



Leveraging Artificial Intelligence for Career Development: The Effect of AI Use Intention on Graduate Employability Through Career Adaptability and Job Search Self-Efficacy

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Abstract

Background: Fresh graduates face an increasingly difficult school-to-work transition, while artificial intelligence (AI) has become a routine study and job-search companion; yet how the intention to use AI translates into employability, and through which mechanisms, remains unclear.

Objective: Grounded in Social Cognitive Theory, this study tests whether behavioral intention to use AI is associated with self-perceived graduate employability directly and indirectly through career adaptability and job search self-efficacy, and whether AI self-efficacy and AI trust moderate these paths.

Methods: A cross-sectional online survey of 612 Indonesian fresh graduates who use AI for career preparation was analyzed with partial least squares structural equation modeling (PLS-SEM).

Results: AI use intention positively predicted career adaptability ($\beta = 0.305$) and job search self-efficacy ($\beta = 0.249$), and both resources predicted self-perceived employability. The indirect paths through both resources were significant, and a direct effect of AI use intention on employability remained, indicating partial mediation. AI self-efficacy and AI trust showed significant main effects on their resources, while the interaction-related indirect effects were not significant.

Conclusion: AI use intention is associated with self-perceived employability through career adaptability and job search self-efficacy. The cross-sectional findings do not establish causality. Educational institutions and career-service units may use these findings to inform structured AI-supported occupational exploration, skills-gap analysis, résumé refinement, and interview rehearsal, while encouraging critical verification of AI outputs.

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INTRODUCTION

The transition from higher education to the world of work has become one of the most demanding phases in a young person's life course. For decades a university degree was treated as a reliable passport to secure employment, yet labor markets in many countries now absorb graduates far more slowly than they are produced. In Indonesia, data from Statistics Indonesia Statistik (2026) indicate that the total number of unemployed people stood at about 7.24 million in February 2026, drawn from a labor force of roughly 154.91 million, an open-unemployment rate of 4.68 percent; even so, graduates of diploma-IV, undergraduate, and postgraduate programs accounted for 14.27 percent of all unemployed people (about 1.03 million) in February 2026, compared with 28.00 percent for senior high school and 22.35 percent for vocational high school

graduates (Statistik, 2026). Regarding AI use in the Indonesian workforce, a 2024 survey of 19,154 Indonesian workers found that 38 percent used generative AI every month, and study and research was among the reported use cases (41 percent) (Kaya et al., 2024). However, that survey did not report job-search or career-preparation use by fresh graduates, so graduate-specific evidence remains limited. Public and academic commentators alike have described the predicament of new entrants as an “experience trap”: employers demand prior experience that fresh graduates have not yet had the opportunity to accumulate, while structural forces automation, corporate efficiency drives, and persistent skills mismatch continue to narrow the pool of entry-level positions. Against this backdrop, understanding what makes fresh graduates both become and feel employable is not merely an academic curiosity but a pressing social and economic concern.

Employability itself is best understood not only as an objective stock of credentials but also as a psychosocial and perceptual construct. In this study, employability is operationalized as self-perceived employability, that is, graduates’ subjective appraisal of their own capacity to obtain and sustain appropriate employment, rather than as objective employment status. The self-perceived employability perspective Rothwell et al. (2008), Rothwell and Arnold (2007) and Nghia et al. (2026)

defines employability as an individual’s perceived capacity to obtain and sustain employment appropriate to their qualification level, encompassing both an internal dimension confidence in one’s own skills, attributes, and marketability and an external dimension that reflects perceptions of labor-market demand for one’s field. Brown et al. (2024) and Fugate and Kinicki (2008).

similarly conceptualize employability as a proactive, dispositional constellation of adaptability, career identity, and social and human capital. For new entrants who possess little verifiable track record, such perceptions are consequential: they shape job-search motivation, persistence, and well-being, and they frequently guide behavior more powerfully than objective indicators do. It is therefore analytically fruitful to ask which personal resources elevate graduates’ perceptions of their own employability during the school-to-work transition.

Simultaneously, artificial intelligence (AI) has entered everyday study and work at an unprecedented pace. Generative and assistive tools such as ChatGPT and Copilot now support résumé and cover-letter writing, mock interviews, skills-gap analysis, personalized learning, job matching, and career guidance. In this study, AI refers specifically to generative and conversational tools that graduates use themselves for career preparation and job search, rather than to employer-side algorithmic recruitment systems. A growing body of scholarship documents how AI reshapes learning and creative processes in higher education, offering diverse perspectives, scaffolding complex information, and reducing the burden of routine tasks (Chan & Hu, 2023; Dai et al., 2023; Habib et al., 2024; Marrone et al., 2022). Yet the same literature cautions that uncritical or excessive reliance on AI may erode independent thinking and originality (Mazhar & Arseven, 2026). Emerging evidence specific to the graduate transition reinforces this promise: among fresh graduates, AI-based learning experiences have been linked to stronger career commitment and clearer occupational trajectories (Maulana et al., 2025), and student acceptance of AI has been shown to translate into perceived employability partly by strengthening career adaptability (Shen et al., 2026). For fresh graduates who confront limited experience, acute uncertainty, and intense competition the willingness to adopt these tools may function as a valuable personal resource. Employers, moreover, increasingly treat AI fluency as a baseline competency, so a graduate’s orientation toward using AI plausibly shapes both actual and perceived readiness for work. Consistent with this, perceptions of AI have been found to forge career adaptability through skill development (Burhan, 2024), while AI literacy and self-efficacy have been tied to graduates’ career expectations (Ho & Le, 2026).

