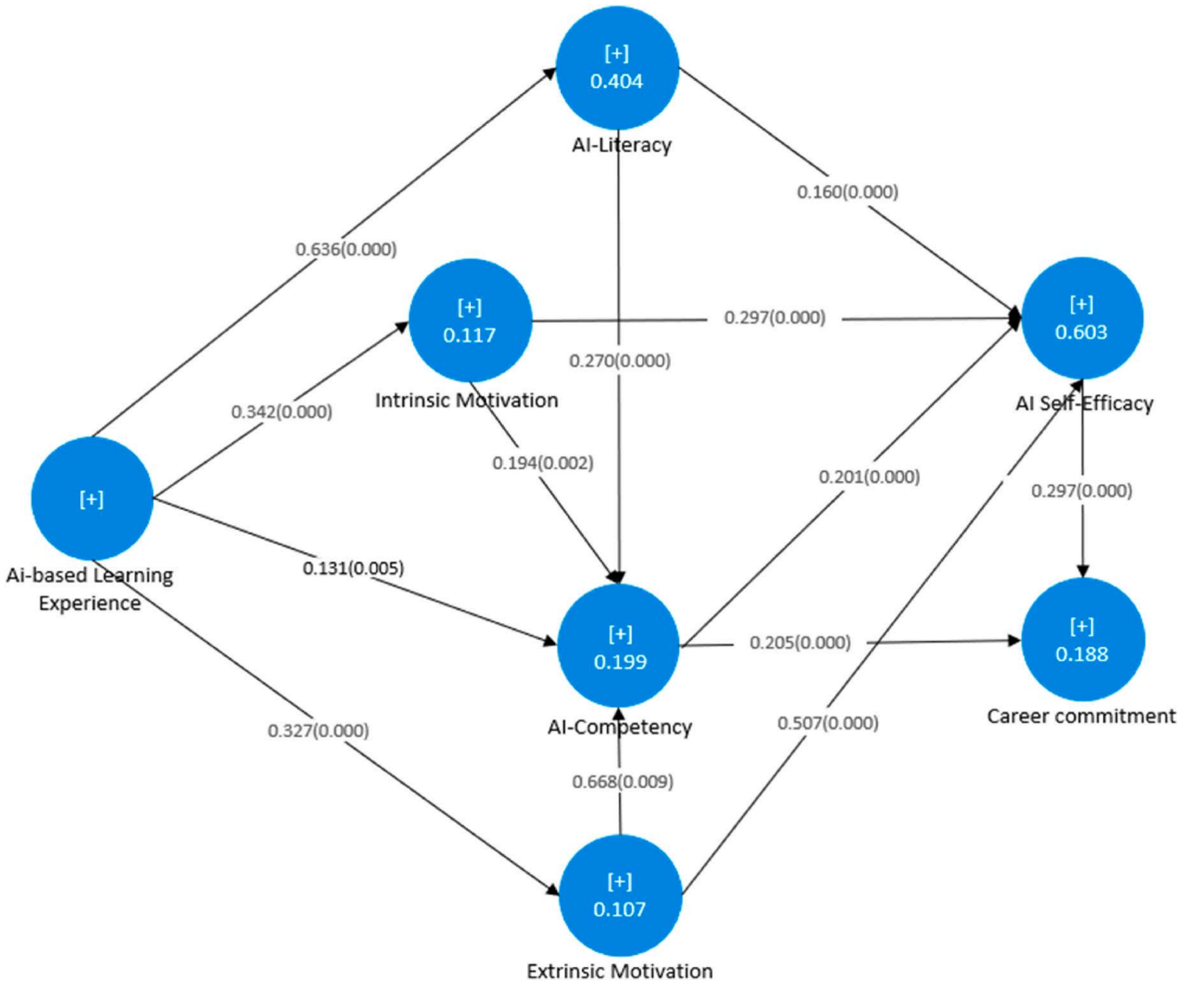

Fig. 2. Structural model results.

