The Mediating Role of Career Adaptability in the Relationship Between AI Literacy and Career Competencies in Hospitality Internship

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ABSTRACT

Undergraduate hospitality programmes commonly place students in hotels before graduation, and many of those hotels are introducing artificial intelligence and robots. Published studies of these technologies have mainly surveyed hotel employees and guests. This study examines fourth-year students who are learning the occupation during a supervised placement. It tests whether career adaptability mediates the relationship between AI literacy and career competencies, and whether STARA awareness moderates the paths from AI literacy. Main effects of STARA awareness were estimated without a predicted direction. The direct path, the indirect path, and the two interactions were estimated in one model. Data from 564 fourth-year hotel interns in mainland China, collected online in April and May 2026, were analyzed in SmartPLS 4.1 with a two-stage interaction and 5,000 percentile bootstrap samples. AI literacy was positively related to career adaptability (β = 0.487) and directly to career competencies (β = 0.366). Career adaptability had a small positive association with career competencies (β = 0.186). The indirect effect (0.091) was smaller than the direct effect, so mediation was partial. Main effects of STARA awareness were nonsignificant. The interactions were positive (β = 0.310 and 0.258), and the moderated mediation index was 0.058. The indirect effect was significant at the mean and at high STARA awareness. At low STARA awareness it was 0.033 (percentile interval excluded zero; normal-theory p = .111). Internship programmes can combine practice in using and evaluating artificial intelligence with discussion of possible replacement in the target job. The associations of AI literacy with both career outcomes are stronger when STARA awareness is higher.

Keywords: AI Literacy; Career Adaptability, Career Competencies, Stara Awareness, Hospitality Internship, Moderated Mediation

INTRODUCTION

Undergraduate hospitality programmes commonly require a hotel internship before graduation. During the placement, students work under supervision in hotel operations. Many of those operations are introducing artificial intelligence and robots (Bowen & Morosan, 2018). Service tasks require mechanical, analytical, intuitive, and empathetic intelligence, and artificial intelligence is developing across these forms at different rates (Huang & Rust, 2018). Research on automation has therefore examined changes in tourism and hospitality jobs (Ivanov, 2020). In the wider employment literature, jobs with more routine task content are treated as more susceptible to computerisation (Frey & Osborne, 2017). For a fourth-year student on placement, the relevant question is which knowledge and career skills are associated with preparation for this kind of hotel work.

Most of this research samples employees who already hold hotel jobs, or guests who evaluate the service. Service robots are already used in hospitality service encounters (Tuomi et al., 2021). Guests' evaluations of service quality in human-robot interaction have been studied separately (Choi et al., 2020). Reviews of artificially intelligent devices also focus on the device and on service delivery (Chi et al., 2020). Conceptual work on service robots identifies customers, employees, and policymakers as the groups whose acceptance is relevant to adoption

(McCartney & McCartney, 2020). Hotel interns are not included in these groups. They are in the hotel for a fixed placement, and the purpose of the placement is to learn the occupation.

The placement is part of the school-to-work transition, which involves a change in role identity (Ng & Feldman, 2007). Hospitality internship programmes have been studied as an influence on students' career development (Chen & Shen, 2012). Their stated educational purpose is to connect classroom learning with workplace practice (Stansbie et al., 2016). That purpose now includes technologies that many curricula have only recently begun to teach. This study examines one learnable resource for that purpose: AI literacy, defined as the ability to recognize artificial intelligence, use it, evaluate its output, and judge related ethical issues. The outcome is career competencies, which are the skills students use to direct their own careers.

The outcome in this study is career competencies. During the placement, students can develop reflective, communicative, and behavioral competencies: how they evaluate their motives and qualities, how they present themselves, whom they learn from, and how they explore hotel work. These competencies can be observed while students are still in supervised hotel work. Career adaptability is specified separately as concern, control, curiosity, and confidence. The model estimates a direct path from AI literacy to career competencies and an indirect path through career adaptability. STARA awareness is included as a moderator. It is the student's judgment that smart technology, automation, robotics, and artificial intelligence could replace work in the hospitality and tourism job being prepared for.

LITERATURE REVIEW AND HYPOTHESES

Career Construction and the Assignment of Roles

Career construction theory orders the constructs used here. People bring resources to an occupational transition, respond through a psychosocial capacity for adapting, and accumulate adaptation results (Savickas et al., 2009). The present model follows that order and assigns one role to each construct before the direction of the paths is stated.

AI literacy is the resource. Knowledge and skills are included among the resources people use in constructing a career (Hirschi, 2012). In this study the relevant knowledge and skills are specific: recognizing artificial intelligence, using it, evaluating its output, and judging the ethical issues in that use. A curriculum and a placement can change this resource. Career construction theory uses the term adaptivity for stable personal readiness, and it uses adaptation results for outcomes of the transition. AI literacy is specified separately from both.

Career adaptability is the mediator. A systematic review describes it as psychosocial readiness and resources for vocational tasks, occupational transitions, and unexpected challenges, and research usually measures it as concern, control, curiosity, and confidence (Johnston, 2018). Concern refers to attention to the future of the work. Control refers to a sense that one can influence the direction of preparation. Curiosity refers to exploring how the work is changing. Confidence refers to attempting an unfamiliar task. These four dimensions are distinct from AI literacy and from the career competencies that follow.