The relevance of AI to the graduate transition is amplified by a parallel transformation of hiring itself. Recruitment has become increasingly algorithmic, with applicant-tracking systems, automated résumé screening, and AI-assisted assessment now mediating the earliest stages of selection; candidates who can navigate these tools tailoring materials to machine-readable formats, rehearsing with AI interviewers, and interpreting algorithmic feedback may enjoy a tangible advantage. Employers, too, report a shortage of graduates with the required AI skills: in a 2026 survey of more than 2,700 students, educators, and employers across six countries, more

than half of employers reported difficulty finding graduates with the AI skills they need (Pearson & Services, 2026). Signal-evaluation systems for job applications have been designed to assess applicants' qualification signals (Shen et al., 2025; Twyman et al., 2020). This study, however, focuses on the AI tools that graduates use themselves and treats employer-side screening only as a contextual condition. This shift coincides with a broader youth-employment challenge that is global as well as national. Across many economies, elevated rates of young people not in employment, education, or training, together with credential inflation and the erosion of clear entry-level ladders, have made the first job harder to secure and the signaling value of a degree less certain. Recent evidence that generative AI is already reshaping the earliest rungs of the labor market, dampening short-term hiring for tasks now handled by these tools, sharpens this entry-level squeeze for new graduates (Hui et al., 2024). Within this environment, the personal orientations and capabilities that graduates bring to the search rather than credentials alone become decisive, and the intention to enlist AI as an ally in that search takes on genuine developmental significance rather than remaining a matter of mere technological preference.

The willingness to adopt technology has long been theorized through the lens of behavioral intention. The Theory of Reasoned Action (Fauzi et al., 2024; Fishbein & Ajzen, 1975), the Theory of Planned Behavior (Ajzen, 1985; Imbrisca et al., 2026), the Technology Acceptance Model (Davis, 1989), and the Unified Theory of Acceptance and Use of Technology Venkatesh et al. (2003) and Chong et al. (2022) converge on behavioral intention as the proximal, unidimensional predictor of actual use, with perceived usefulness, ease of use, attitude, subjective norms, and facilitating conditions positioned as antecedents rather than components of intention. This tradition has been extraordinarily productive in explaining what drives adoption. Its analytical attention, however, has concentrated on the moment of adoption; comparatively little work has followed behavioral intention downstream to ask what adoption ultimately yields for a person's career. This asymmetry constitutes a first, theoretically consequential gap: intention has been studied largely as an endpoint rather than as an agentic orientation with distal career consequences. Moreover, the evidence on which this tradition rests is largely cross-sectional and self-reported, and its outcome variables are typically usage-related rather than career-related; whether intention reflects sustained and consequential engagement therefore remains largely untested.

The acceptance tradition has itself evolved in ways that make this omission more visible. Extensions such as UTAUT2, which incorporate hedonic motivation, price value, and habit, have broadened the explanation of consumer technology use (Neves et al., 2025; Venkatesh et al., 2012), and a rapidly growing stream now applies acceptance logic specifically to generative AI, examining how usefulness, enjoyment, and anxiety shape students' willingness to engage such tools. Running through this work is the insight traceable to computer self-efficacy research Compeau and Higgins (1995) and Whipple et al. (2023) that beliefs about one's own capability with a technology powerfully condition both its adoption and the benefits realized from it. Yet even these richer models remain oriented toward predicting use rather than tracing use into human-capital or career outcomes. Moreover, many of these studies are conducted in classroom or consumer settings and rely on self-reported perceptions, which limits their transferability to the labor-market transition that fresh graduates face. The present study takes the next logical step, treating the intention to use AI not as the terminus of an acceptance model but as the entry point of a developmental process whose end state is employability. In doing so it responds to repeated calls to connect what people intend to do with technology to what that technology ultimately does for them.

A second gap concerns the mechanism linking AI use to outcomes. Technology by itself is inert; its value is realized only through the psychosocial resources that individuals cultivate while using it. Merely intending to use AI, or even using it, does not mechanically translate into a better job. What matters is whether AI use is channeled into the development of career-relevant capabilities. Two such resources are especially pertinent to the graduate transition. Career adaptability, derived from Career Construction Theory (Savickas, 2005; Savickas & Porfeli, 2012; Wang & Li, 2024), denotes a psychosocial self-regulatory resource that equips individuals to cope with vocational tasks, occupational transitions, and work-related uncertainty; it comprises concern for the vocational future, control over one's career, curiosity in exploring possible selves, and confidence in solving the problems that transitions demand. Because the central

developmental task of fresh graduates is precisely a career transition, adaptability is highly germane. Graduates who use AI to explore occupations, benchmark and develop skills, and plan concrete next steps can expand the information, feedback, and rehearsal opportunities available for career self-management, thereby strengthening adaptability.

The empirical case for treating adaptability as a lever of employability is well established. The Career Adapt-Abilities Scale has demonstrated measurement equivalence across many national contexts ([Savickas & Porfeli, 2012](#); [Wang & Li, 2024](#)), and a substantial body of evidence links its four dimensions to constructive adapting responses and favorable adaptation results. A meta-analysis synthesizing this literature reports that adaptability is positively associated with career and employment outcomes and with the adaptive behaviors exploration, planning, and self-regulation that produce them ([Kara et al., 2022](#); [Rudolph et al., 2017](#)), while longitudinal work among job seekers shows that adaptability resources translate into more effective job-search behavior and improved reemployment prospects ([Koen et al., 2010](#); [Ouyang et al., 2025](#)). Much of this evidence, however, derives from cross-sectional or self-reported designs and from general samples of job seekers, which leaves the role of technology-mediated career exploration largely unexamined. What this evidence does not yet clarify is how contemporary tools reshape the raw material from which adaptability is built. Because adaptability is nourished by information, feedback, and opportunities to rehearse possible futures, AI capable of generating occupational information on demand, simulating scenarios, and personalizing guidance stands to enrich exactly the inputs that adaptive self-regulation requires, making the AI-to-adaptability link both plausible and, as this study argues, empirically tractable.

Job search self-efficacy is the second resource. As a domain-specific instantiation of Bandura's self-efficacy, formalized within Social Cognitive Career Theory Lent et al. ([1994](#)) and refined for the job-search context by Saks and Ashforth ([1999](#)), Saks et al. ([2015](#)) and Biramo et al. ([2025](#)), it captures a person's confidence in performing job-search behaviors preparing applications, networking, searching effectively and in obtaining outcomes such as interviews and offers. AI tools that draft and critique résumés, simulate interviews, and surface relevant vacancies furnish precisely the mastery experiences, vicarious models, and performance feedback that Bandura identified as the primary sources of efficacy beliefs. Graduates who intend to use, and who actually use, such tools should therefore report greater confidence in both executing job-search tasks and achieving job-search outcomes.