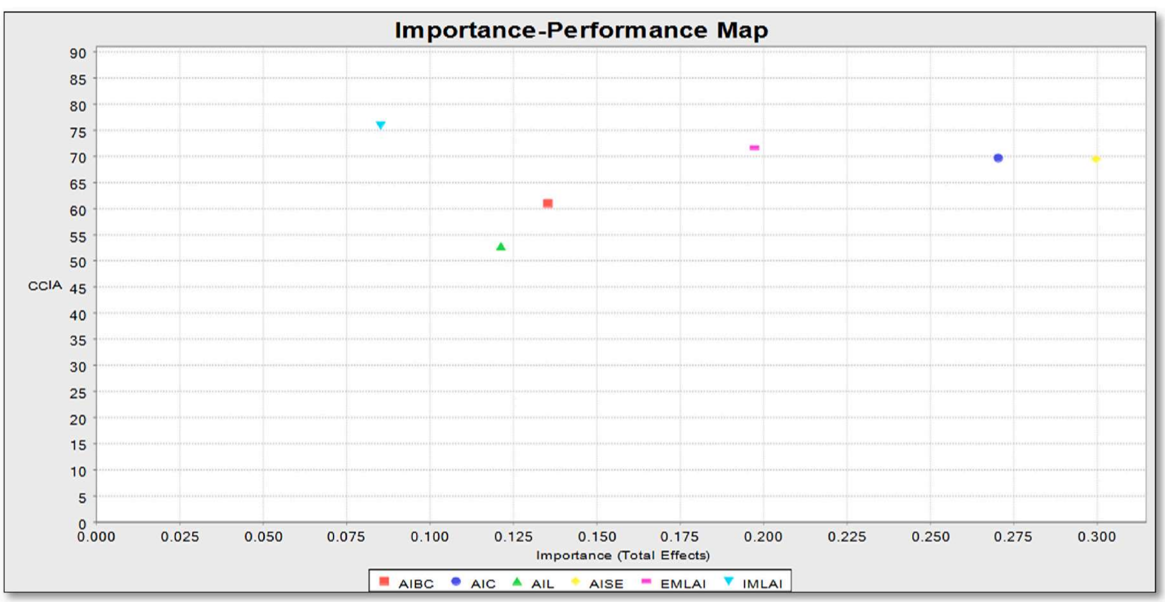

Fig. 3. Importance-performance map (IPMA) for career commitment.. (For the interpretation of color references in this figure legend, readers are advised to consult the online version of the article.)

intrinsic and extrinsic motivations (0.085 and 0.197) and AI literacy (0.121).

6. Discussion

This study offers valuable theoretical and managerial insights by exploring the relationship between AI-driven learning in higher education and graduates' career intentions. The findings contribute to understanding human resource development in accounting amid ongoing AI advancements.

First, this study confirms a significant positive relationship between AI-based learning experiences and AI literacy, in line with the findings in AI and higher education conducted by Tzirides et al. (2024). Their finding emphasizes the importance of integrating AI tools in education. This work suggests that providing a hands-on AI in the learning process is essential, specifically including AI within higher education curricula, which would enhance the AI literacy of the students when they graduate. In this context, fresh graduates with intensive AI-focused learning are better equipped to understand artificial intelligence and apply its functions effectively in their accounting careers.

This study empirically investigated the link between AI-based learning experiences and intrinsic and extrinsic motivation to master AI. The findings are consistent with Qu and Wu (2024), emphasizing the role of AI tools in learning to enhance motivation to master these technologies and advance their learning process. Moreover, Jia and Tu's (2024) findings illustrate how AI-based learning experiences fuel intrinsic and extrinsic motivation and confirm that learning experiences involving and interacting with AI tools and technology significantly and positively foster these forms of motivation. Particularly, the findings emphasise how intrinsic and extrinsic motivation for mastering AI tools improves AI competency and validate that this influence is positive and significant. Thus, it is concluded that fresh graduates who receive extensive experience using AI during their studies, specifically when they use AI software for accounting or a particular course included in information system-based courses, tend to be eager and keen to acquire extensive knowledge about AI tools for personal and skill development.

Third, this study examines the impact of AI-based learning experiences on AI competency. Similar to the previous findings of Hsu et al. (2021), This impact was significant and positive, indicating that fresh graduates involved with AI tools for learning develop high AI competency. Thus, if the graduates have an intensive learning interaction using AI tools during their study, they will be more competent with AI tools when they graduate. In other words, their experience learning AI tools and software enables them to be more capable of leveraging these tools.