Career competencies are the outcome. They are the integrated knowledge, skills, and abilities used to develop a career under current employment conditions (Kuijpers & Scheerens, 2006). The reflective competencies are reflection on motivation and reflection on qualities. The communicative competencies are networking and self-profiling. The behavioral competencies are work exploration and career control. AI literacy may be associated with these competencies through career adaptability. It may also be associated with them directly, because several competencies require knowledge of how the job is changing. Both paths are retained in the model.

STARA awareness is the moderator. It records the student's judgment that smart technology, automation, robotics, and artificial intelligence could replace work in the job being prepared for. The instrument's definition uses the word automation, and this paper follows that definition. The judgment can change how strongly a resource is associated with later career variables, while remaining distinct from the resource itself. The main effects of STARA awareness on career adaptability and career competencies are estimated, because an

interaction term requires the corresponding main effects in the equation. Those main effects have no directional hypotheses. The hypotheses concern AI literacy, career adaptability, and the positive interactions of STARA awareness with AI literacy.

AI Literacy and Career Adaptability

AI literacy has been defined as a set of competencies that allow a person to evaluate artificial intelligence, to communicate and collaborate with it, and to use it as a tool (Long & Magerko, 2020). In education, a review treats knowing, using, evaluating, and ethical judgment as separate parts of the construct (Ng et al., 2021). The same construct has been specified for employees in digital workplaces (Cetindamar et al., 2024). Hotel interns are students and, for the period of the placement, they are also in a workplace. Awareness, use, evaluation, and ethics are therefore used as indicators of one AI literacy construct. On this specification, higher literacy means higher scores across these four contents.

A positive path from AI literacy to career adaptability is expected because hotel work is changing with the introduction of these technologies. Students who can identify relevant changes are in a better position to show concern. Students who can evaluate an output can make a more specific decision about what to learn next, which is relevant to control. Curiosity has a concrete focus in the placement, namely how hotel tasks are being reorganized. Confidence is more likely when the student has some competence with the tool required for an unfamiliar task. Training studies already show that career adaptability can be developed during the school-to-work transition (Koen et al., 2012). AI literacy is treated here as one input to that development.

H1. AI literacy is positively related to career adaptability.

Adaptability, Career Competencies, and the Direct Path

Career adaptability is expected to be positively related to career competencies. Concern directs attention to the future that reflection and career control address. Control supports the practice of self-profiling. Curiosity supports work exploration and the search for people from whom the intern can learn. Confidence supports attempting the unfamiliar parts of the job. A meta-analysis reported associations between the adaptability dimensions and adaptation results (Rudolph et al., 2017). Career competencies are treated here as adaptation results in the form of self-regulatory career skills. The meta-analysis provides the basis for the positive sign.

Career construction theory has already been applied to hotel employees. Among frontline hotel employees in Nigeria, work social support was positively related to career adaptability (Karatepe & Olugbade, 2017). That study used social support as the resource and sampled employees. This study uses AI literacy as the resource and samples interns. Career adaptability has also been examined in hospitality research as an antecedent of turnover intentions (Rasheed et al., 2020). That outcome is an intention to leave. The outcome in the present model is career competencies. There is also evidence from Chinese higher education, at a later stage than the internship. A three-wave study of Chinese university graduates examined career adaptability together with job-search self-efficacy and employment outcomes (Guan et al., 2013). Those respondents had finished university. The students in the present study were still on placement. The graduate study indicates that career adaptability is associated with career variables in the Chinese university-to-work sequence. It does not provide estimates for hotel interns.

H2. Career adaptability is positively related to career competencies.

The direct path from AI literacy to career competencies is hypothesized separately. Reflection on one's qualities, exploration of the work, and self-profiling in a department depend in part on what the student knows about the technology used in that work. Career competencies have been observed among students in higher vocational education (Kuijpers & Meijers, 2012). They have also been linked to subjective career success through job crafting (Akkermans & Tims, 2017). Interns have not yet reached those later career outcomes. The outcome estimated here is therefore the competency itself.

H3. AI literacy is positively related to career competencies.

STARA Awareness as a Condition on the Slopes

Hotel studies have often examined artificial intelligence through employees' job insecurity (Koo et al., 2021). That approach is understandable for employees whose current tasks may be removed, and a negative main effect would be one possible prediction. In this study the main effects are estimated without a predicted sign. Challenge appraisals of STARA awareness were positively related to competitive productivity among restaurant employees (Ding, 2021). The same level of awareness can therefore be connected with different responses. Awareness and skill are also different. Two interns may both judge the target job to be exposed to replacement and still differ in their ability to use and evaluate the technology. The judgment changes the situation in which that ability is relevant.

When STARA awareness is high, the possible replacement of hotel work is salient. AI literacy then has a clearer connection with concern, control, curiosity, and confidence. When STARA awareness is low, the same positive associations are expected to be smaller. The same difference is expected for the direct path to reflection, networking, self-profiling, work exploration, and career control. At low awareness the slopes are expected to stay positive and to be smaller than the slopes at high awareness. The moderated paths are the path from AI literacy to career adaptability and the direct path from AI literacy to career competencies. The path from career adaptability to career competencies is estimated as the same coefficient at each level of STARA awareness. This is the moderated mediation estimated below.