Decades of job-search scholarship reinforce why this confidence matters. Meta-analytic evidence identifies job-search self-efficacy as one of the most consistent motivational predictors of job-search behavior and employment status, operating alongside self-regulatory processes that sustain effort during a frequently discouraging process ([Kanfer et al., 2001](#); [Mammadov & Avci, 2025](#); [Wanberg, 2012](#)). Much of this work predates generative AI and treats job-search resources as conventional ones, so how AI-mediated job-search support shapes efficacy beliefs has not yet been examined. The job search is best understood as a self-managed, goal-directed endeavor in which setbacks are routine and persistence is decisive; efficacy beliefs govern whether graduates initiate demanding tasks, how much effort they invest, and how quickly they recover from rejection. AI tools intervene at precisely these pressure points lowering the cost of producing a strong application, providing safe rehearsal for high-stakes interviews, and offering immediate, non-judgmental feedback thereby supplying the mastery experiences and models that build efficacy. This positions job search self-efficacy as a natural conduit through which the intention to use AI could be converted into tangible job-search confidence, and ultimately into perceived employability, provided that graduates engage AI actively rather than passively.

Framing AI use as a resource that must be actively converted, rather than as a benefit that accrues automatically, is consistent with the mixed evidence that now characterizes research on AI and human capability. Some studies report that AI enriches learning and creative processes by supplying diverse perspectives and cognitive scaffolding ([Chan & Hu, 2023](#); [Dai et al., 2023](#); [Habib et al., 2024](#)), whereas others warn that uncritical reliance can hollow out the very skills it appears to support ([Mazhar & Arseven, 2026](#)). A recent large-sample study reconciles part of this tension by showing that AI use relates to student creativity not directly but through knowledge-based capabilities, and that trust in AI can weaken rather than strengthen those links ([Wang et al., 2026](#)). The lesson generalizes to the career domain: the value of AI is contingent on how it is used, and the decisive question is whether graduates transform AI inputs into durable personal resources.

This is exactly the transformation that career adaptability and job search self-efficacy are theorized to represent, and it is why a mediation model rather than a simple direct-effect model best captures how AI use intention relates to employability.

These strands cohere under a single grand theory. Social Cognitive Theory Bandura (1986) and Bhati and Sethy (2022) explains human functioning through triadic reciprocal determinism, in which personal factors, behavior, and the environment continuously and reciprocally shape one another. Crucially, SCT portrays people as agentic capable of self-reflection, self-regulation, forethought, and intentional action rather than as passive recipients of circumstance. Its theoretical core, self-efficacy (Bandura, 1977, 1997; Bhati & Sethy, 2022), governs the goals people set, the effort and persistence they invest, and their resilience to setbacks. Within the present model, self-efficacy appears twice: as job search self-efficacy and as AI self-efficacy. The two forms share a common theoretical core but operate in different domains: job search self-efficacy concerns confidence in career-related search behaviors, whereas AI self-efficacy concerns confidence in using AI tools. AI self-efficacy is therefore introduced here as a domain-specific counterpart of job search self-efficacy that moderates the first stage of the model. SCT thus supplies a unifying logic: an agentic graduate forms an intention to use AI (a personal motivational orientation) and may, through AI-supported behavior in a technological environment, develop cognitive and psychosocial resources (personal factors) that shape a valued career outcome perceived employability. The middle-range theories of technology acceptance, career construction, and social cognitive career development each specify one segment of this chain, but SCT integrates them into a coherent whole.

Reasoning from this integrated framework yields the study's core mediation logic. Because a stronger intention to use AI reflects a proactive orientation toward learning, self-assessment, and job search, it should foster the two psychosocial resources; thus, behavioral intention to use AI is expected to positively influence career adaptability (H1) and job search self-efficacy (H2). Because adaptable graduates scan opportunities, plan, and adjust more effectively, and because efficacious job seekers act more persistently and skillfully, both resources should elevate perceived employability; hence career adaptability (H3) and job search self-efficacy (H4) are expected to positively influence graduate employability. In addition, an intention to use AI may be associated with a graduate's own appraisal of technological readiness, beyond adaptability and job search self-efficacy. Signaling research concerns observable indicators that reduce employers' uncertainty about applicants' qualifications (Shen et al., 2025; Twyman et al., 2020); however, intention is not itself an observed competence signal, and employer evaluations are not measured here. Accordingly, behavioral intention to use AI is expected to exert a positive direct effect on employability (H5). Taken together, H1 through H4 imply that career adaptability and job search self-efficacy mediate the relationship between AI use intention and employability.

Yet the strength with which intention is converted into resources is unlikely to be uniform, which motivates a third gap concerning boundary conditions. SCT's reciprocal determinism implies that the same behavioral orientation can yield different personal outcomes depending on other personal factors here, how capable of, and how trusting toward, AI a graduate is. AI self-efficacy confidence in operating and learning AI tools, a domain-specific application of self-efficacy theory validated in recent scale work Kaya et al. (2024) should strengthen the conversion of intention into adaptability, because efficacious users engage AI more deeply, persist through difficulty, and extract more usable guidance. AI trust positive beliefs that AI outputs are reliable and can be acted upon Glikson and Woolley (2020) Lockey et al. (2021) and Kumar et al. (2023) should shape the conversion of intention into job-search confidence. The role of trust, however, is theoretically contested: while trust is necessary for meaningful reliance, an emerging line of evidence warns that excessive trust can shade into uncritical over-reliance that dampens the active, effortful engagement on which genuine capability depends (Kulal, 2025). Recent studies in higher-education and generative-AI settings accordingly treat AI trust as an important but double-edged moderator of how AI experiences translate into learning outcomes (Chiu, 2025; Kong et al., 2023; Wang et al., 2026). It is important to distinguish AI self-efficacy from the general computer self-efficacy on which it builds. Whereas early measures captured confidence in operating computers in general (Compeau & Higgins, 1995), contemporary AI tools are conversational, generative, and probabilistic, so competence with them involves not only technical operation but also the pragmatics of interaction framing effective prompts, iterating on outputs, and judging

