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Min Zheng

min.zheng@188.com

Kunming Medical University Haiyuan College

Article

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Generative AI dependence, perceived AI threat, career adaptability, and post-graduation anxiety among Chinese university students: a cross-sectional survey

Min Zheng

Kunming Medical University Haiyuan College, No. 389 Haiyuan North Road, Kunming 650106, Yunnan, China

Corresponding author: Min Zheng, email: min.zheng@188.com

Abstract

Generative artificial intelligence (AI) has become part of university students' everyday learning, yet research on its consequences has focused mainly on immediate learning outcomes. This study examined whether the way students use generative AI in their studies is connected with how they appraise their professional futures. Drawing on research on cognitive offloading, appraisal theories of stress and emotion, and career construction theory, I tested whether AI dependence—letting AI do the cognitive work of learning tasks and accepting its output with little verification—rather than frequency of use was associated with anxiety about post-graduation destinations, whether perceived AI threat accounted for part of this association, and whether career adaptability buffered the threat–anxiety link. In a cross-sectional survey of 965 Chinese university students, AI dependence was positively associated with post-graduation anxiety when frequency was controlled ($\beta = .36$), whereas frequency was not ($\beta = .00$). Perceived AI threat accounted for an indirect association amounting to 41% of the total. Career adaptability was associated with lower anxiety, but, contrary to the buffering hypothesis, the threat–anxiety association was stronger among more adaptable students, and adaptability was unrelated to anxiety when perceived threat was high. In exploratory analyses, critical use of AI output was associated with higher adaptability but not with threat or anxiety. Because the data are cross-sectional and self-reported, the findings are associations compatible with the proposed pathway rather than evidence of causation.

Implications for AI-integrated teaching and assessment, AI literacy, and career guidance in higher education are discussed.

Keywords: Generative artificial intelligence, AI dependence, Cognitive offloading, Perceived AI threat, Career adaptability, Post-graduation anxiety, Higher education

Introduction

Generative artificial intelligence (AI) has moved from novelty to routine in higher education within a few years. In a 2025 survey of 1,041 undergraduates in the United Kingdom, 92% reported using AI tools, up from 66% one year earlier, and 88% had used generative AI for assessments (Freeman, 2025). In China, the number of generative AI users reached 515 million by June 2025, nearly three quarters of whom were younger than 40 (China Internet Network Information Center [CNNIC], 2025). Research on the consequences of this shift has concentrated on immediate learning outcomes. A meta-analysis of 69 experimental studies found that ChatGPT use was associated with better academic performance and lower reported mental effort, but not with higher self-efficacy (Deng et al., 2025). Other studies suggest that performance obtained with AI does not necessarily translate into learning that students can demonstrate on their own (Bastani et al., 2025; Fan et al., 2025), and frequent ChatGPT use has been linked to procrastination and lower academic performance (Abbas et al., 2024). Such mixed findings become interpretable once one asks how AI changes learners' cognitive activities: AI can substitute for, augment, or redefine learning activities, but it can also invert them, inviting learners to offload the very processing that learning requires (Bauer et al., 2025).

Higher education, however, prepares students not only to learn but also to enter labor markets that AI is reshaping. Large language models could affect at least 10% of the work tasks of about 80% of the U.S. workforce (Eloundou et al., 2024). Generative AI assistance raises the productivity of novice workers more than that of experienced workers

(Brynjolfsson, Li, & Raymond, 2025), and early payroll evidence indicates relative employment declines of about 16% among workers aged 22–25 in the most AI-exposed occupations, concentrated where AI automates rather than augments work (Brynjolfsson, Chandar, & Chen, 2025). For students approaching graduation—12.7 million in China in 2026 alone (CCTV News, 2025)—the question of what AI can do is therefore a question not only about learning but also about the future value of the competencies they are building. Students themselves voice both enthusiasm about AI's benefits for learning and concern about its implications for their careers (Chan & Hu, 2023).

Two bodies of research speak to this situation but have developed largely in isolation. Research on learning with AI examines how AI use affects cognitive engagement, reliance, and performance (Bauer et al., 2025; F. Wang et al., 2025; Zhai et al., 2024; Zhang et al., 2024) but rarely follows these effects beyond the task to students' appraisals of their own futures. Research on AI and careers examines constructs such as AI anxiety, AI literacy, and career self-efficacy and their links with outcomes such as job-seeking anxiety (Li et al., 2025; X. Wang, 2026; Y.-Y. Wang & Wang, 2022) but usually treats students' AI-related cognitions as attitudes rather than as products of how they actually use AI in learning. As a result, little is known about whether the way students use generative AI in their coursework is connected with how they appraise the threats AI poses to their professional futures and with how anxious they feel about life after graduation. A further limitation is that AI use is often indexed by frequency or adoption, although research on digital technology has repeatedly shown that the amount of use explains little and that the way a technology is used matters more (Orben & Przybylski, 2019; Verduyn et al., 2017).

This study addresses these gaps with a survey of 965 students enrolled in higher vocational, undergraduate, and postgraduate programs across China. Drawing on research on cognitive offloading (Bauer et al., 2025; Risko & Gilbert, 2016), appraisal theories of stress

and emotion (Lazarus & Folkman, 1984; Pekrun, 2006), and career construction theory (Savickas & Porfeli, 2012), it asks three questions. First, is dependent use of generative AI, rather than frequent use, associated with students' anxiety about their destinations after graduation? Second, does perceived AI threat—the appraisal that AI endangers the future value of one's developing competencies—account for part of this association? Third, is career adaptability associated with lower anxiety, and does it weaken the link between perceived threat and anxiety? The answers matter for higher education because they indicate whether AI-integrated teaching, AI literacy education, and career guidance should attend to how students use AI rather than merely to whether and how often they use it.

Literature review

Learning with generative AI: frequency versus dependent use

I define AI dependence as a pattern of use in which students let generative AI carry out the cognitive work of learning tasks—producing answers, drafts, or solutions—accept the output with little elaboration or verification, and come to find it difficult to complete tasks without AI. The concept draws on research on cognitive offloading, the use of external tools to reduce the cognitive demands of a task (Risko & Gilbert, 2016). Offloading frees resources and can improve immediate performance, but when the offloaded processes are those on which learning depends, it can reduce the generative processing—selecting, organizing, and integrating information—through which durable understanding is built (Fiorella & Mayer, 2016). In the ISAR model (inversion, substitution, augmentation, and redefinition; Bauer et al., 2025), this corresponds to an inversion effect, in which AI use reduces learners' cognitive engagement. Experimental evidence is consistent with this view. High school students who practiced with an unrestricted GPT-4 interface performed better while they had access but 17% worse than controls once access was removed, whereas a version with pedagogical guardrails largely avoided this cost (Bastani et al., 2025). University students who revised

essays with ChatGPT improved their texts but showed no greater gains in knowledge or transfer, a pattern Fan et al. (2025) described as metacognitive laziness.

Offloading is not harmful in itself. Early analyses of large language models in education stressed that their benefits depend on learners' understanding of the models' limitations and on continued critical thinking and fact-checking (Kasneci et al., 2023). Recent work in higher education distinguishes strategic delegation, which can coexist with critical vigilance and free resources for higher-order reflection, from offloading that replaces students' own processing (S. Wang & Zhang, 2026). Similarly, students' reliance on and resistance to generative AI have been modeled as distinct responses rather than as the two ends of one attitude (F. Wang et al., 2025), and high-achieving students have been described as using AI selectively while checking its output and keeping it subordinate to their own judgment (Zagami, 2026). Dependence, as defined here, therefore refers to uncritical offloading. Critical use, in which students verify AI output, judge it against what they have learned, and weigh alternative views, is a related but separate aspect of how students use AI.

Dependence is also distinct from frequency. When most students use AI on most days, frequent use may simply reflect how embedded AI has become in ordinary learning routines, and a frequent user may use AI mainly to check work completed independently. Research on behavioral addictions has similarly cautioned against equating high engagement with problematic use (Billieux et al., 2015). Existing instruments capture related but broader phenomena, such as problematic AI use linked to academic stress and performance expectations (Zhang et al., 2024) and general dependence on AI tools (Morales-García et al., 2024). The present focus is narrower: task-level cognitive dependence in learning, which is not a clinical construct and does not imply addiction. If the mode of use matters more than its amount, the psychological correlates of generative AI use should depend more on whether students use AI dependently than on how often they use it.