H4. STARA awareness strengthens the positive relationship between AI literacy and career adaptability.

H5. STARA awareness strengthens the positive relationship between AI literacy and career competencies.

If the path from AI literacy to career adaptability is steeper at higher STARA awareness, and if career adaptability is positively related to career competencies, the indirect effect is larger at higher STARA awareness. The index of moderated mediation is the product of the interaction coefficient on career adaptability and the coefficient from career adaptability to career competencies. A positive index means that the indirect effect increases as STARA awareness increases. Because the second-stage path has no interaction, the conditional indirect effect equals the conditional first-stage slope multiplied by the path from career adaptability to career competencies.

H6. The index of moderated mediation is positive: STARA awareness strengthens the indirect relationship between AI literacy and career competencies through career adaptability.

Figure 1 shows the constructs and the six hypotheses.

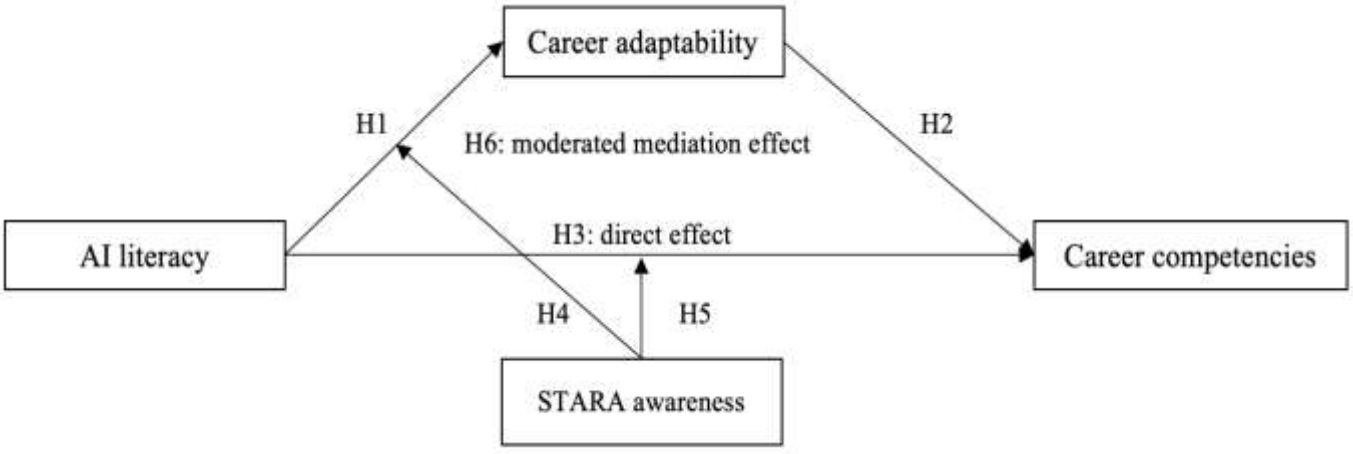

Figure 1. Conceptual model.

Boundaries of the Hypotheses

Two related constructs are kept distinct from STARA awareness. Willingness to integrate a service robot is an employee's inclination to work with the machine, and it has a separate scale (Lu et al., 2019). A student may

report high replacement awareness and high willingness, or low awareness and low willingness. The moderator in this study is the replacement judgment. Emotional intelligence has been examined alongside artificial intelligence among hotel employees (Prentice et al., 2020). Emotional intelligence and AI literacy are different capabilities. The resource in H1 and H3 is AI literacy.

STARA awareness is expected to vary across interns. Adoption of artificial intelligence and robotics in hotels involves both prospects and organizational difficulties (Nam et al., 2021), so properties and students will not report the same level of exposure. The moderator is the student's judgment. Service robots in frontline service are expected to change service production and the tasks performed by employees (Wirtz et al., 2018). Those tasks are the work to which AI literacy refers. Research on automation in tourism is now a distinct body of work (Tussyadiah, 2020). Within that literature, the present hypotheses concern the career variables of students who are in hotels to learn the occupation.

METHODOLOGY

Participants and Procedure

The participants were fourth-year undergraduates who were interning in hotels. Recruitment used snowball sampling. Participating interns passed the questionnaire to colleagues who were also on a hotel placement. Data were collected online in mainland China in April and May 2026. Cities, universities, and hotels are not identified. Participation was voluntary and anonymous. Students were told the purpose of the study, gave informed consent, and could stop without penalty. 650 questionnaires were distributed and 587 were returned. Questionnaires with long runs of identical answers were removed. There were no missing values on the items used in the model. The analyzed sample was 564. Students were at different points in the placement. The sample size was not set by an a priori power analysis. In the SmartPLS sensitivity results, a standardized path of .186 at alpha = .05 requires 178 cases for power of .80 and 247 cases for power of .90.

Table 1 describes the sample. Female were 415 of the 564 students (73.6%) and male were 149 (26.4%). Age was recorded in three bands: 113 students were 18 to 20 (20.0%), 406 were 21 to 23 (72.0%), and 45 were 24 or above (8.0%). The internship hotel was an international brand for 243 students (43.1%) and a local brand for 321 (56.9%). Gender, age, and brand describe who answered. Every student was in the fourth year. Internship duration, department, star rating, and hotel size were not recorded due to the anonymity principles.