Fourth, this study investigates the link between AI literacy and competencies, and the findings align with the results of Singh et al. (2024), who indicated that these links were significant and positive. The result underscores the importance of AI literacy in shaping graduate competency, particularly in how students engage with AI tools for learning and professional development. In other words, when the graduates possess a high level of AI literacy, their capability to use AI tools for accounting is enhanced. Hence, graduates with a strong understanding and familiarity with AI concepts and tools are better equipped to apply them effectively in accounting roles. For example, when the graduates acquire a high level of understanding or fundamental knowledge of AI, they can effectively use software like ZAHIR, MYOB, SAP Accounting, and Accurate.

Fifth, this study examines the influence of AI literacy on AI self-efficacy; the link was significant and positive. Consistent with existing findings asserting that AI literacy improves self-efficacy (Criollo et al., 2024; Hsu et al., 2021). Prior empirical evidence shows AI literacy's direct and indirect influence on AI self-efficacy through AI competency. In other words, higher AI literacy leads to strong AI competency. Therefore, this finding explains that when fresh graduates understand the concept and function of AI tools or have a strong AI proficiency, they can use the AI tools easily and effectively, meaning that they can easily manage, leverage, and make the most of AI tools for their careers.

Sixth, this work examines the link between motivations for mastering AI and AI self-efficacy; this motivation is intrinsic or extrinsic. Intrinsic motivation often relates to personal factors, such as getting new skills and the benefits of using AI. Besides, extrinsic motivation is the benefit that graduates expect in their careers. The findings are consistent with prior evidence indicating strong motivation to master the AI tools that shape the AI efficacy of the fresh graduate (Qawaqneh et al., 2023; Yilmaz & Karaoglan Yilmaz, 2023). This indicates that when graduates are motivated to acquire the necessary knowledge and ability to use AI tools, they are likelier to see them as easy to use and convenient.

Besides, the influence of motivations, intrinsic and extrinsic, on AI competency was investigated in this study and empirically confirmed to be significant and positive, which is in line with the prior empirical evidence of Bargmann et al. (20220 and Lin et al. (2021) and followed by Razak (2021). The findings indicate that when graduates are strongly motivated to master AI tools, they improve their capability to operate AI/accounting software. For example, when graduates have a deeper desire to improve their personal development or are eager to improve their skills or acquire necessary skills that can bring future benefits to them or give them a competitive advantage in future job searches, they are more likely to be capable of manipulating AI software for an accounting career.

Moreover, this work examines the relationship between AI competency and AI self-efficacy. The empirical findings are similar to the previous findings of Alamäki et al. (2024), suggesting that AI competency positively influences AI self-efficacy. These results emphasise that. An individual with a fundamental knowledge of AI tools can leverage AI tools to solve a complex problem, which is also evident for a fresh graduate. Furthermore, it is evident that when fresh graduates have acquired sufficient knowledge about AI and can apply it, they will perceive that they can use AI effectively. They will find that these AI tools would be beneficial for their career.

Furthermore, this study examines the impact of AI competency on career commitment. The findings align with the existing findings of Dogar and Scorte (2023) and Musyaffi et al. (2023), Illustrating how AI competency improves career engagement. The results indicate a significant and positive impact of AI competency on career commitment among graduates, asserting that when graduate students are capable of using AI accounting software, they develop a strong commitment to the career of an accountant. Therefore, higher AI competency among graduates will lead to a strong career commitment when they become accountants.

In addition, this work investigates the impact of AI self-efficacy on career commitment and empirically validates that this link is significant and positive. The finding aligns with prior empirical evidence of Zhang and Zhang (2022). It explains that the higher the AI self-efficacy of the graduates, the more likely they are to commit to this career as accountants. In other words, when fresh graduates can use and leverage AI tools easily and effectively, they tend to be more committed to their jobs. As accountants, they feel they have control over their tasks and possess the knowledge they need to complete their assignments and achieve their career goals.

Lastly, the findings established the mediating role of AI literacy, motivations, and competency in the relationship between AI-based learning experiences, self-efficacy, and the career commitment of fresh graduates.