From dependent use to appraisals of AI as a career threat

Why might a learning behavior be connected with how students appraise their professional futures? Social cognitive theory identifies mastery experiences—successfully completing challenging tasks through one's own effort—as the most influential source of self-efficacy (Bandura, 1997; Usher & Pajares, 2008). Dependent use substitutes AI's performance for the student's own, so tasks are completed without the corresponding mastery experiences. Consistent with this, knowledge workers who place more confidence in generative AI report engaging less in critical thinking, whereas those with more confidence in their own abilities report engaging more (Lee et al., 2025), and AI dependency among students is associated with lower academic self-efficacy and higher academic stress (Zhang et al., 2024). Dependent use may also make AI's capabilities salient in a particular way: each delegated task offers first-hand evidence that AI can do what the student is training to do. Among employees, awareness that technologies can perform one's work tasks is associated with perceived job insecurity (Brougham & Haar, 2018; Lingmont & Alexiou, 2020). Students who use AI critically, by contrast, verify, integrate, and take responsibility for AI output—activities that remain human tasks when generative AI is used (Lee et al., 2025)—and may therefore experience AI as augmenting rather than replacing their competencies.

I define perceived AI threat as the appraisal that AI will replace tasks in the occupations associated with one's field of study, render one's skills obsolete, and make it harder to find suitable work after graduation. The construct is related to employees' awareness of smart technology, AI, robotics, and algorithms (STARA; Brougham & Haar, 2018), to the job replacement facet of AI anxiety (Y.-Y. Wang & Wang, 2022), and to techno-insecurity (Tarafdar et al., 2007). For students, it is an anticipatory appraisal about occupations they have not yet entered, comparable to the anticipatory component of job

insecurity (Shoss, 2017). Such appraisals are subjective; they need not correspond to the objective automation risk of an occupation.

Perceived AI threat and post-graduation anxiety

Post-graduation anxiety refers to the tension, worry, and stress students experience when they think about their destinations after graduation, whether employment or further study. It belongs to the family of career and future anxieties (Pisarik et al., 2017; Vignoli, 2015; Zaleski, 1996). I refer to destinations rather than employment because many graduates, in China and elsewhere, pursue further study, and their worries about this transition would be missed by measures of job-search anxiety alone.

Appraisal theories treat threat appraisals as proximal antecedents of anxiety (Lazarus & Folkman, 1984). In educational psychology, control–value theory specifies this logic: prospective emotions such as anxiety arise when an outcome is important and perceived control over it is low or uncertain (Pekrun, 2006, 2024). Perceived AI threat lowers students' perceived control over a highly valued outcome—a successful transition after graduation—and should thereby heighten anxiety. Among employees, STARA awareness is related to lower career satisfaction and to higher turnover intentions and depression (Brougham & Haar, 2018), and AI awareness is related to job burnout (Kong et al., 2021) and job insecurity (Koo et al., 2021). Among Canadian medical students, anxiety about AI discouraged many from considering radiology as a specialty (Gong et al., 2019). Taken together, these lines of research suggest that dependent use may be linked with post-graduation anxiety partly because it is linked with stronger threat appraisals.

Two qualifications are important. First, threat appraisal and anxiety must be empirically distinguishable; because both concern the future, measures must show that they are not the same construct. Second, the argument does not imply a single causal direction. Anxious students may turn to AI as a way of coping: in a longitudinal study of adolescents,

mental health problems predicted later AI dependence rather than the reverse (Huang et al., 2024), and academic stress has been linked to greater AI dependency (Zhang et al., 2024). The relations examined here are therefore potentially recursive, and cross-sectional data can show only whether the observed associations are compatible with the proposed pathway.

Career adaptability: resource or buffer?

Career construction theory defines career adaptability as a set of psychosocial resources for coping with developmental tasks, transitions, and unexpected changes (Savickas, 2005). It comprises four dimensions: concern (orientation toward and planning for the future), control (ownership of one's career decisions), curiosity (exploration of the self and of opportunities), and confidence (belief in one's ability to solve problems and overcome obstacles; Savickas & Porfeli, 2012). Meta-analytic evidence links adaptability to a broad range of adaptation results (Rudolph et al., 2017); among Chinese graduates, adaptability predicted job search self-efficacy and employment outcomes (Guan et al., 2013), and among Chinese university students, it was negatively associated with AI anxiety (X. Wang, 2026).

Appraisal theories also suggest that resources shape whether a given threat turns into distress. Anxiety arises when threat appraisals are coupled with appraisals that one's coping resources are insufficient (Lazarus & Folkman, 1984), and individuals with more resources are less vulnerable to threats of resource loss (Hobfoll, 1989; Hobfoll et al., 2018). Students high in adaptability may therefore appraise AI-related changes as challenges to be met rather than as uncontrollable threats (Ding, 2021). These two roles of adaptability need to be kept apart. A resource can be associated with lower anxiety on average without weakening the link between a specific threat and anxiety, and only the interaction between threat and adaptability can test the buffering role.

The present study

Figure 1 summarizes the hypothesized model. Because the data were collected at one time point, the hypotheses concern associations, and the arrows denote theoretically specified directions rather than established causal order.

H1: Controlling for frequency of use, AI dependence is positively associated with post-graduation anxiety.

H2: AI dependence is positively associated with perceived AI threat.

H3: AI dependence is indirectly associated with post-graduation anxiety through perceived AI threat.

H4a: Career adaptability is negatively associated with post-graduation anxiety.

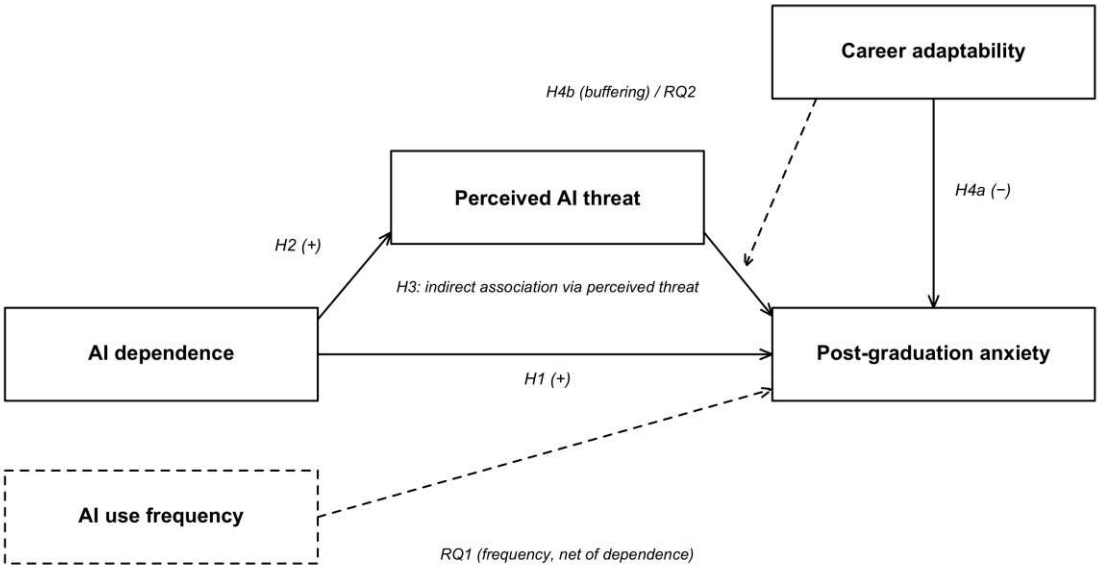
H4b: The association between perceived AI threat and post-graduation anxiety is weaker at higher levels of career adaptability.

In addition, RQ1 asks whether frequency of use is associated with anxiety once dependence is taken into account. Combining H3 and H4b implies a second-stage moderated mediation model (Hayes, 2015; Preacher et al., 2007), which I examine as an exploratory research question (RQ2). Finally, because dependence and critical use are related but separate aspects of how students use AI, RQ3 explores how critical use is associated with perceived threat, anxiety, and career adaptability once dependence is held constant.

The hypotheses were formulated on the basis of two pilot studies before the main data collection, and the target sample size (N = 1,000) was fixed in advance. The study was not preregistered. One analytic decision departs from the initial plan. AI dependence was originally to be scored as a single bipolar composite of usage-mode and critical-use items; because the measurement analyses reported below did not support a single bipolar factor, the main analyses use the three dependence items, and results for the originally planned composite are reported as a robustness check.