when an answer is trustworthy. Recent scale-development work accordingly conceptualizes AI self-efficacy as a multidimensional belief spanning assistance, anthropomorphic interaction, comfort, and technological skill (Kaya et al., 2024), and treats it as distinct from AI literacy or mere frequency of use. This distinction matters for the present model because it is confidence in this richer, interactive sense not generic digital familiarity that should determine how much developmental value a graduate extract from AI when building career resources. Trust in AI, likewise, is more than a global positive attitude. Foundational work on trust in automated systems locates it in perceptions of reliability, competence, predictability, and the user's willingness to act on system output (Jian et al., 2000), and reviews of human-AI trust emphasize that trust develops dynamically as users accumulate experience and observe the system's performance (Glikson & Woolley, 2020; Papagiannidis et al., 2025). Because job-relevant AI often operates as an opaque, probabilistic adviser, trust becomes the pivotal determinant of whether a graduate acts on its recommendations or sets them aside. This dual potential trust as the enabler of useful reliance and, in excess, the gateway to uncritical dependence is what makes trust an especially interesting boundary condition, and it foreshadows the possibility that its effect on resource-building may not be monotonic. The human-automation literature has long distinguished appropriately calibrated trust from miscalibrated trust, warning that over-trust breeds complacency and automation bias an uncritical acceptance of machine outputs that displaces the user's own vigilance and effort. Applied to learning and job search, this implies that trust is beneficial up to the point at which it begins to substitute for, rather than support, the graduate's active engagement. On balance, we advance the strengthening expectations that AI self-efficacy positively moderates the AI use intention-career adaptability relationship (H6) and that AI trust positively moderates the AI use intention-job search self-efficacy relationship (H7), while remaining alert consistent with the calibration argument to the possibility that trust operates as something other than a simple amplifier. Each moderator is paired with a single resource on theoretical grounds: AI self-efficacy is linked to career adaptability because adaptability is built through exploration and information seeking, which depend on confidence in using AI tools, whereas AI trust is linked to job search self-efficacy because efficacy in concrete search behaviors depends on whether graduates act on AI-generated outputs. Pairing each moderator with both resources, or reversing the pairings, would require theoretical rationales that were not specified a priori, so testing these alternative moderated paths is left for future research.

Framing the problem in this way is deliberately interdisciplinary, in keeping with the character of research on economics, business, and human development. The question of how graduates convert AI into employability sits at the intersection of the economics of education and labor, which is concerned with credential value, skills mismatch, and the returns to human capital; vocational and social psychology, which theorizes the self-regulatory resources that guide the transition to work; and information systems, which explains how and why individuals adopt and rely on digital tools. Treating any one of these lenses in isolation yields an incomplete picture: an adoption model without career outcomes, a vocational model blind to technology, or a labor-market account inattentive to individual agency. The Indonesian setting sharpens the stakes of this integration. Higher-education enrollment has expanded rapidly while the absorptive capacity of the formal labor market has lagged, producing precisely the kind of graduate oversupply and entry-level bottleneck described above; at the same time, Indonesian students are among the most enthusiastic adopters of generative AI, making the country a revealing site in which to observe whether widespread AI use is being translated into genuine career capability or merely into convenient shortcuts.

The perceptual nature of employability deserves emphasis because it clarifies why psychosocial resources, and not only objective skills, occupy the center of the model. Perceived employability is not a passive mirror of the labor market; it is an appraisal that shapes the very behaviors that determine outcomes. Graduates who believe themselves employable search more intensively, persist longer, negotiate more assertively, and protect their well-being under the strain of rejection, whereas those who doubt their prospects may disengage in ways that make those doubts self-confirming (Brown et al., 2024; Fugate & Kinicki, 2008). For fresh graduates, whose objective record is thin, appraisal is especially influential and especially malleable precisely the conditions under which interventions that build adaptability and job-search confidence can shift both perception and behavior. This is why the study foregrounds the pathway from AI use

intention through psychosocial resources to perceived employability: it is along this pathway that education and career services can realistically intervene.

Synthesizing these gaps clarifies the study's novelty and contribution. Whereas technology-acceptance research has largely stopped at adoption and vocational-psychology research has rarely linked its core resources to AI, the present study integrates the two traditions under Social Cognitive Theory to explain how, and under what conditions, the intention to use AI becomes graduate employability. It does so in the under-examined context of Indonesian fresh graduates, whose acute labor-market pressures make the question locally urgent, while the mechanism it proposes AI adoption converted into employability through psychosocial career resources speaks to a global debate about whether and when AI genuinely benefits human development. Accordingly, this study pursues three objectives: (1) to examine whether behavioral intention to use AI affects graduate employability directly and indirectly; (2) to test whether career adaptability and job search self-efficacy mediate this relationship; and (3) to examine whether AI self-efficacy and AI trust moderate the effect of intention on these psychosocial resources. Figure 1 presents the conceptual model that organizes these relationships and guides the empirical analysis that follows.

In sum, the study advances a single, theoretically integrated argument with seven interlocking expectations. It holds that behavioral intention to use AI builds career adaptability and job search self-efficacy, that these psychosocial resources elevate perceived employability and thereby carry the influence of AI use intention, that AI use intention also exerts a residual direct effect on employability, and that AI self-efficacy and AI trust condition the first stage through which intention becomes resources. These expectations are examined jointly, so that the direct, mediating, and moderating components are estimated within one model rather than as isolated fragments. Figure 1 depicts this structure and situates the moderators, the psychosocial-resource block, and the employability outcome in relation to one another; the sections that follow describe how the model was operationalized and tested and then report and interpret the results. The seven hypotheses are: H1, behavioral intention to use AI positively affects career adaptability; H2, behavioral intention to use AI positively affects job search self-efficacy; H3, career adaptability positively affects graduate employability; H4, job search self-efficacy positively affects graduate employability; H5, behavioral intention to use AI positively affects graduate employability directly; H6, AI self-efficacy positively moderates the path from behavioral intention to career adaptability; and H7, AI trust positively moderates the path from behavioral intention to job search self-efficacy.