Table 1 Sample Characteristics

Characteristic	**Category**	**n**	**%**
Gender	Female	415	73.6
	Male	149	26.4
Age (years)	18-20	113	20.0
	21-23	406	72.0
	24 and above	45	8.0
Internship hotel	International brand	243	43.1
	Local brand	321	56.9

Measures

All items were answered on seven-point scales. The AI literacy items kept their published seven-point agreement format. Career adaptability, career competencies, and STARA awareness were published with five points and were administered here with seven points, so that the questionnaire used one response length. The scored wording was an English adaptation for hospitality and tourism students. Where an item referred to work, a job, a career, a task, or an industry, the referent was the hospitality and tourism work the student was preparing to

enter. Item direction and reverse wording were unchanged. The adaptation changes the referent only. The questionnaire was administered in Chinese. The adapted English wording was translated into Chinese and back-translated.

AI literacy was measured with the 12-item Artificial Intelligence Literacy Scale (Wang et al., 2023). The scale covers four dimensions with three items each: awareness, usage, evaluation, and ethics. Respondents indicated agreement from 1 (strongly disagree) to 7 (strongly agree). Three items are negatively worded, one in awareness, one in usage, and one in ethics. Those items were reverse scored before the dimension means were calculated. Career adaptability was measured with the 24-item Career Adapt-Abilities Scale (Savickas & Porfeli, 2012). Four dimensions of six items cover concern, control, curiosity, and confidence. Career competencies were measured with the 21-item Career Competencies Questionnaire (Akkermans et al., 2013). The six competencies are reflection on motivation (three items), reflection on qualities (four), networking (four), self-profiling (three), work exploration (three), and career control (four). Here, work was defined as the internship together with the hospitality and tourism work the student was preparing to enter. STARA awareness was measured with four items (Brougham & Haar, 2018). The source reports one factor, alpha of .85, and 71.9% of variance on that factor. The published stem refers to the current job. The stem used here referred to the hospitality and tourism job the student was preparing to enter. The items ask whether the job could be replaced, whether one's present tasks could be replaced, and whether one is worried about the future in the organization and in the industry because of that replacement.

The indicators in the structural model were the four AI literacy means, the four career adaptability means, the six career competency means, and the four STARA items. Each dimension mean is a parcel defined by the published scale, which is a domain-representative form of parceling (Little et al., 2002).

Analytic Strategy

The model was estimated in SmartPLS 4.1 with partial least squares structural equation modeling. This estimator was used because the questions concern path coefficients among latent composites, including one mediator and one moderator on two paths. Reporting follows the guidelines for path coefficients, bootstrap intervals, coefficients of determination, effect sizes, and indicator diagnostics (Hair et al., 2019). Values of f^2 at .02, .15, and .35 were treated as small, medium, and large. Estimation used the path weighting scheme, a maximum of 3,000 iterations, and a stop criterion of 1×10^{-7}. The coefficients are standardized.

The product of STARA awareness and AI literacy was specified with the two-stage approach (Henseler & Chin, 2010). AI literacy, career adaptability, and career competencies remain first-order constructs. The product has one indicator, and its loading was fixed at 1. That value is part of the specification. Heterotrait-monotrait ratios that include the product term are not used as evidence of discriminant validity.

Inference used 5,000 bootstrap samples, percentile 95% confidence intervals, and two-tailed tests at alpha = .05, with a fixed seed. For indirect effects and conditional indirect effects, the percentile interval was specified in advance as the criterion. The normal-theory p value is reported with it. If the interval and the p value disagree, both are reported and the interval is used for the conclusion. Conditional direct and indirect effects were estimated at one standard deviation below the mean of STARA awareness, at the mean, and at one standard deviation above the mean. In the standardized solution, the conditional direct effect at the mean equals the corresponding main-path coefficient.

The index of moderated mediation was defined as the product of the interaction path to career adaptability and the path from career adaptability to career competencies (Hayes, 2015). The product was tested with the partial least squares bootstrap. A regression program was not used for the index. The index indicates whether the indirect effect changes with the moderator when the second-stage path is the same at each level of the moderator.

Common method bias was addressed in the procedure and in the analysis. Participation was voluntary and responses were anonymous (Podsakoff et al., 2003). Inner-model variance inflation factors and full collinearity variance inflation factors of the four composite scores were compared with 3.3 (Kock, 2015). No marker-variable test was conducted. Discriminant validity among the four constructs was assessed with the heterotrait-monotrait

ratio, using .85 as the benchmark (Henseler, Ringle, & Sarstedt, 2015). The standardized root mean square residual was reported for the saturated model and the estimated model. Values below .08 were treated as acceptable (Henseler, Hubona, & Ray, 2016). Cronbach's alpha was calculated for each full scale and each published dimension. A maximum likelihood confirmatory factor analysis of those dimensions was estimated in semopy (Igolkina & Meshcheryakov, 2020). A principal component analysis of the 61 items was used as a further check on common method variance. The hypothesis tests remain the partial least squares estimates.