Figure 1

Hypothesized research model



Note. Solid arrows denote hypothesized associations (H1–H4a). The dashed arrow from career adaptability denotes the hypothesized buffering of the threat–anxiety association (H4b) and the exploratory moderated mediation (RQ2). The dashed box and arrow denote AI use frequency, included as a contrast variable (RQ1). Arrows denote theoretically specified directions, not established causal order. All models control for gender, age, and educational level.

Method

Participants and procedure

Data were collected in October 2026 through the participant pool of Credamo, a Chinese online survey platform. Eligible participants were students currently enrolled in higher vocational (sub-degree), undergraduate, or postgraduate programs. The questionnaire, administered in Chinese, opened with a page describing the purpose of the study, the anonymity of responses, and the voluntary nature of participation; participants gave informed consent on this page before proceeding. No names, student numbers, or contact details were collected, and IP addresses, geolocation, and city information were removed from the analysis file. Participants were compensated by the platform. The study protocol was approved by the Ethics Committee of Haiyuan College, Kunming Medical University

(approval number: HYXY2026X0026). All methods were performed in accordance with the relevant guidelines and regulations, including the Declaration of Helsinki.

Two pilot rounds (each n = 100) preceded the main survey. After the first pilot, four items on the critical use of AI output were added to distinguish modes of use. A set of items on self-efficacy for using AI showed pronounced ceiling effects in the second pilot (for five of the six items, 84%–96% of responses fell in the two highest categories; α = .59) and was removed. Pilot participants were excluded from the main survey.

Two instructed-response items were embedded, one in the perceived AI threat scale and one in the career adaptability scale. Following recommendations for detecting careless responding (Curran, 2016; Ward & Meade, 2023), I applied predefined exclusion criteria: failure on an attention check (threat block, n = 18; adaptability block, n = 16), completion time below one third of the median (median = 326 s; threshold ≈ 109 s; n = 4), identical responses to all 24 career adaptability items (n = 1), enrollment outside the target educational levels (n = 3), and duplicate or pilot participation (n = 0). Because some cases met more than one criterion, 34 of the 1,000 responses (3.4%) were excluded. Because the study focuses on higher education, I additionally excluded one respondent enrolled in secondary vocational education, which left 965 participants.

The final sample comprised 965 students (729 women, 75.5%; age 18–31 years, M = 21.52, SD = 2.07; 98.2% full-time). Of these, 963 attended institutions in 30 provincial-level regions of mainland China, and two studied in Hong Kong, Macao, Taiwan, or abroad. Sixty-one students (6.3%) were enrolled in higher vocational (sub-degree) programs, 685 (71.0%) in undergraduate programs, and 219 (22.7%) in postgraduate programs (202 master's and 17 doctoral students). By type of institution, 308 (31.9%) attended universities in China's national Double First-Class initiative, 488 (50.6%) other public undergraduate institutions, 101 (10.5%) private undergraduate institutions or independent colleges, 47 (4.9%) higher

vocational colleges, and 21 (2.2%) other institutions. All participants reported having used generative AI, and 44.2% reported using it almost every day during the previous 30 days. One participant had not used AI during the previous 30 days and was therefore not shown the items on usage mode and critical use; analyses involving these variables are based on n = 964.

Measures

Unless noted otherwise, items were rated on 5-point scales and averaged, with higher scores indicating higher levels of the construct. The self-developed items were written in Chinese. English translations, prepared by the author for this report, are given in Appendix A; they were not used for data collection and were not back-translated. The Chinese wording is provided in Additional file 1. Reliability and validity statistics are reported in Table 2.

Generative AI use frequency

One item asked how often during the previous 30 days participants had used generative AI for learning or practical tasks, counting several uses on the same day as one day. The six response options (0 days, 1–3 days, 4–7 days, 8–14 days, 15–24 days, and 25–30 days) were coded 0–5. I treated this ordinal score as approximately interval in the regression models.

AI dependence

Three self-developed items, informed by research on cognitive offloading (Risko & Gilbert, 2016) and AI dependence (Morales-García et al., 2024; Zhang et al., 2024), described dependent use during the previous 30 days and were rated for how well they described the respondent's behavior (1 = completely untrue of me, 5 = completely true of me): "When facing a task, I often directly ask AI for the answer without thinking further myself," "I mostly use the content AI gives me as it is, with few modifications," and "Without AI's help, I would find it hard to complete my learning or practical tasks" (α = .70,

ω = .71). The same block contained a reverse-keyed item describing an independent first attempt ("I first think it through myself, or write a first draft, and then ask AI to supplement, improve, or check it"), which was used only in the originally planned composite described below.

Critical use

Four self-developed items asked how often participants engaged in critical practices when using AI for learning or practical tasks during the previous 30 days (1 = never, 5 = always), for example, "I specifically check the sources of information provided by AI or verify its accuracy against other materials" and "When AI offers a viewpoint, I consider whether there are alternative views rather than accepting it directly" (α = .62, ω = .64). Because of its modest reliability, this scale was used only in exploratory analyses (RQ3).

Originally planned dependence composite

The initial analysis plan combined the four usage-mode items (with the first-attempt item reverse-scored) and two critical-use items (checking sources and considering alternative views, both reverse-scored) into a six-item bipolar composite (α = .77). This composite is used only in robustness checks.

Perceived AI threat

Six self-developed items, informed by the content of STARA awareness (Brougham & Haar, 2018) and job replacement anxiety (Y.-Y. Wang & Wang, 2022), referred to the occupations typically associated with participants' field of study (e.g., "I think AI will replace part of the jobs associated with my major"; "I think AI will make it harder for me to find a suitable job after graduation"; 1 = strongly disagree, 5 = strongly agree; α = .86). Students who had not yet chosen a major answered for their intended field.

315 ***Post-graduation anxiety***

316 Four self-developed items, informed by measures of career anxiety (Mahmud et al.,
317 2021; Pisarik et al., 2017), referred to post-graduation destinations, including both
318 employment and further study (e.g., “When I think about where I will go after graduation, I
319 often feel nervous”; 1 = strongly disagree, 5 = strongly agree; α = .90). The scale is not a
320 clinical measure and has no diagnostic cut-off.

321 ***Career adaptability***

322 I used the international form of the Career Adapt-Abilities Scale (CAAS-
323 International; Savickas & Porfeli, 2012), which comprises 24 items, six each for concern,
324 control, curiosity, and confidence (e.g., “Thinking about what my future will be like”; 1 = not
325 strong, 5 = strongest; α = .94). The items were administered in Chinese in their original order
326 and with the original response anchors. Given the high correlations among the dimensions
327 and the fit of a second-order model (see Results), the total score was used in the main
328 analyses; dimension scores were used only in exploratory analyses.

329 ***Covariates and field-related items***

330 Gender (1 = male, 0 = female), age, and educational level (dummy variables for
331 higher vocational and postgraduate programs, with undergraduate as the reference) were
332 included as covariates in all models, because students’ use of and views on AI chatbots differ
333 by gender and academic level (Stöhr et al., 2024) and because gender and age correlated with
334 study variables. Three single items described students’ judgments about their field: the share
335 of learning tasks in their major that AI could complete (1 = almost none, 5 = almost all), the
336 pace of change in occupations associated with their major (1 = almost no change, 5 = very
337 rapid change), and their teachers’ overall stance on student AI use (1 = explicitly prohibited,
338 5 = required and used in teaching).

Data analysis

Analyses were conducted in R 4.6.0, using lavaan 0.6-21 (Rosseel, 2012) for confirmatory factor analysis (CFA) and structural equation modeling and psych 2.6.5 (Revelle, 2026) for exploratory factor analysis (EFA) and reliability estimation.