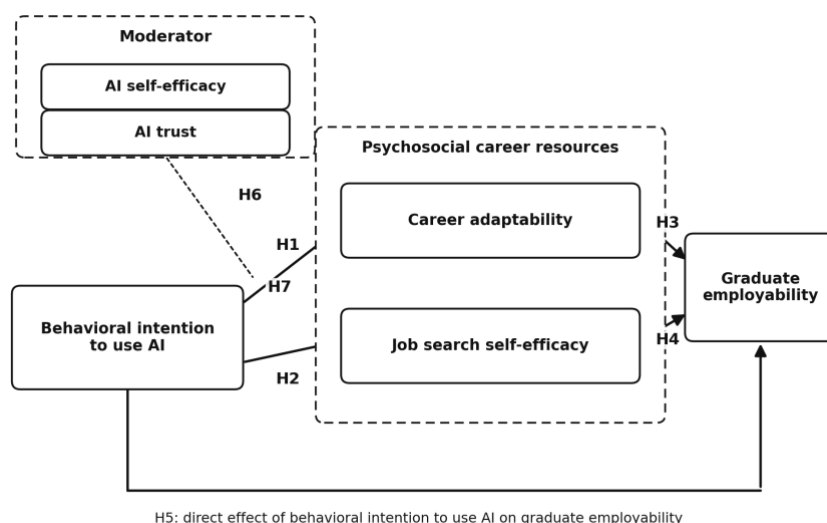


Figure 1. Conceptual research model

METHOD

This study employed a quantitative, cross-sectional survey design, which suits the confirmatory, prediction-oriented aim of testing a mediation-and-moderation model derived from theory. Because a cross-sectional design captures all constructs at a single point in time, it cannot establish longitudinal causal relationships; the structural paths are therefore interpreted as theory-consistent associations rather than as proven causal effects. The target population was Indonesian fresh graduates operationalized as individuals within two years of graduation who had used AI tools such as ChatGPT or Copilot during career preparation or job search; this frame was chosen because the school-to-work transition is the life stage at which career adaptability and job-search confidence are most consequential and because prior AI experience is a precondition for meaningfully reporting AI use intention, self-efficacy, and trust. Respondents were recruited through purposive sampling using an online self-administered questionnaire distributed via social media and alumni networks, an approach appropriate for reaching a dispersed yet specific population at feasible cost. Two screening items confirmed eligibility on fresh-graduate status and prior or current AI use for career purposes, and respondents who did not meet both criteria were routed out of the instrument. Data were collected through an online questionnaire from eligible Indonesian fresh graduates who had used AI tools for career preparation or job-search purposes. After applying the study's eligibility and data-screening criteria, 612 valid responses were retained for analysis.

All constructs were measured reflectively using multi-item, five-point Likert scales ranging from 1 (strongly disagree) to 5 (strongly agree). The items were adapted from established instruments and contextualized for fresh graduates using AI for career preparation and job search. Behavioral intention to use AI was measured using four items; career adaptability using sixteen items; job search self-efficacy using ten items; graduate employability using eight items; and AI self-efficacy and AI trust using eight items each. Table 1 summarizes the constructs, dimensions, and item counts.

Data were analyzed using partial least squares structural equation modeling (PLS-SEM); Hair et al. (2019) and Aburumman et al. (2023), which is well suited to complex models that combine mediation and moderation and to research emphasizing prediction and theory extension. The measurement model was assessed through indicator loadings, internal-consistency reliability (Cronbach's alpha and composite reliability ρ_a and ρ_c), convergent validity (average variance extracted), and discriminant validity via the heterotrait-monotrait ratio (Cheung et al., 2024; Henseler et al., 2015).

The structural model was evaluated through standardized path coefficients whose significance was obtained by bootstrapping; mediation was examined through the significance of specific indirect effects, and the two moderating hypotheses were tested through latent interaction terms constructed with the two-stage approach. The coefficient of determination (R^2) was used to describe explanatory power. Following Hair et al. (2019) and Aburumman et al. (2023), R^2 values of 0.25, 0.50, and 0.75 indicate weak, moderate, and substantial explanatory power, respectively. Ethically, this study involved voluntary adult participants who provided informed consent after being briefed on the study's purpose and the confidential, anonymous handling of their responses; all data were collected in accordance with institutional ethical standards, and no personally identifying information was disclosed at any stage.

Table 1

Constructs, dimensions, and number of items

Construct (role)	Dimensions (as in source theory)	Items
Behavioral intention to use AI (X)	Unidimensional	4
Career adaptability (M1)	Concern; Control; Curiosity; Confidence	16
Job search self-efficacy (M2)	Behavior efficacy; Outcome efficacy	10
Graduate employability (Y)	Self-confidence/proactivity; Field of study; Institutional reputation; External labor market	8
AI self-efficacy (Z1)	Assistance; Anthropomorphic interaction; Comfort; Technological skills	8
AI trust (Z2)	Reliability; Competence/predictability; Confidence in AI; Suspicion (r)	8

RESULTS AND DISCUSSION

Result

Sample Characteristics

The final sample comprised 612 fresh graduates, all of whom confirmed that they had graduated within the previous two years and had used AI tools for career or job-search purposes. Men constituted a slight majority (51.8%), most respondents were between 22 and 25 years old (64.2%), and the great majority held a bachelor's (S1) degree (85.3%). At the time of the survey, 49.5% were employed, 39.2% were not yet employed, and 11.3% were pursuing entrepreneurship, indicating that the sample captured graduates at varied points of the transition. Respondents also spanned a broad range of disciplines most commonly informatics engineering, management, accounting, and information systems supporting the diversity of the sample. The composition is summarized in Table 2.

Table 2

Respondent demographic profile (N = 612)

Characteristic	Category	n	%
Gender	Male	317	51.8
	Female	295	48.2
Age	< 22 years	129	21.1
	22–25 years	393	64.2
	> 25 years	90	14.7
Education	Diploma (D3)	49	8.0
	Bachelor (S1)	522	85.3
	Master (S2)	41	6.7
Employment status	Employed	303	49.5
	Not yet employed	240	39.2
	Entrepreneur	69	11.3
Field of study	Informatics engineering	111	18.1
	Management	97	15.8
	Accounting	83	13.6
	Information systems	80	13.1
	Education	65	10.6
	Economics	52	8.5
	Communication science	48	7.8
	Engineering (other)	44	7.2
	Psychology	32	5.2

Measurement Model

All standardized outer loadings exceeded the 0.70 threshold, ranging from 0.730 to 0.875 across constructs, indicating adequate indicator reliability. As shown in Table 3, Cronbach's alpha ranged from 0.872 to 0.964 and composite reliability (ρ_c) from 0.912 to 0.967, indicating internal consistency, while the average variance extracted ranged from 0.642 to 0.722, exceeding the 0.50 criterion and supporting convergent validity. The career adaptability composite reliability of 0.967 warrants checking for potentially redundant items; a high reliability estimate alone does not establish adequate content coverage.