RESULTS

Measurement Model

The indicator means were close to the midpoint of the seven-point scale. The four AI literacy dimensions ranged from 4.03 to 4.07, the four career adaptability dimensions from 4.04 to 4.05, and the six career competency dimensions from 4.02 to 4.07. Standard deviations for these dimension means ranged from 0.67 to 0.86. The four STARA items had means from 3.81 to 4.14 and standard deviations from 1.06 to 1.10, and the observed scores covered the full range from 1 to 7. Table 2 reports the indicator descriptives and the outer loadings.

Table 2 Indicator Descriptives and Outer Loadings

Construct	Indicator	M	SD	Loading
AI literacy	Awareness	4.07	0.83	.882
	Usage	4.03	0.86	.889
	Evaluation	4.05	0.80	.891
	Ethics	4.03	0.82	.890
Career adaptability	Concern	4.04	0.67	.904
	Control	4.04	0.69	.889
	Curiosity	4.05	0.69	.895
	Confidence	4.04	0.68	.900
Career competencies	Reflection on motivation	4.02	0.77	.822
	Reflection on qualities	4.04	0.74	.865
	Networking	4.05	0.75	.844
	Self-profiling	4.05	0.79	.820
	Work exploration	4.04	0.78	.837
	Career control	4.07	0.76	.856
STARA awareness	Job could be replaced	3.81	1.10	.829
	Own tasks could be replaced	4.04	1.06	.792
	Future in the organization	4.14	1.08	.836
	Future in the industry	3.95	1.07	.793

Note. N = 564. Means and standard deviations are sample statistics of the indicators entered in the model. Loadings are standardized. Every loading was significant at $p < .001$. The interaction term is omitted; its single indicator was fixed at a loading of 1.

Every loading exceeded .70. The lowest were .792 and .793, on two of the STARA items, and the highest was .904, on career concern. Reliability and average variance extracted are reported in Table 3. Cronbach's alpha ranged from .835 for STARA awareness to .919 for career adaptability. Composite reliability ρA and ρC were higher than alpha in each case and were above .87 throughout. Average variance extracted ranged from .660 to .805, so each construct accounted for more than half of the variance in its indicators. The largest indicator-level

variance inflation factor was 3.169, on the concern indicator of career adaptability. The remaining indicator variance inflation factors were lower.

The largest heterotrait-monotrait ratio was .563, between career competencies and career adaptability. The ratios of AI literacy with career adaptability and career competencies were .519 and .482. The ratios of STARA awareness with AI literacy, career adaptability, and career competencies were .076, .029, and .053. All six ratios were below .85. These values describe the overlap among the four constructs. They are measurement results, and they are separate from the test of the hypotheses.

Table 3 Reliability, Convergent Validity, and HTMT

Construct	α	ρA	ρC	AVE
AI literacy	.911	.913	.937	.789
Career adaptability	.919	.920	.943	.805
Career competencies	.917	.918	.935	.707
STARA awareness	.835	.874	.886	.660

Note. α = Cronbach's alpha; ρA = reliability coefficient rho_a; ρC = composite reliability rho_c; AVE = average variance extracted. HTMT ratios: career adaptability-AI literacy = .519; career competencies-AI literacy = .482; career competencies-career adaptability = .563; STARA awareness-AI literacy = .076; STARA awareness-career adaptability = .029; STARA awareness-career competencies = .053.

The standardized root mean square residual was .038 for the saturated model and .043 for the estimated model. Both values are below .08. Inner-model variance inflation factors were at most 1.729. The larger of them were 1.729 for the path from career adaptability to career competencies, 1.416 for the path from AI literacy to career competencies, and 1.355 for the path from the interaction to career competencies. The remaining structural variance inflation factors were approximately 1.00 to 1.02. All were below 3.3. Full collinearity variance inflation factors among the four composite scores ranged from 1.010 to 1.522. Item-level Cronbach's alpha was .908 for the 12 AI literacy items, .920 for the 24 career adaptability items, .919 for the 21 career competency items, and .834 for the four STARA awareness items. Alpha for the four AI literacy dimensions ranged from .692 to .726. Alpha for the four career adaptability dimensions ranged from .730 to .753. Alpha for the six career competency dimensions ranged from .587 to .707. Reflection on motivation (.587), reflection on qualities (.664), self-profiling (.611), and work exploration (.622) were below .70. The alphas in Table 3 are the reliabilities of the four constructs indicated by dimension means. Each scale remains one construct in the structural model, and the indicators remain the published dimension means. A principal component analysis of the 61 items gave a first component that accounted for 24.4% of the variance.

Structural Model

Table 4 and Figure 2 report the structural coefficients. H1 was supported. AI literacy was positively related to career adaptability, $\beta = .487$, $t = 14.862$, $p < .001$, 95% CI [.423, .550], $f^2 = .409$. This effect size is large by the benchmarks in the analytic strategy. The coefficient of determination for career adaptability was $R^2 = .422$ (adjusted $R^2 = .419$). H2 was supported. Career adaptability was positively related to career competencies, $\beta = .186$, $t = 3.317$, $p < .001$, 95% CI [.104, .341], $f^2 = .035$. The confidence interval excludes zero and is wide relative to the coefficient, so the path is significant and imprecisely estimated. The effect size is small. H3 was supported. The direct path from AI literacy to career competencies was positive, $\beta = .366$, $t = 8.565$, $p < .001$, 95% CI [.268, .439], $f^2 = .164$. The effect size is medium. It is larger than the adaptability path. The specific indirect effect of AI literacy on career competencies through career adaptability, at the mean of the moderator in this standardized solution, was .091, $t = 3.260$, $p = .001$, 95% CI [.050, .164]. The indirect effect is positive, and it is smaller than the direct effect of .366. The result is partial mediation. The coefficient of determination for career competencies was $R^2 = .423$ (adjusted $R^2 = .419$).