First, I examined the measurement of the usage-related items and of the full set of constructs. For the eight usage-mode and critical-use items, I compared a single bipolar factor with two-factor models defined by content (dependence vs. self-directed and critical use) and by item block, which coincided with response format (agreement vs. frequency), and I compared one- and two-factor models of the seven items retained for scoring. I then estimated a seven-factor CFA (AI dependence, perceived AI threat, post-graduation anxiety, and the four adaptability dimensions) with robust maximum likelihood (MLR) and compared it with a model in which adaptability was a second-order factor, with models merging threat and anxiety or dependence and threat, and with a single-factor model. Comparative fit index (CFI) and Tucker–Lewis index (TLI) values $\geq .90$ and root mean square error of approximation (RMSEA) and standardized root mean square residual (SRMR) values $\leq .08$ served as guidelines (Hu & Bentler, 1999). Composite reliability (CR), average variance extracted (AVE), the Fornell–Larcker criterion (Fornell & Larcker, 1981), and the heterotrait–monotrait ratio (HTMT $< .85$; Henseler et al., 2015) were used to evaluate convergent and discriminant validity. Because the scales other than the CAAS were self-developed, I additionally split the sample at random, conducting an EFA with parallel analysis (Horn, 1965) in one half and a CFA in the other; this is an internal cross-check rather than an independent validation. Measurement invariance of the self-developed scales across gender and between undergraduate and postgraduate students was tested by comparing configural, metric, and scalar models ($\Delta CFI \geq -.010$ and $\Delta RMSEA \leq .015$ as guidelines; Chen, 2007). Common method variance was examined with Harman's single-factor test, the

single-factor model, and an unmeasured latent method factor (Podsakoff et al., 2003; Williams et al., 1989); none of these diagnostics, however, can rule out method bias (Podsakoff et al., 2024).

Second, to test H1 and RQ1, post-graduation anxiety was regressed on dependence and frequency together with the covariates. Because a nonsignificant coefficient does not establish the absence of an effect, I interpret the frequency coefficient through its confidence interval. Third, to test H2 and H3, I regressed threat on dependence (path *a*) and anxiety on threat and dependence (paths *b* and *c′*), controlling for the covariates, and tested the indirect association *ab* with percentile bootstrap confidence intervals based on 5,000 resamples (Hayes, 2022). With cross-sectional data, *ab* describes a decomposition of covariances that is compatible with, but cannot establish, a mediation process (Maxwell & Cole, 2007). Fourth, to test H4a and H4b, I entered the covariates and the mean-centered main effects of threat and adaptability in Step 1 and their product in Step 2. The buffering hypothesis implies a negative interaction. Significant interactions were probed with simple slopes at ±1 *SD* (Aiken & West, 1991) and with the Johnson–Neyman technique (Johnson & Neyman, 1936). Fifth, RQ2 was examined with a second-stage moderated mediation model in which path *b* depended on adaptability (equivalent to PROCESS Model 14), using the index of moderated mediation (Hayes, 2015) and conditional indirect associations at −1 *SD*, the mean, and +1 *SD* of adaptability. Finally, RQ3 was examined by adding critical use to the models for threat, anxiety, and adaptability.

Robustness checks comprised adding frequency to all path models; replacing the dependence score with the originally planned six-item composite, a four-item usage-mode score, or a two-item score omitting the item on difficulty completing tasks without AI; controlling for critical use; and estimating the indirect association in a latent variable model. Exploratory analyses examined which adaptability dimensions accounted for the moderation

pattern and whether anxiety approached the ceiling of the scale among students perceiving high threat. A sensitivity analysis indicated that, with $n = 964$, $\alpha = .05$, and power = .80, the regression models could detect an effect as small as $f^2 = .008$ (partial $r \approx .09$) for a single coefficient (Lakens, 2022). Missing data were limited to the one participant without usage-mode and critical-use scores; all models used complete cases. Group differences by type of institution, educational level, field of study, region, and gender were analyzed with Welch's tests (Welch, 1951) and Holm-corrected pairwise comparisons (Holm, 1979) and are reported in Additional file 1.

Results

Measurement

Structure of the usage-mode and critical-use items

A single bipolar factor fit the eight usage-mode and critical-use items poorly, $\chi^2(20) = 192.0$, CFI = .884, TLI = .838, RMSEA = .102, SRMR = .058 (Table 1). Separating dependence from self-directed and critical use improved fit, $\Delta\chi^2(1) = 32.19$, $p < .001$, but only to a modest level (CFI = .915, TLI = .875, RMSEA = .089), whereas separating the two item blocks, which also differed in response format, fit best (CFI = .949, TLI = .924, RMSEA = .070, SRMR = .040). For the seven items retained for scoring, two correlated factors fit well, $\chi^2(13) = 60.4$, CFI = .960, TLI = .936, RMSEA = .065, SRMR = .038, and markedly better than one factor, $\Delta\chi^2(1) = 69.62$, $p < .001$; the latent correlation between dependence and critical use was −.72, 95% CI [−.80, −.64]. The items therefore did not form a single bipolar continuum. Dependence and critical use were strongly related but separable, although the distinction cannot be attributed to content alone because the two blocks also differed in response format. One critical-use item (comparing answers across AI tools) loaded weakly (.31), and the critical-use factor showed low convergent validity (AVE = .31), which is why critical use was treated as exploratory.

Table 1

Fit of alternative factor models for the usage-mode and critical-use items

Model	χ^2	*df*	CFI	TLI	RMSEA [90% CI]	SRMR	BIC
Eight items (four usage-mode and four critical-use items)							
A. One bipolar factor	192.0	20	.884	.838	.102 [.089, .115]	.058	19,334
B. Two factors by content	148.0	19	.915	.875	.089 [.076, .103]	.049	19,285
C. Two factors by item block	96.6	19	.949	.924	.070 [.056, .084]	.040	19,228
Seven items retained for scoring							
D1. One factor	149.8	14	.883	.824	.108 [.092, .124]	.060	17,149
D2. Dependence and critical use	60.4	13	.960	.936	.065 [.049, .082]	.038	17,051

Note. n = 964. Robust maximum likelihood; scaled χ^2 and robust CFI, TLI, and RMSEA. Model B: dependence (three items) versus the first-attempt item and the four critical-use items. Model C: the four usage-mode items (agreement format) versus the four critical-use items (frequency format). Model D2 corresponds to the scoring used in this article. Factor correlations (dependence direction): B, −.82; C, −.72; D2, −.72. Scaled difference tests: A vs. B, $\Delta\chi^2(1) = 32.19$; D1 vs. D2, $\Delta\chi^2(1) = 69.62$; both $p < .001$. BIC = Bayesian information criterion. Standardized loadings are reported in Additional file 1.

Measurement model

The seven-factor model fit the data well, $\chi^2(608) = 1{,}353.4$, CFI = .950, TLI = .945, RMSEA = .038, SRMR = .040, and considerably better than the model merging threat and anxiety, $\chi^2(614) = 2{,}443.9$, CFI = .877, TLI = .866, RMSEA = .060, SRMR = .052, $\Delta\chi^2(6) = 1{,}509.3$, $p < .001$, the model merging dependence and threat (CFI = .920, TLI = .913, RMSEA = .048, SRMR = .059), or the single-factor model, $\chi^2(629) = 7{,}078.9$, CFI = .563, TLI = .538, RMSEA = .111, SRMR = .131. The model treating adaptability as a second-order factor fit similarly well, $\chi^2(619) = 1{,}408.2$, CFI = .947, TLI = .943, RMSEA = .039, SRMR = .045. Standardized loadings ranged from .55 to .89, and CR was at least .72 for all factors (Table 2). AVE exceeded .50 for threat, anxiety, and confidence but fell slightly below .50 for dependence (.46) and for concern, control, and curiosity (.45–.47).

Threat and anxiety were clearly distinguishable: their latent correlation (.61) was lower than the square roots of their AVEs (.72 and .84), and their HTMT ratio was .60. Dependence correlated .39 with threat and .45 with anxiety at the latent level (HTMT = .43 and .50). The adaptability dimensions were highly correlated (.69–.87; HTMT up to .87 for curiosity and confidence), which is consistent with a higher-order construct and supports the

use of a total score. In the split-sample analysis of the 13 focal self-developed items (dependence, threat, and anxiety), parallel analysis suggested three factors (Kaiser–Meyer–Olkin [KMO] = .894; Bartlett's $\chi^2(78) = 3{,}207.4$, $p < .001$), which explained 57.8% of the variance. All items loaded on their intended factors (.43–.89), and the largest cross-loading was .22 (the dependence item on difficulty completing tasks without AI, on the anxiety factor). The three-factor model fit acceptably in the other half, CFI = .941, TLI = .926, RMSEA = .077, SRMR = .058. When the critical-use items were added, parallel analysis again suggested three factors, with dependence and critical-use items loading in opposite directions on a common factor (Additional file 1), which is consistent with their strong latent correlation. The self-developed scales showed configural, metric, and scalar invariance across gender and between undergraduate and postgraduate students (all $\Delta CFI \geq -.005$ and $\Delta RMSEA \leq .001$; Additional file 1). Regarding common method variance, the first unrotated factor explained 29.1% of the variance in the 37 items, and adding a latent method factor improved fit modestly ($\Delta CFI = .016$, $\Delta TLI = .015$, $\Delta RMSEA = .006$, $\Delta SRMR = .011$).