Table 3

Reliability and convergent validity

Construct	Loading range	α	ρ_a	ρ_c	AVE
AI self-efficacy	0.738–0.859	0.923	0.930	0.937	0.650
AI trust	0.756–0.870	0.927	0.933	0.940	0.663
Behavioral intention to use AI	0.841–0.870	0.872	0.873	0.912	0.722
Career adaptability	0.730–0.875	0.964	0.966	0.967	0.649
Graduate employability	0.754–0.851	0.922	0.925	0.936	0.648

Construct	Loading range	α	rho_a	rho_c	AVE
Job search self-efficacy	0.757–0.843	0.938	0.940	0.947	0.642

Discriminant validity was assessed with the HTMT criterion (Table 4). All ratios fell below the conservative 0.85 threshold the largest being 0.419 indicating that the constructs are empirically distinct.

Table 4*Discriminant validity (HTMT ratios)*

	AI self-efficacy	AI trust	Behavioral intention to use AI	Career adaptability	Graduate employability	Job search self-efficacy
1. AI self-efficacy						
2. AI trust	0.378					
3. Behavioral intention to use AI	0.323	0.330				
4. Career adaptability	0.291	0.331	0.390			
5. Graduate employability	0.306	0.241	0.321	0.419		
6. Job search self-efficacy	0.338	0.324	0.351	0.404	0.381	

Structural Model, Mediation, and Moderation

The structural results appear in Table 5 and are depicted in Figure 2. Behavioral intention to use AI significantly and positively predicted career adaptability ($\beta = 0.305$, $t = 7.952$, $p < 0.001$) and job search self-efficacy ($\beta = 0.249$, $t = 6.216$, $p < 0.001$), supporting H1 and H2. Both psychosocial resources significantly predicted graduate employability career adaptability ($\beta = 0.271$, $t = 6.749$, $p < 0.001$) and job search self-efficacy ($\beta = 0.213$, $t = 5.348$, $p < 0.001$) supporting H3 and H4, and the direct effect of AI use intention on employability remained significant ($\beta = 0.123$, $t = 3.158$, $p = 0.001$), supporting H5. The two moderators exhibited significant positive main effects on their respective resources: AI self-efficacy on career adaptability ($\beta = 0.192$, $t = 5.125$, $p < 0.001$) and AI trust on job search self-efficacy ($\beta = 0.233$, $t = 6.154$, $p < 0.001$). Figure 2 reports $R^2 = 0.164$ for career adaptability, $R^2 = 0.151$ for job search self-efficacy, and $R^2 = 0.220$ for graduate employability, corresponding to 16.4%, 15.1%, and 22.0% of explained variance, respectively. These values indicate limited explanatory power under the thresholds stated in the Method section.

Table 5*Structural model: path coefficients and hypothesis tests*

Path	β (O)	STDEV	t	p	Decision
BI → Career adaptability	0.305	0.038	7.952	< 0.001	Supported
BI → Job search self-efficacy	0.249	0.040	6.216	< 0.001	Supported
Career adaptability → Employability	0.271	0.040	6.749	< 0.001	Supported
Job search self-efficacy → Employability	0.213	0.040	5.348	< 0.001	Supported
BI → Graduate employability (direct)	0.123	0.039	3.158	0.001	Supported

Table 6 reports the interaction-related indirect effects examined in the model. Career adaptability significantly mediated the relationship between AI use intention and graduate employability ($\beta = 0.083$, $t = 5.223$, $p < 0.001$), as did job search self-efficacy ($\beta = 0.053$, $t = 3.983$, $p < 0.001$). Because the direct effect of AI use intention on graduate employability remained significant, the findings indicate partial mediation through both psychosocial resources. In contrast, the indirect effects involving the interaction terms were not significant. The effect

involving AI self-efficacy was not significant ($\beta = -0.004$, $t = 0.388$, $p = 0.349$), nor was the effect involving AI trust ($\beta = 0.004$, $t = 0.543$, $p = 0.294$). The reported results therefore provide no evidence of significant interaction-related indirect effects through either career resource.

Table 6

Interaction-related indirect effects

Indirect path	β (O)	STDEV	t	p
AI self-efficacy $\times$ BI $\rightarrow$ Career adaptability $\rightarrow$ Employability	-0.004	0.010	0.388	0.349
AI trust $\times$ BI $\rightarrow$ Job search self-efficacy $\rightarrow$ Employability	0.004	0.008	0.543	0.294

Comparing the two mediated routes, the indirect effect transmitted through career adaptability (0.083) was larger than that transmitted through job search self-efficacy (0.053), and among the direct structural paths the effect of AI use intention on career adaptability (0.305) was the strongest in the model. The moderator main effects (0.192 and 0.233) were positive and significant but smaller than the effect of AI use intention itself, whereas the interaction-related indirect effects in Table 6 were small and non-significant. The larger adaptability-mediated estimate does not establish a statistically significant difference between the two indirect effects without a formal comparison.