H4 was supported. The interaction of STARA awareness and AI literacy was positively related to career adaptability, β = .310, t = 7.777, p < .001, 95% CI [.228, .362], f^2 = .337. The effect size is above the medium benchmark and below the large benchmark. H5 was supported. The same interaction was positively related to career competencies, β = .258, t = 6.396, p < .001, 95% CI [.149, .309], f^2 = .176, a medium effect. H6 was supported. The index of moderated mediation was .058, t = 3.676, p < .001, 95% CI [.030, .093]. The indirect effect of AI literacy on career competencies through career adaptability increases as STARA awareness increases. The index is small in absolute value because the second-stage path is small (β = .186). The confidence interval for the index excludes zero.

Table 4 Structural Paths, Indirect Effects, and the Index of Moderated Mediation

Path	**β**	**t**	**p**	**95% CI**	**f^2**
AI literacy → career adaptability	.487	14.862	< .001	[.423, .550]	.409
AI literacy → career competencies	.366	8.565	< .001	[.268, .439]	.164
Career adaptability → career competencies	.186	3.317	< .001	[.104, .341]	.035
STARA awareness → career adaptability	-.039	0.875	.381	[-.122, .052]	.003
STARA awareness → career competencies	.028	0.695	.487	[-.055, .102]	.001
STARA × AI literacy → career adaptability	.310	7.777	< .001	[.228, .362]	.337
STARA × AI literacy → career competencies	.258	6.396	< .001	[.149, .309]	.176
AI literacy → adaptability → competencies	.091	3.260	.001	[.050, .164]	n.a.
STARA → adaptability → competencies	-.007	0.744	.457	[-.027, .012]	n.a.
Index of moderated mediation	.058	3.676	< .001	[.030, .093]	n.a.

Note. N = 564. Coefficients are standardized. Confidence intervals are percentile intervals from 5,000 bootstrap samples. f^2 is reported for structural paths. n.a. = not applicable. R^2 = .422 for career adaptability (adjusted .419) and R^2 = .423 for career competencies (adjusted .419).