Table 2

Reliability and convergent validity of the measures

Scale	Items	α	Loadings	CR	AVE
AI dependence	3	.70	.55–.79	.72	.46
Critical use (exploratory)	4	.62	.33–.65	.63	.31
Perceived AI threat	6	.86	.60–.81	.86	.52
Post-graduation anxiety	4	.90	.75–.89	.90	.70
Career adaptability (total)	24	.94	—	—	—
Concern	6	.84	.59–.79	.84	.47
Control	6	.83	.60–.77	.84	.46
Curiosity	6	.83	.60–.78	.83	.45
Confidence	6	.87	.68–.78	.88	.54

Note. $n = 964$. Standardized loadings, composite reliability (CR), and average variance extracted (AVE) are from the seven-factor model estimated with robust maximum likelihood; values for critical use are from an eight-factor model that additionally included this factor (CFI = .945, TLI = .940, RMSEA = .037, SRMR = .040).

Descriptive statistics and correlations

Table 3 presents descriptive statistics and correlations. Students used AI frequently (M = 3.96, about four to five days a week), reported low to moderate dependence (M = 2.69), relatively frequent critical use (M = 3.72), and levels of perceived threat (M = 3.35) and post-graduation anxiety (M = 3.57) above the scale midpoint. Frequency was only weakly related to dependence (r = .12) and critical use (r = .15) and unrelated to threat (r = .05) and anxiety (r = .05), but it was positively related to adaptability (r = .16). Dependence correlated positively with threat (r = .33) and anxiety (r = .40) and negatively with critical use (r = −.45) and adaptability (r = −.29). Threat showed the strongest correlation with anxiety (r = .53). Among the field-related single items, students who believed that AI could complete a larger share of the learning tasks in their major reported more dependence (r = .33) and more threat (r = .32), and students who perceived faster change in the occupations associated with their major reported more threat (r = .35). Teachers' stance on AI use was associated with frequency (r = .15), critical use (r = .14), and adaptability (r = .17) but not with dependence, threat, or anxiety ($|r| \leq .05$).

Table 3

Descriptive statistics and correlations among study variables

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. AI use frequency	3.96	1.15							
2. AI dependence	2.69	0.79	.12***						
3. Critical use	3.72	0.61	.15***	−.45***					
4. Perceived AI threat	3.35	0.80	.05	.33***	−.14***				
5. Post-graduation anxiety	3.57	0.93	.05	.40***	−.14***	.53***			
6. Career adaptability	3.41	0.65	.16***	−.29***	.45***	−.13***	−.20***		
7. Gender (male = 1)	0.24	0.43	.00	−.17***	.07*	−.11***	−.26***	.15***	
8. Age	21.52	2.07	.09**	−.13***	.21***	−.00	−.06	.15***	.04

Note. N = 965 (964 for correlations involving AI dependence and critical use). Frequency was coded 0–5; the other scales range from 1 to 5. *p < .05. **p < .01. ***p < .001.

Usage mode versus frequency (H1, RQ1)

Controlling for the covariates, AI dependence was positively associated with post-graduation anxiety, $B = 0.43$, $SE = 0.04$, 95% CI [0.36, 0.50], $\beta = .36$, $p < .001$, supporting H1 (Table 4, Model 1). Frequency was not, $B = 0.00$, 95% CI [−0.04, 0.05], $\beta = .00$, $p = .867$ (RQ1). The upper confidence limit implies that, net of dependence, a one-category increase in frequency was associated with at most about 0.05 points more anxiety on the 5-point scale. In a supplementary model with adaptability as the outcome, frequency was positively ($\beta = .17$, $p < .001$) and dependence negatively ($\beta = -.27$, $p < .001$) associated with adaptability, suggesting that the two aspects of use have different psychological correlates.

The indirect association through perceived AI threat (H2, H3)

AI dependence was positively associated with perceived AI threat, $B = 0.34$, $SE = 0.03$, 95% CI [0.28, 0.40], $\beta = .33$, $p < .001$, supporting H2 (Table 4, Model 2). When threat was added to the model for anxiety, it was strongly associated with anxiety, $B = 0.52$, 95% CI [0.45, 0.58], $\beta = .44$, $p < .001$, and the coefficient for dependence decreased from $B = 0.43$ to $B = 0.26$, 95% CI [0.19, 0.32], $\beta = .22$ (Model 3). The indirect association was $ab = 0.174$, bootstrap $SE = 0.022$, 95% CI [0.132, 0.220], with a standardized value of 0.147, 95% CI [0.112, 0.187], accounting for 40.5% of the total association (Table 5). This pattern is consistent with H3; the direct association also remained significant.

The indirect association was robust to alternative specifications (Additional file 1). It was virtually unchanged when frequency was added to all models, $ab = 0.175$, 95% CI [0.133, 0.221], or when critical use was controlled, $ab = 0.172$, 95% CI [0.129, 0.220]. With the originally planned six-item composite, the results were very similar: dependence was associated with anxiety ($\beta = .31$) and threat ($\beta = .29$), and the indirect association was 0.193, 95% CI [0.143, 0.248]. The same held for a four-item usage-mode score ($ab = 0.183$, 95% CI [0.137, 0.231]) and for a two-item score omitting the item on difficulty completing tasks

without AI (β = .28 for anxiety; *ab* = 0.145, 95% CI [0.107, 0.184]). In a latent variable model correcting for measurement error, $\chi^2(106) = 453.3$, CFI = .940, TLI = .926, RMSEA = .061, SRMR = .057, the standardized indirect association was .20, 95% CI [.15, .25], about half of the total association (β = .41, 95% CI [.33, .49]).

Table 4

Regression models for AI dependence, use frequency, perceived AI threat, and post-graduation anxiety

Predictor	*B*	*SE*	95% CI	β
Model 1 (H1, RQ1). Outcome: post-graduation anxiety, R^2 = .20				
AI use frequency	0.00	0.02	[−0.04, 0.05]	.00
AI dependence	0.43***	0.04	[0.36, 0.50]	.36
Gender (male)	−0.43***	0.06	[−0.56, −0.31]	−.20
Age	−0.01	0.02	[−0.04, 0.03]	−.02
Higher vocational program	−0.02	0.11	[−0.25, 0.20]	−.01
Postgraduate program	0.03	0.09	[−0.14, 0.20]	.01
Model 2 (H2). Outcome: perceived AI threat, R^2 = .12				
AI dependence	0.34***	0.03	[0.28, 0.40]	.33
Gender (male)	−0.09	0.06	[−0.20, 0.02]	−.05
Age	−0.01	0.02	[−0.04, 0.02]	−.02
Higher vocational program	−0.20	0.10	[−0.40, 0.00]	−.06
Postgraduate program	0.14	0.08	[−0.01, 0.29]	.07
Model 3 (H3). Outcome: post-graduation anxiety, R^2 = .37				
Perceived AI threat	0.52***	0.03	[0.45, 0.58]	.44
AI dependence	0.26***	0.03	[0.19, 0.32]	.22
Gender (male)	−0.39***	0.06	[−0.50, −0.28]	−.18
Age	−0.00	0.02	[−0.03, 0.03]	−.01
Higher vocational program	0.08	0.10	[−0.12, 0.28]	.02
Postgraduate program	−0.04	0.08	[−0.19, 0.11]	−.02

Note. n = 964. Gender was coded 1 = male, 0 = female; educational level was dummy-coded with undergraduate as the reference. Model 1: $F(6, 957) = 39.29$; Model 2: $F(5, 958) = 26.66$; Model 3: $F(6, 957) = 92.79$; $p < .001$ for all models. ***$p < .001$.

Table 5

Total, direct, indirect, and conditional indirect associations of AI dependence with post-graduation anxiety

Effect	Estimate	*SE*	95% CI
Simple indirect association model (H3)			
Total association (*c*)	0.429	0.035	[0.360, 0.498]
Direct association (*c′*)	0.255	0.033	[0.191, 0.320]
Indirect association via perceived AI threat (*ab*)	0.174	0.022	[0.132, 0.220]
Second-stage moderated model (RQ2, exploratory)			
Indirect association at low adaptability (−1 *SD*)	0.126	0.022	[0.084, 0.173]
Indirect association at mean adaptability	0.166	0.021	[0.126, 0.209]
Indirect association at high adaptability (+1 *SD*)	0.206	0.025	[0.157, 0.256]
Index of moderated mediation	0.061	0.017	[0.030, 0.096]

Note. n = 964. Unstandardized estimates; all models control for gender, age, and educational level. Confidence intervals for c and c′ are based on ordinary least squares; those for indirect associations are percentile bootstrap intervals (5,000 resamples), and the corresponding SEs are bootstrap standard deviations.