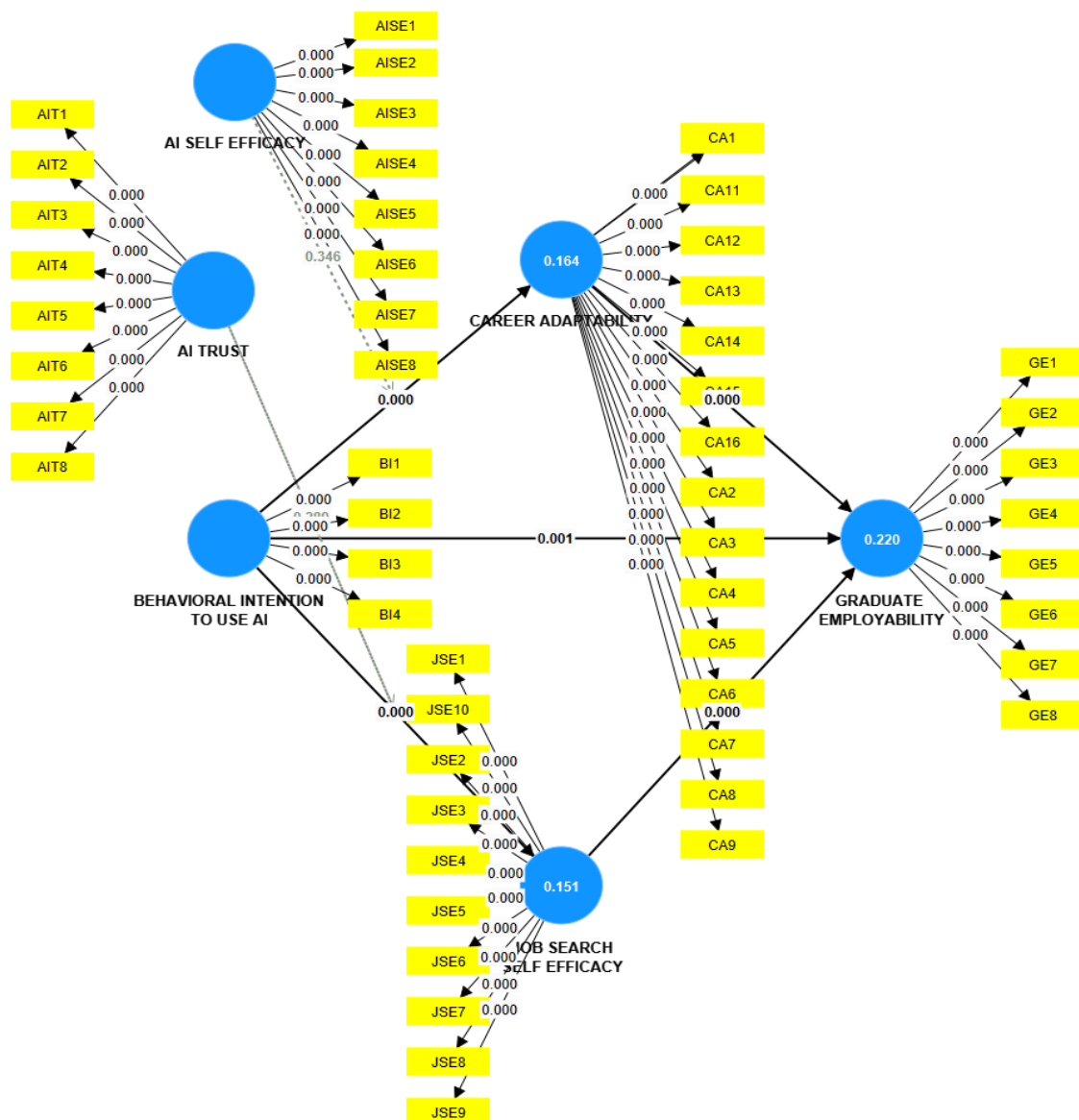


Figure 2. Bootstrapped model showing p-values on the arrows and R² values within the endogenous construct circles. Displayed p-values of 0.000 indicate p < 0.001

Discussion

The findings coalesce into a clear account: the intention to use AI is associated with self-perceived graduate employability through the psychosocial resources through which graduates manage their own transition. The two mediating paths through career adaptability and job search self-efficacy were both significant, and because a positive direct effect persisted, the mediation is complementary rather than full. Interpreted through Social Cognitive Theory, this pattern is consistent with an agentic account in which intention, adaptability, and job-search confidence are associated with perceived employability. The design does not establish the temporal sequence or demonstrate that AI engagement caused these resources to develop. The result thus answers the first two research questions affirmatively and, more importantly, specifies the mechanism that technology-acceptance research has typically left unexamined by stopping at adoption.

The findings distinguish the main effects of AI self-efficacy and AI trust from the interaction-related indirect effects. Both main effects were positive and significant, whereas the interaction-related indirect effects in Table 6 were not significant. This pattern is consistent with AI self-efficacy and trust being associated with career resources independently of intention. It does not, by itself, resolve H6 and H7, which concern first-stage interaction paths. Prior studies discuss the possibility that high trust encourages over-reliance (Kulal, 2025; Wang et al., 2026), but the present findings do not demonstrate that mechanism.

These results carry contributions that reaffirm the study's novelty. Theoretically, the study extends the technology-acceptance tradition beyond the moment of adoption to distal career outcomes, positioning behavioral intention to use AI as an agentic orientation associated with self-perceived employability, and it integrates that tradition with vocational psychology under a single social-cognitive logic something rarely attempted in prior work that examined these literatures in isolation. It also contributes to the micro-foundations of career self-regulation by identifying associations between a technological disposition, adaptability, and job-search efficacy, and to the emerging AI-in-careers literature by identifying the specific psychosocial channels associated with AI use intention and self-perceived employability. Substantively, by identifying significant moderator main effects and non-significant interaction-related indirect effects, it refines the boundary-condition question, redirecting attention from whether AI capability and trust magnify intention toward how they are independently associated with the resources that underpin employability.

The practical implications follow directly and are addressed to several audiences. For educators and curriculum designers, the results suggest considering psychosocial career resources alongside AI use intention. The effectiveness of specific educational interventions remains to be tested. Learning tasks should therefore embed AI within authentic career work requiring students to explore occupations, benchmark and close skills gaps, iterate on résumés, and rehearse interviews with the aim of supporting adaptability and job-search confidence. Assessment can reinforce this by asking students to document how they interrogated, revised, and improved upon AI-generated material, making active engagement rather than passive acceptance the graded behavior.

For university career-service units and policymakers, the significant main effects of AI self-efficacy and AI trust argue for a two-pronged capability agenda. On one side, institutions should build hands-on AI competence through guided practice, prompt-writing workshops, and mastery experiences, with particular attention to students of lower AI self-efficacy who may otherwise struggle to translate access into benefit. On the other, they should cultivate calibrated rather than maximal trust: although over-reliance was not measured in this study, students should be taught to treat AI outputs as drafts to be verified against reliable sources and refined through their own judgment. At the policy level, initiatives to widen AI access in education could be paired with AI-literacy provision and clear guidance on responsible, critical use; the aim of policy should be not simply more AI in classrooms but the conversion of AI into the durable career capabilities on which graduate employability depends.