7. Implication

7.1. Theoretical implications

This research offers valuable theoretical insights into integrating advanced technologies in education and their impact on career development. *Firstly*, this study provides empirical evidence that positive experiences with AI-based learning significantly increase fresh graduates' self-confidence in mastering AI skills while reducing their anxiety about AI replacing them in accounting roles. As a result, their commitment to pursuing a career in accounting is strengthened. AI-based learning also improves students' digital literacy and competence, enhancing their readiness to handle accounting tasks in the industry. This process stimulates intrinsic and extrinsic motivation to develop their AI skills further. Graduates gain satisfaction, self-validation, and improved bargaining position in accounting, thanks to their practical accounting knowledge and advanced AI capabilities.

In general, this study has extended the SCT (Bandura, 1999) and SCCT (Segal et al., 2002) by proving that the cognitive process of increasing knowledge (literacy and competency) and outcome expectations (motivations) in AI-related skills through the AI-based learning process can ignite their career decision-making to become accountants. Specifically, it underscores the role of AI-based learning as a transformative strategy that influences career trajectories, particularly in technology-driven fields like accounting. *Secondly*, the study advances theoretical understanding by illustrating how AI literacy, motivation (both intrinsic and extrinsic), AI competency, and self-efficacy collectively shape career commitment. Using SCCT as a framework clarifies how individuals make complex career decisions. Additionally, by incorporating SDT, the research shows how AI-based learning environments promote motivation through relatedness, competence, and autonomy, ultimately increasing students' career commitment. Moreover, the findings contribute to the ongoing discussion on the evolving role of higher education in preparing students for careers in an AI-driven world. The research stresses the importance of educational systems in equipping graduates with the cognitive and emotional tools needed to succeed in technology-intensive industries, reinforcing the value of SCCT and SDT in fostering resilience and long-term career commitment. Overall, the study enhances theoretical frameworks on the intersection of technology, education, and career development, providing a comprehensive model for understanding how AI-based learning influences career decisions and professional goals. It sets the stage for future research exploring the dynamic relationships between technological advancements, educational practices, and career outcomes across different sectors and populations.

7.2. Practical implications

This research offers significant practical and managerial insights for educational institutions, policymakers, and industry leaders aiming to enhance career readiness and commitment among recent graduates in the age of AI. The findings emphasise integrating AI-based learning into higher education curricula to equip students with vital competencies and self-efficacy in AI technologies. This approach will better prepare graduates for the evolving demands of AI-driven industries, especially in accounting, where technological proficiency is increasingly essential. For educational administrators, the results stress the need for learning environments that teach technical skills and address motivational and emotional factors, such as AI literacy and competitions. Targeted initiatives to boost intrinsic and extrinsic motivation will enhance student engagement with AI and reinforce their career goals. Mentorship programs and career counseling focused on the relevance of AI in professional contexts can further strengthen students' commitment to their career paths.

Policymakers can use these insights to develop strategies that bridge education and industry. Incentivizing institutions to adopt AI-focused programs and providing resources for faculty training and infrastructure can ensure graduates possess the skills necessary for a competitive job market and shift in auditing, finance, and accounting practices. Collaborations between industry and academia can also offer students practical exposure to AI applications through internships and experiential learning. The research provides practical guidance on workforce development for organizational leaders in the accounting profession. Employers can create recruitment and training programs that build on new hires' AI competencies, fostering their long-term commitment to the profession.

Additionally, workplaces encouraging continuous learning and addressing AI-related concerns can ease the transition into AI-integrated environments. In sum, this research outlines a strategic framework for stakeholders to enhance students' educational and professional development, aligning their skills and aspirations with the evolving demands of the AI era. Implementing these strategies will help create a workforce that is not only technologically adept but also committed to thriving in AI-driven fields like accounting.