Career adaptability: main effect and moderation (H4a, H4b)

In Step 1 (Table 6), career adaptability was negatively associated with anxiety, B = −0.15, SE = 0.04, 95% CI [−0.22, −0.07], β = −.10, $p < .001$, supporting H4a. In Step 2, the Threat × Adaptability interaction was significant, B = 0.18, SE = 0.04, 95% CI [0.10, 0.27], β = .10, $p < .001$, $\Delta R^2 = .012$, $F(1, 956) = 16.99$, $p < .001$, but it was positive rather than negative. The association between threat and anxiety was therefore stronger, not weaker, at higher levels of adaptability: B = 0.44, 95% CI [0.35, 0.53], at −1 *SD*; B = 0.56, 95% CI [0.50, 0.62], at the mean; and B = 0.68, 95% CI [0.60, 0.76], at +1 *SD*. H4b was not supported.

Viewed from the other direction, adaptability was associated with lower anxiety when perceived threat was low (−1 *SD*: B = −0.30, 95% CI [−0.40, −0.19]) or average (B = −0.15, 95% CI [−0.23, −0.08]) but not when it was high (+1 *SD*: B = −0.01, 95% CI [−0.11, 0.09], p = .856). The Johnson–Neyman analysis showed that the negative association between adaptability and anxiety was significant only when perceived threat was below 3.75 on the 5-point scale, a range that included 64.2% of the sample (Figure 2). At low threat, predicted

anxiety was 2.94 for students high in adaptability and 3.33 for students low in adaptability; at high threat, the predicted values were nearly identical (4.03 and 4.04). The interaction remained when frequency was controlled, $B = 0.19$, 95% CI [0.10, 0.27]; in this model, frequency itself showed a small positive association with anxiety, $\beta = .06$, $p = .030$. The observed interaction ($f^2 = .018$) exceeded the minimum detectable effect but was small.

Table 6

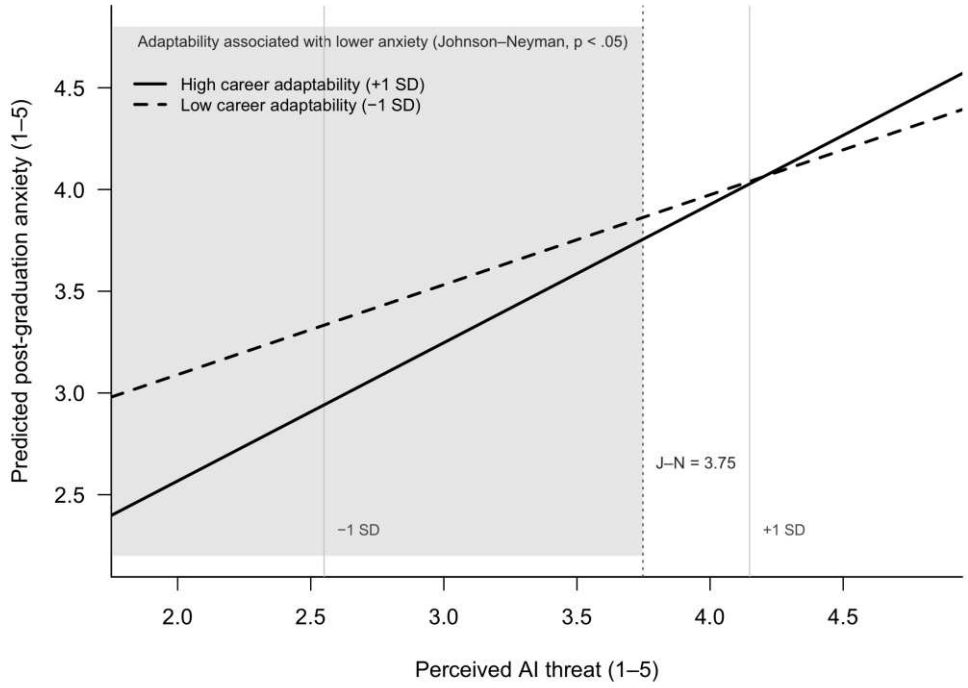
Hierarchical regression of post-graduation anxiety on perceived AI threat, career adaptability, and their interaction

	Step 1		Step 2	
Predictor	*B* (*SE*)	β	*B* (*SE*)	β
Perceived AI threat (centered)	0.58 (0.03)***	.50	0.56 (0.03)***	.48
Career adaptability (centered)	−0.15 (0.04)***	−.10	−0.15 (0.04)***	−.11
Threat × Adaptability			0.18 (0.04)***	.10
Gender (male)	−0.42 (0.06)***	−.19	−0.41 (0.06)***	−.19
Age	−0.01 (0.02)	−.02	−0.00 (0.02)	−.01
Higher vocational program	0.12 (0.10)	.03	0.10 (0.10)	.02
Postgraduate program	−0.05 (0.08)	−.02	−0.06 (0.08)	−.03
R^2	.34		.35	
ΔR^2			.012***	

Note. $n = 964$. Standardized coefficients for the interaction were computed from the product of standardized variables. Step 1: $F(6, 957) = 81.48$; Step 2: $F(7, 956) = 73.43$; $p < .001$ for both steps. ***$p < .001$.

Figure 2

Predicted post-graduation anxiety by perceived AI threat at low and high career adaptability

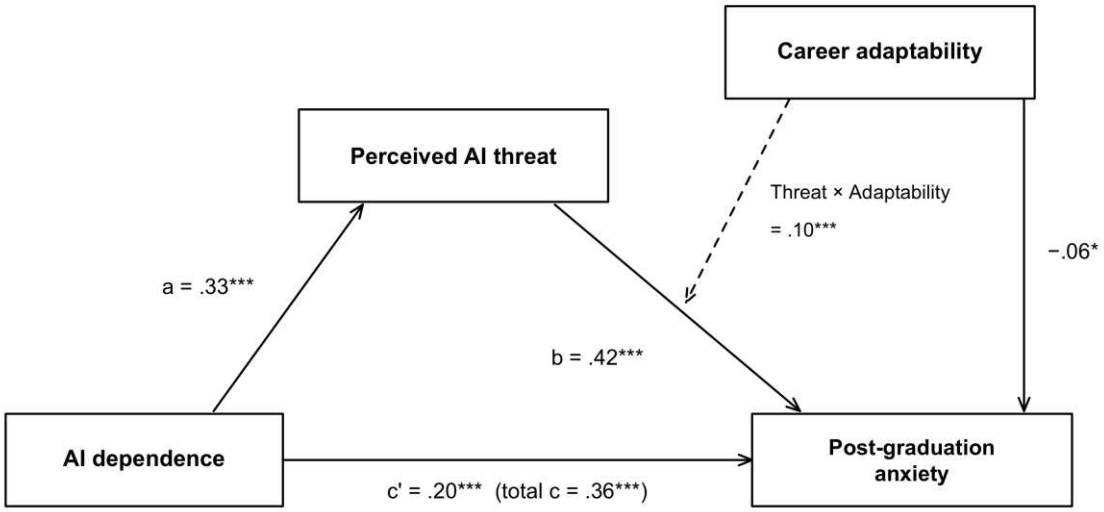


Note. Predicted values with covariates at their means. The shaded area marks the range of perceived AI threat (below 3.75) in which career adaptability was significantly associated with lower anxiety according to the Johnson–Neyman technique. Vertical gray lines mark ±1 *SD* of perceived AI threat.

The exploratory moderated model (RQ2; Figure 3, Table 5) yielded a significant index of moderated mediation, 0.061, 95% CI [0.030, 0.096]. In line with the interaction, the indirect association of dependence with anxiety via threat was larger at higher adaptability (0.206 at +1 *SD* vs. 0.126 at −1 *SD*), although it was significant at all three levels.

Figure 3

Standardized estimates of the second-stage moderated mediation model



Note. Coefficients are from the model in which the threat–anxiety path depends on career adaptability (RQ2); n = 964. The dashed arrow denotes the Threat × Adaptability interaction. Gender, age, and educational level were controlled. *p < .05. ***p < .001.