Career adaptability and job search self-efficacy are related resources but differ in scope. Adaptability concerns exploration and planning, whereas job search self-efficacy concerns confidence in concrete activities such as preparing applications, networking, and interviewing. These distinctions provide a theoretical basis for examining different AI-related beliefs alongside each resource. However, the non-significant interaction-related indirect effects do not

demonstrate a dampening effect of trust, over-reliance, or an asymmetry between the two pathways. Such explanations remain hypotheses for future research rather than findings established by this study.

Social Cognitive Theory provides an interpretive framework for the associations among intention, efficacy beliefs, career resources, and perceived employability. Behavioral intention represents a personal motivational orientation rather than observed AI-use behavior. Because the model uses cross-sectional self-reports and specifies paths in one direction, it does not test triadic reciprocal determinism or establish reciprocal relationships among personal factors, behavior, and environment. The positive main effects of AI self-efficacy and trust are consistent with their potential relevance as personal resources. Capability-based accounts offer a related theoretical perspective (Wang et al., 2026), but longitudinal evidence is needed to establish how these resources develop and interact over time.

For graduates themselves, the findings reframe what it means to use AI well during the transition to work. The advantage lies not in delegating career tasks to AI but in using it as a partner for thinking: to widen the range of occupations considered, to obtain candid feedback on drafts and rehearsals, and to convert that feedback into one's own improved judgment and action. Active engagement and verification are practical recommendations; the present survey did not compare these practices or test whether uncritical acceptance reduces capability. The practical counsel is therefore to pair enthusiasm for AI with the deliberate habits of verification and reflection that turn assistance into genuine, transferable career skill.

The findings may inform research on AI-supported career development beyond Indonesia, but their transferability has not been established. Replication across labor markets is needed to determine whether the observed associations between AI use intention, psychosocial resources, and self-perceived employability recur in other settings. Calibrated trust remains a potential educational objective informed by the wider literature; the present study does not establish its cross-cultural benefits.

Several limitations temper these conclusions and frame the study's scope. The cross-sectional, self-report design constrains causal inference and may introduce common-method concerns; although the theoretical ordering is grounded in Social Cognitive Theory, only longitudinal or experimental evidence could establish the temporal precedence the model assumes. The self-perceived employability measure captures perceptions rather than realized outcomes such as time-to-employment, number of offers, or job-qualification fit, and while perceptions are consequential in their own right, they are not a substitute for behavioral and objective indicators. The focus on fresh graduates in a single national context bounds generalizability, since assessment norms, labor-market structures, and cultural orientations toward technology differ across systems and could reshape the observed relationships. Finally, the general AI-trust measure may not fully separate healthy, calibrated trust from maladaptive over-reliance; whether this measurement distinction explains the non-significant interaction-related indirect effect remains untested, and it points to the need for instruments that distinguish trust from dependence. These limitations are not fatal flaws but honest markers of the terrain the study did not cover, and they motivate the directions set out in the conclusion longitudinal and experimental designs, objective employment indicators, finer measurement of trust versus over-reliance, and cross-national replication that would allow the model's boundary conditions to be mapped with greater precision.

CONCLUSION

This study examined the relationships between behavioral intention to use AI and self-perceived employability among Indonesian fresh graduates, drawing on Social Cognitive Theory. AI use intention was positively associated with employability directly and indirectly through career adaptability and job search self-efficacy, consistent with partial mediation in the specified model. AI self-efficacy and AI trust had significant positive main effects on their respective career resources, while the interaction-related indirect effects were not significant. The findings connect technology-acceptance and vocational-psychology perspectives, but the cross-sectional design does not establish causality.

The findings suggest that educational institutions and career-service units should embed AI within structured career activities, such as occupational exploration, skills-gap analysis,

résumé refinement, and interview rehearsal, while cultivating calibrated rather than maximal trust. Future research should adopt longitudinal or experimental designs, incorporate objective employment indicators, distinguish calibrated trust from over-reliance, and replicate the model across disciplines and countries.

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AUTHOR CONTRIBUTION STATEMENT

Maria Christiana Iman Kalis: conceptualization, methodology, formal analysis, and writing of the original draft. Pramana Saputra Effzi: data curation, validation, visualization, and review and editing. Both authors read and approved the final manuscript.

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APPENDIX

Survey instrument (summary). *Response scale: 1 = strongly disagree ... 5 = strongly agree. Items were administered bilingually (English / Bahasa Indonesia).*

Code	Item (English)	Item (Bahasa Indonesia)
BI1–BI4	Intention to use AI for future career planning, job search, routine career development, and key application stages.	<i>Niat menggunakan AI untuk perencanaan karier, pencarian kerja, pengembangan karier rutin, dan tahapan penting melamar kerja..</i>
CA1–CA4	Concern: thinking about and preparing for the career future.	<i>Concern: memikirkan dan mempersiapkan masa depan karier.</i>
CA5–CA8	Control: taking responsibility and being decisive about career choices.	<i>Control: bertanggung jawab dan tegas atas pilihan karier.</i>
CA9–CA12	Curiosity: exploring opportunities and different ways of working.	<i>Curiosity: mengeksplorasi peluang dan cara kerja yang berbeda.</i>
CA13–CA16	Confidence: solving problems and achieving career goals.	<i>Confidence: memecahkan masalah dan mewujudkan tujuan karier.</i>
JSE1–JSE5	Behavior efficacy: preparing CVs, networking, interviewing, and searching effectively.	<i>Behavior efficacy: menyusun CV, memanfaatkan jejaring, wawancara, dan mencari lowongan efektif.</i>
JSE6–JSE10	Outcome efficacy: obtaining interviews, offers, and a suitable job.	<i>Outcome efficacy: memperoleh wawancara, tawaran, dan pekerjaan yang sesuai.</i>
GE1–GE8	Self-confidence and proactivity, field-of-study relevance, institutional reputation, and external labor-market conditions.	<i>Keyakinan diri dan proaktivitas, relevansi bidang studi, reputasi institusi, dan kondisi pasar kerja eksternal.</i>
AISE1–AISE8	Assistance, effective interaction/prompting, comfort, and technical skills with AI.	<i>Bantuan, interaksi/prompt efektif, kenyamanan, dan keterampilan teknis menggunakan AI.</i>
AIT1–AIT8	Reliability, competence/predictability, confidence in AI, and appropriate caution (reverse-scored).	<i>Keandalan, kompetensi/prediktabilitas, keyakinan pada AI, dan kehati-hatian (reversed).</i>