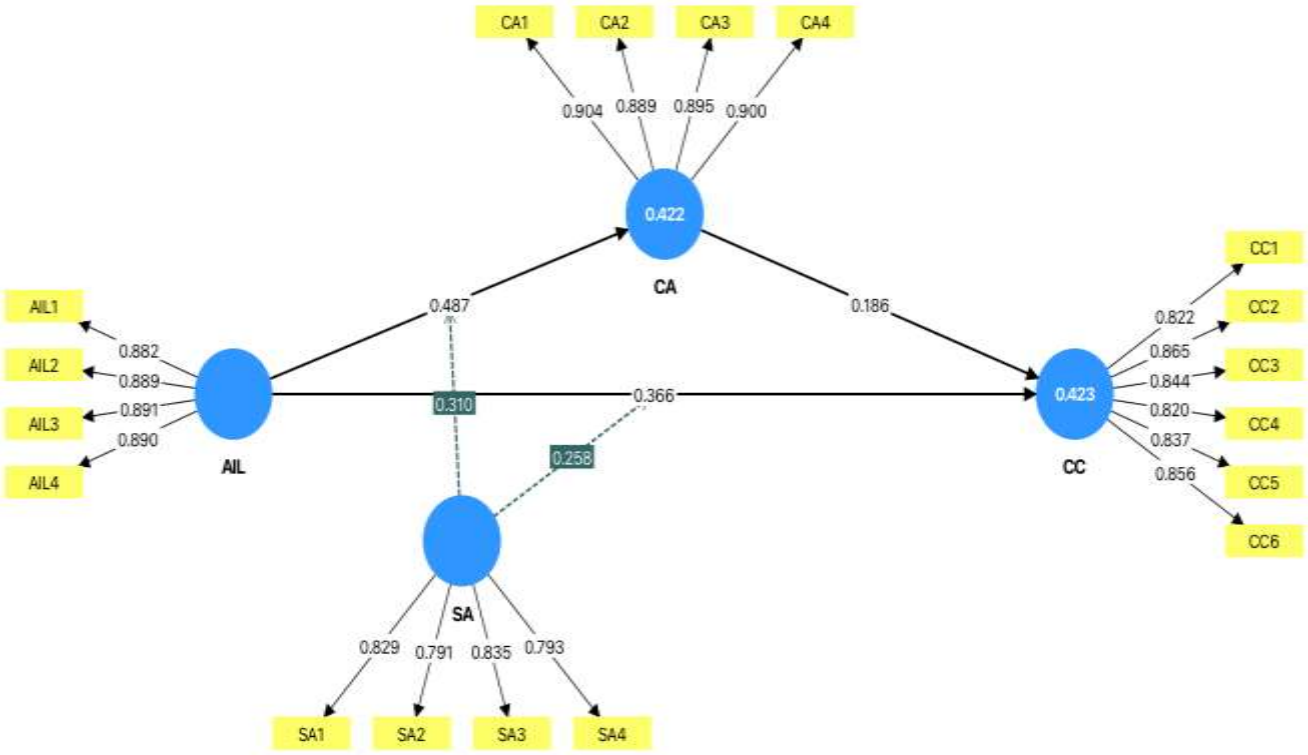

Figure 2: Structural model results from SmartPLS 4.1

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Conditional Effects

Table 5 reports the conditional effects. For career adaptability, the effect of AI literacy was .178 at low STARA awareness, t = 3.154, p = .002, 95% CI [.083, .297]. At the mean it was .487, which is the main-path estimate. At high STARA awareness it was .797, t = 17.189, p < .001, 95% CI [.699, .863]. The slope at low awareness is positive. The slope at high awareness is larger.

Figure 3 plots these slopes from the standardized equation, which includes the main effect of STARA awareness: career adaptability = .487 AI literacy - .039 STARA awareness + .310 AI literacy × STARA awareness. The lines intersect slightly above the mean of AI literacy, at about +0.13 standard deviations. At one standard deviation below the mean of AI literacy, standardized career adaptability is -.138 at low STARA awareness and -.836 at high STARA awareness. At one standard deviation above the mean of AI literacy, the values are .216 and .758. The lowest value among these points is high STARA awareness combined with low AI literacy. The highest value is high STARA awareness combined with high AI literacy.

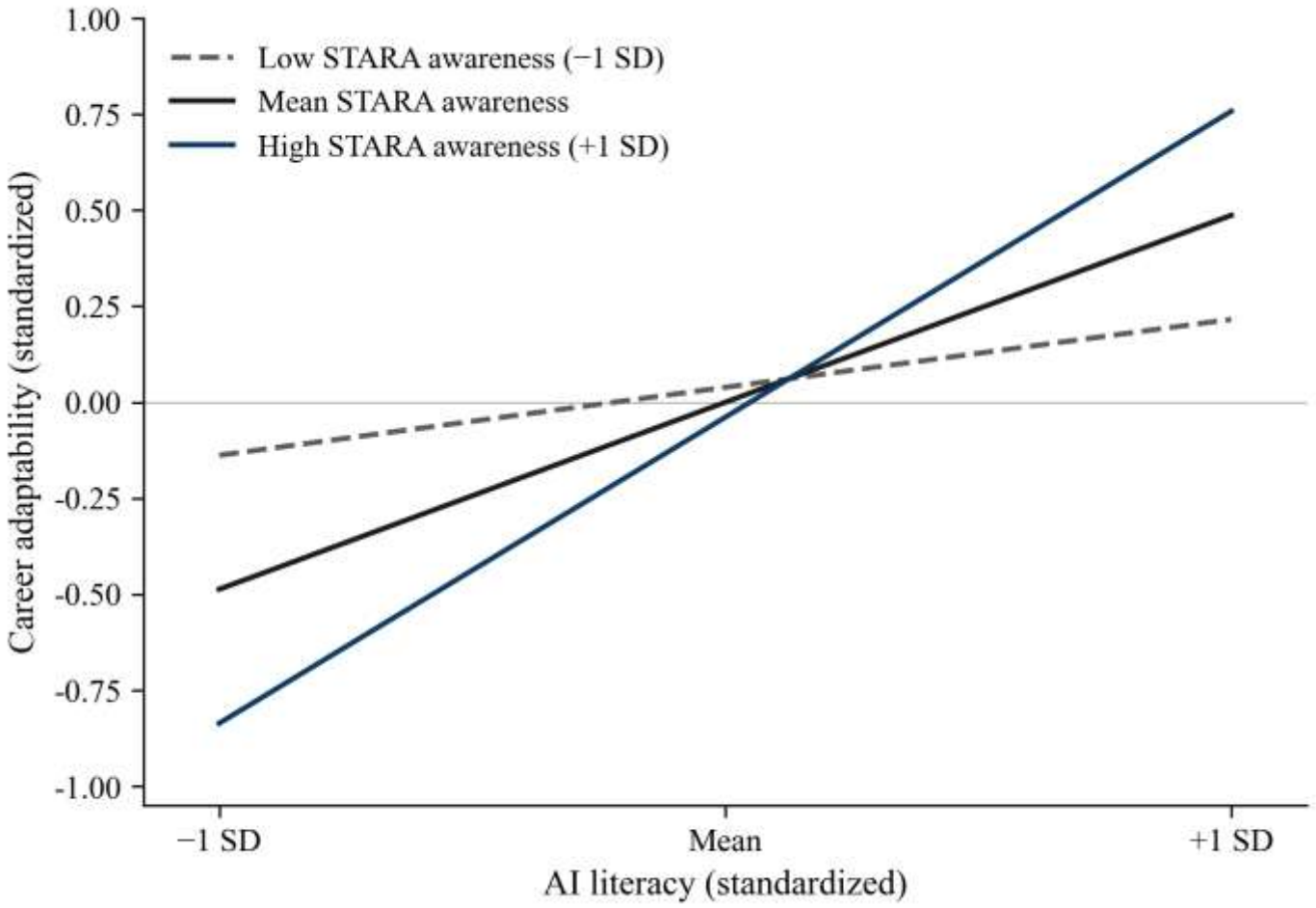

Figure 3. Simple slopes of AI literacy on career adaptability at three levels of STARA awareness.