Exploratory analyses

Critical use (RQ3)

Once dependence was held constant, critical use was not associated with perceived threat, β = −.01, p = .768, or with anxiety, β = .05, p = .174, and its indirect association with anxiety via threat was negligible, ab = −0.007, 95% CI [−0.053, 0.038]. It was, however, positively associated with career adaptability, B = 0.39, 95% CI [0.32, 0.46], β = .36, p < .001, and the association between dependence and adaptability shrank from β = −.27 to β = −.11 (p < .001) when critical use was added. Critical use correlated .37 to .41 with each of the four adaptability dimensions.

Which dimensions of adaptability account for the interaction?

In separate models, each adaptability dimension interacted positively with threat: concern, B = 0.17, β = .11, p < .001; confidence, B = 0.16, β = .11, p < .001; control, B = 0.13, β = .08, p = .002; and curiosity, B = 0.12, β = .08, p = .001. When all four dimensions

and their interactions with threat were entered simultaneously (Table 7; all variance inflation factors ≤ 3.24), only the Threat × Concern interaction remained significant, $B = 0.11$, 95% CI [0.00, 0.22], $\beta = .07$, $p = .043$. The Threat × Confidence interaction was marginal, $p = .056$, and the interactions with control and curiosity were close to zero. The dimensions also differed in their unique main effects: control was associated with lower anxiety, $B = -0.25$, $\beta = -.19$, $p < .001$, whereas concern was associated with higher anxiety, $B = 0.17$, $\beta = .14$, $p < .001$, once the other dimensions were held constant. These results should be interpreted cautiously, given the high intercorrelations among the dimensions (observed correlations .57–.74), their limited discriminant validity, and the number of tests.

Table 7

Exploratory model of post-graduation anxiety with the four career adaptability dimensions

Predictor	*B*	*SE*	95% CI	β	*p*
Perceived AI threat (centered)	0.54	0.03	[0.48, 0.60]	.46	< .001
Concern	0.17	0.04	[0.08, 0.25]	.14	< .001
Control	−0.25	0.05	[−0.35, −0.15]	−.19	< .001
Curiosity	0.02	0.05	[−0.09, 0.12]	.01	.759
Confidence	−0.09	0.05	[−0.19, 0.02]	−.07	.095
Threat × Concern	0.11	0.05	[0.00, 0.22]	.07	.043
Threat × Control	−0.02	0.06	[−0.15, 0.10]	−.01	.708
Threat × Curiosity	−0.02	0.06	[−0.13, 0.10]	−.01	.802
Threat × Confidence	0.12	0.06	[−0.00, 0.25]	.08	.056

Note. $n = 964$. Dimension scores were mean-centered. Gender, age, and educational level were controlled (coefficients not shown). $R^2 = .38$, $F(13, 950) = 44.50$, $p < .001$.

Is the pattern explained by a ceiling on anxiety?

Among students whose perceived threat was at least 1 *SD* above the mean, anxiety was high but rarely at the scale maximum: $M = 4.24$ ($SD = 0.54$) for those below the median of adaptability ($n = 87$) and $M = 4.03$ ($SD = 0.83$) for those at or above it ($n = 85$); 46.0% and 36.5%, respectively, scored 4.5 or higher, and fewer than 10% in either group scored 5. The smaller variance among low-adaptability students who perceived high threat suggests that range restriction near the top of the scale may have contributed to their flatter slope. A pure

ceiling artifact, however, would not readily explain why the interaction was attributable to concern rather than to control, the dimension most strongly associated with lower anxiety.

Group differences

Differences across types of institution, educational levels, and fields of study were small ($\eta^2 \leq .052$). Students at Double First-Class universities reported more frequent use than students at all other types of institutions, more critical use and higher adaptability than students at other public undergraduate institutions and higher vocational colleges, and lower anxiety than students at private undergraduate institutions; students at higher vocational colleges reported the lowest critical use and adaptability. From higher vocational to undergraduate to postgraduate programs, frequency, critical use, and adaptability increased while dependence decreased. Women reported higher anxiety than men ($d = 0.63$), as well as higher dependence ($d = 0.40$), higher threat ($d = 0.26$), and lower adaptability ($d = 0.35$). Differences across regions were negligible ($\eta^2 \leq .008$). Detailed results are provided in Additional file 1.

Discussion

This study set out to connect two literatures that have developed largely separately: research on how generative AI changes learning and research on how AI shapes students' career-related appraisals and emotions. In a sample of 965 Chinese university students, the way students used generative AI, rather than how often they used it, was associated with their anxiety about life after graduation, and perceived AI threat accounted for about two fifths of this association. Career adaptability was associated with lower anxiety, but it did not buffer the association between perceived threat and anxiety; instead, its protective association was confined to low and moderate levels of threat.

Mode of use, not frequency

When AI use is nearly universal—44% of the participants used it almost every day—frequency carried little information about students' anxiety, whereas dependence did. This parallels research on digital technology, in which the amount of use explains little about well-being once the way technology is used is considered (Orben & Przybylski, 2019; Verduyn et al., 2017), and it is consistent with the ISAR distinction between inversion and other effects of AI on learning (Bauer et al., 2025). It also fits recent higher education research suggesting that what matters is how students position themselves toward AI output: whether they delegate strategically while remaining vigilant (S. Wang & Zhang, 2026), how far they rely on or resist it (F. Wang et al., 2025), and whether they keep it subordinate to their own judgment (Zagami, 2026).

The measurement results add a methodological point. Dependent and critical use were strongly related but did not form a single continuum, and they had different correlates: dependence was associated with threat and anxiety, whereas critical use was associated with adaptability but not with threat or anxiety once dependence was held constant. Frequency, in turn, was positively associated with adaptability. These patterns caution against indexing AI use by frequency alone and against treating critical use as merely the absence of dependence, because measures that combine these aspects may conflate processes with different psychological correlates. Frequency was not entirely irrelevant: once adaptability was controlled, it showed a small positive association with anxiety. This effect was small and model-dependent and warrants replication before interpretation.

From learning behavior to appraisals of the future

The indirect association through perceived threat is consistent with the idea that students' learning experiences with AI inform their appraisals of the future value of their competencies. Inversion effects may matter not only for what students learn but also for how

they appraise themselves and their prospects—outcomes that, according to control–value theory, shape future-oriented emotions and thereby motivation and well-being (Pekrun, 2006, 2024). The field-related items point in the same direction: students who believed that AI could complete more of the learning tasks in their major reported both more dependence and more threat, as would be expected if first-hand experiences of AI's capabilities in one's field feed into threat appraisals.

Three caveats apply. First, the direct association between dependence and anxiety remained substantial, so other pathways are likely, such as lower academic self-efficacy (Zhang et al., 2024) or diminished mastery experiences that were not measured here. Second, the latent variable model suggested that measurement error attenuated the indirect association, which may be about half of the total association rather than the 41% estimated with observed scores. Third, and most important, the data are equally compatible with the reverse direction, in which anxious students, or students who already perceive AI as a threat, rely more heavily on AI (Huang et al., 2024). The indirect association should thus be read as showing that the proposed pathway is plausible, not that it operates.

Career adaptability: a resource with boundaries

The finding that most clearly calls for further research concerns career adaptability. Adaptability was associated with lower anxiety on average, but its protective association vanished when perceived threat was high, and the threat–anxiety association was steeper, not flatter, among highly adaptable students. Because H4b predicted the opposite pattern, the following interpretations are post hoc and should be treated as hypotheses for future research.

One possibility follows from control–value theory. Anxiety depends not only on perceived control but also on the value attached to the outcome at stake (Pekrun, 2006, 2024). The concern dimension of adaptability—attending to and planning for one's vocational future—plausibly raises the subjective importance of career outcomes, so that a strong threat

to these outcomes may weigh more heavily on students who care most about them. The dimension-level analyses fit this account: concern accounted for the interaction and, once the other dimensions were controlled, was associated with higher anxiety, whereas control was associated with lower anxiety and did not moderate the threat–anxiety association. A second possibility concerns the match between resources and threats. AI-related threats to one's field are structural and largely outside individual influence, and resources that help with individual career tasks, such as planning, exploring, and problem solving, may do little to counter a threat appraised as structural (Hobfoll et al., 2018). Reverse buffering, in which a resource strengthens rather than weakens a stressor–strain association, has been documented for social support at work (Beehr et al., 2010). A third, methodological possibility is that compression near the top of the anxiety scale among low-adaptability students flattened their slope; the ceiling analysis suggests that this may have contributed but is unlikely to account for the dimension-specific pattern.