8. Conclusion

8.1. Key takeaways

This study represents a robust empirical exploration of the influence of AI-based learning experiences in higher education on AI self-efficacy and the career commitment of fresh graduates in accounting and finance programs to be an accountant. Specifically, it delves into the mediating effects of AI literacy, competency, and motivations for mastering AI. Our findings underscore the pivotal role of positive experiences perceived by fresh graduates in AI-based curricula implementation on steering their career trajectory and AI self-efficacy. Drawing insights from SDT and SCCT, our research suggests that positive AI-based learning experiences can ignite SDT elements of relatedness, autonomy, and competence, as well as SCCT elements of personal goals, outcome expectations, and self-efficacy of students in mastering AI, as exemplified by constructs of AI literacy, motivations, and AI competency. These elements, in turn, kindle their commitment to pursue a career as an accountant.

Intriguingly, the study provides key insights into the role of AI-based learning implementation in shaping fresh graduates' career commitment. It highlights that positive AI learning experiences significantly influence graduates' perceptions and capabilities, ultimately enhancing their commitment to the profession. The educational process builds essential competencies and self-efficacy in engaging with AI technologies by fostering AI literacy and motivation. The findings reveal that AI literacy, motivations, and competency mediate the relationship between AI learning and career outcomes. Additionally, AI self-efficacy is identified as a secondary mediator, suggesting that enhancing AI-related skills and confidence is vital for sustaining positive career commitment.

The research emphasizes the importance of AI-based curricula in higher education, demonstrating that such programs help students view accounting careers as dynamic and future-oriented. These results contribute to the theoretical understanding of career development, particularly within the frameworks of SCCT and SDT, while offering practical strategies for equipping graduates with the skills necessary for a technology-driven profession. In sum, this study highlights the transformative impact of AI on career development, offering a comprehensive link between educational practices, competencies, and career aspirations in accounting. In sum, the proposed framework is overarched within the integration of SCCT and SDT to understand AI-based learning and fresh graduates' career commitment in Indonesia. The findings advance to validate the implementation of SCCT and SDT in this context and broaden the existing literature. The results align with the past research, and the findings are implacable beyond the present context; however, considering situational and contextual factors, including socio-economics and culture, is essential.

8.2. Limitations and future research directions

Although this study represents a significant step forward in understanding the mechanism of how AI-based learning experiences in higher education can affect fresh graduates' AI self-efficacy and career commitment to be an accountant, it is essential to acknowledge several limitations. *Firstly*, data were collected in a single country (Indonesia), which may restrict the generalizability of the findings to the broader workforce. Future research should replicate this study using samples from diverse countries to strengthen the robustness and applicability of the results. *Second,* using self-reported surveys to measure all variables may result in common method bias. Yet, the measured latent marker variable and collinearity test have confirmed the absence of this issue. *Third*, the cross-sectional design of this study limits the ability to establish clear cause-and-effect relationships. However, this limitation is mitigated by grounding each hypothesized relationship in theories and prior research, with causal inferences further supported through structural equation modeling. *Fourth,* this study focuses on the positive influence of AI learning on career commitment, which might have overlooked the adverse impact of AI Learning. However, understanding the negative influence of AI learning would provide insight from other angles; therefore, this study suggests future research to tap into this issue, specifically focusing on exploring the role of negative emotions or psychological states such as fears, anxiety, and depression. *Fifth,* this work mainly investigated the formation of AI efficacy and Career commitment to be an accountant, focusing on the general context. Future research is encouraged to conduct a comparative study exploring the different impacts of AI tools on learning across different graduates to expand its practical contribution and contextual insight. *Lastly*, this study focused on the mediating role of AI literacy, competency, and motivations in accounting. Future studies may consider examining other pivotal moderating or mediating factors (e.g., institutional support, technological readiness) influencing career commitment in other contexts, such as engineering, hospitality, or healthcare.

CRediT authorship contribution statement

Agung Maulana: Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Rakotoarisoa Maminirina Fenitra:** Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Slamet Sutrisno:** Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration. **Kurniawan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration.

Statements on open data and ethics

The study was approved by an ethical committee of Nusa Putra University with ID: 303/RCSU/UNsP/XI/2024. Informed consent was obtained from all participants, and their privacy rights were strictly observed. The data can be obtained by sending request e-mails to the corresponding author.

Declaration of generative AI and AI-assisted technologies in the writing process

While preparing this work, the authors used *Grammarly* and *Quillbot* to deal with grammatical errors. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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