These possibilities are not mutually exclusive, and the interaction was small. Testing them requires preregistered replication, direct measures of value and control appraisals, longitudinal designs, and experimental manipulation of threat information. The exploratory moderated model points in the same direction for practice: the indirect association of dependence with anxiety via threat was largest among highly adaptable students, which suggests that fostering adaptability alone is unlikely to neutralize the association between dependent use and threat-related anxiety.

Implications for higher education

Because the data are correlational, the following implications are hypotheses for intervention research rather than recommendations based on demonstrated effects. First, AI-integrated teaching and assessment could be designed to support augmentation and redefinition rather than inversion (Bauer et al., 2025). Requiring an independent first attempt

before AI is consulted, asking students to document and justify how they used AI, assessing the process of learning as well as its products, and using AI tutors with pedagogical guardrails (Bastani et al., 2025) are concrete options. Second, AI literacy education can treat critical use as a skill to be taught rather than a disposition to be assumed. Verifying sources, judging AI output against disciplinary knowledge, and considering alternative views correspond to the activities that remain human when generative AI is used (Lee et al., 2025), and in this study critical use was the aspect of AI use most closely associated with career adaptability. Teachers' general stance toward AI was related to how often and how critically students used AI but not to dependence, threat, or anxiety, which suggests that permitting or prohibiting AI is not enough and that concrete guidance on how to use it may matter more.

Third, threat appraisals can be addressed within disciplinary teaching and career guidance. Discussing concretely which tasks in a field AI automates, which it augments, and which competencies gain value may help students form calibrated rather than global appraisals of AI's implications for their futures. Fourth, career services should continue to foster adaptability, which was associated with lower anxiety at low to moderate levels of threat. For students who perceive strong AI threats, however, adaptability training may need to be combined with realistic labor-market information, opportunities to build skills that complement AI, and support in translating concern for the future into a sense of control over it. Because dependence was higher and critical use and adaptability were lower among students in higher vocational programs, these students may deserve particular attention.

Limitations and future research

Several limitations qualify these conclusions. First, the cross-sectional design does not allow causal inference. The indirect association is a statistical decomposition of covariances and not evidence of mediation (Maxwell & Cole, 2007). Reverse and reciprocal processes are plausible (Huang et al., 2024; Zhang et al., 2024), and unmeasured third variables, such as

trait anxiety, academic self-efficacy, or labor-market conditions in particular fields, could produce the observed associations. Longitudinal designs with at least three waves, random-intercept cross-lagged models, and experience sampling of AI use episodes are needed to examine temporal order.

Second, all variables were self-reported by the same respondents at the same time. Several diagnostics did not indicate that method variance dominated, but such diagnostics cannot rule it out (Podsakoff et al., 2024). Logs of students' interactions with AI, teacher ratings, and performance measures would strengthen future studies. Third, the dependence, critical use, threat, and anxiety scales were self-developed. The dependence scale was short (three items, $\alpha = .70$) and had an AVE slightly below .50, and one of its items cross-loaded weakly on anxiety, although results were similar without it. The critical-use scale had modest reliability, and because dependence and critical use were measured with different response formats, the distinction between them cannot be attributed to content alone. Future studies should measure both aspects with parallel formats and examine convergent validity with existing instruments and behavioral indicators. The scoring of dependence also departed from the initial plan, although the originally planned composite yielded very similar results.

Fourth, the sample was recruited from an online participant pool; women and undergraduates were overrepresented, students at higher vocational colleges were underrepresented (4.9%), and the context was China, where graduate labor markets and further-study pathways have particular features. Replication in other populations and countries is needed. Fifth, the study was not preregistered; the interpretation of the reversed interaction and the dimension-level analyses were post hoc, the interaction effect was small, and multiple tests were conducted. Latent interaction models were not estimated.

Conclusion

As generative AI becomes part of how students learn, it also becomes part of how they think about their futures. This study suggests that what matters is less how often students use AI than how they use it. Dependent use was associated with stronger appraisals that AI threatens one's professional future and with greater anxiety about life after graduation, whereas frequent use was not, and critical use was associated with greater career adaptability. Career adaptability was associated with lower anxiety but did not buffer strong AI threats. For higher education, the findings suggest that preserving students' own cognitive engagement when they learn with AI, teaching critical use as part of AI literacy, and helping students appraise AI's implications for their fields realistically may matter both for their learning and for how they face the transition after graduation. Longitudinal and intervention research is needed to test these possibilities.

Appendix A: Items of the self-developed measures

Table A1

English translations of the self-developed items

Measure and response format	Item
AI use frequency (0 = 0 days, 1 = 1–3 days, 2 = 4–7 days, 3 = 8–14 days, 4 = 15–24 days, 5 = 25–30 days)	In the past 30 days, about how often did you use generative AI to complete learning or practical tasks? Several uses on the same day count as one day.
Usage mode (1 = completely untrue of me, 5 = completely true of me)	D1. When facing a task, I often directly ask AI for the answer without thinking further myself.
	D2. I mostly use the content AI gives me as it is, with few modifications.
	D3. Without AI's help, I would find it hard to complete my learning or practical tasks.
	F. I first think it through myself (or write a first draft), and then ask AI to supplement, improve, or check it. (Planned composite only, reverse-scored)
Critical use (1 = never, 5 = always)	C1. I specifically check the sources of information provided by AI or verify its accuracy against other materials.
	C2. I use what I have learned to judge whether AI's answers are correct.
	C3. When AI offers a viewpoint, I consider whether there are alternative views rather than accepting it directly.
	C4. I ask different AI tools (or the same tool several times) the same question and compare the answers before deciding which to use.
Perceived AI threat (1 = strongly disagree, 5 = strongly agree)	T1. I think AI will replace part of the jobs associated with my major.
	T2. I think AI can complete many tasks in this kind of work faster and better than I can.
	T3. I think some of the professional skills I am learning now will become useless in the future because of AI.
	T4. I think that by the time I graduate, my professional knowledge and skills may not keep up with the changes brought about by AI.
	T5. I think the development of AI has made the employment prospects of my major uncertain.
	T6. I think AI will make it harder for me to find a suitable job after graduation.
Post-graduation anxiety (1 = strongly disagree, 5 = strongly agree)	A1. When I think about where I will go after graduation (employment or further study), I often feel nervous.
	A2. Worrying about my destination after graduation often interferes with my studies or rest.
	A3. I feel uneasy about whether I will be able to find a suitable path after graduation.
	A4. Whenever I think about my destination after graduation, I feel a lot of pressure.

Note. AI dependence = mean of D1–D3; critical use = mean of C1–C4. The originally planned six-item composite comprised D1–D3, F, C1, and C3, with F, C1, and C3 reverse-scored (6 − response). Items were administered in Chinese; the Chinese originals are provided in Additional file 1. The threat scale and the career adaptability scale each contained one instructed-response item that was not scored. For perceived AI threat, the instruction asked participants to think of the occupations typically associated with their major (or intended major).

Abbreviations

AI: Artificial intelligence

AVE: Average variance extracted

CAAS: Career Adapt-Abilities Scale

CFA: Confirmatory factor analysis

CFI: Comparative fit index

CI: Confidence interval

CR: Composite reliability

EFA: Exploratory factor analysis

HTMT: Heterotrait–monotrait ratio

ISAR: Inversion, substitution, augmentation, and redefinition

KMO: Kaiser–Meyer–Olkin measure

MLR: Robust maximum likelihood

RMSEA: Root mean square error of approximation

RQ: Research question

SD: Standard deviation

SRMR: Standardized root mean square residual

STARA: Smart technology, artificial intelligence, robotics, and algorithms

TLI: Tucker–Lewis index

Supplementary Information

Additional file 1 (.docx). Supplementary Tables S1–S10: standardized loadings of the alternative factor models, exploratory factor analyses, measurement invariance tests, robustness checks, group differences, and the Chinese wording of the self-developed items.

Declarations

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and/or analysed during the current study and the R analysis scripts are available from the corresponding author on reasonable request.

Competing interests

The author declares that they have no competing interests.

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Authors' contributions

MZ conceived and designed the study, collected and analysed the data, interpreted the results, and drafted and revised the manuscript. The author read and approved the final manuscript.

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