Note. Lines are drawn from the standardized equation career adaptability = .487 AI literacy - .039 STARA awareness + .310 AI literacy × STARA awareness. Low and high awareness are one standard deviation below and above the mean.

The direct component of career competencies shows a similar pattern, with smaller values. The conditional direct effect was .108 at low STARA awareness, t = 2.651, p = .008, 95% CI [.029, .186]. It was .366 at the mean and .624 at high STARA awareness, t = 8.600, p < .001, 95% CI [.431, .725]. Figure 4 plots only this direct component: career competencies (direct) = .366 AI literacy + .028 STARA awareness + .258 AI literacy × STARA awareness. The path through career adaptability is excluded from the figure, so the figure shows the

direct moderation only. The lines intersect slightly below the mean of AI literacy. At low AI literacy and high STARA awareness the direct component is -.596. At high AI literacy and high STARA awareness it is .652.

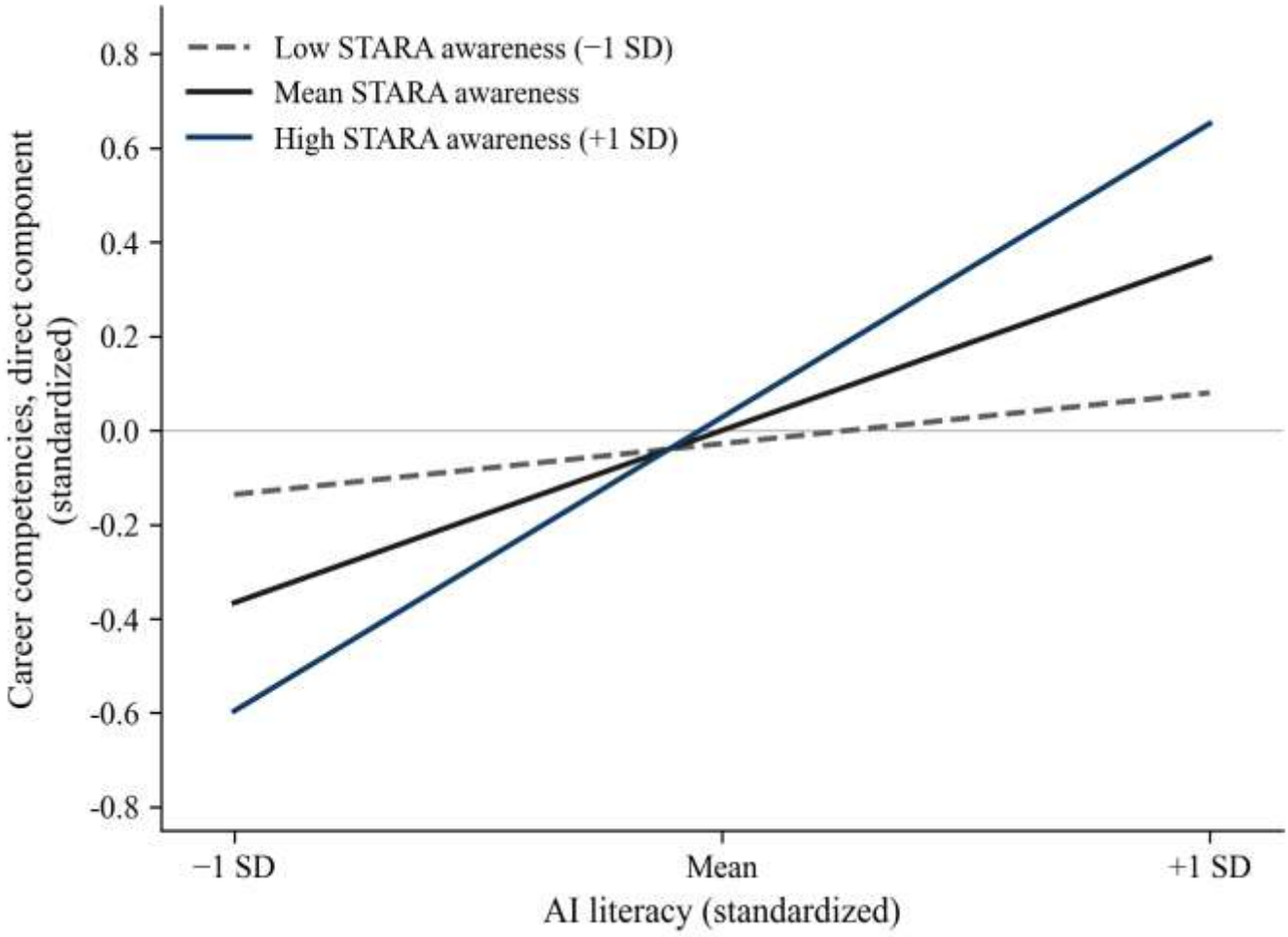

Figure 4. Simple slopes for the direct component of career competencies at three levels of STARA awareness.

Note. Lines are the direct component only and do not include the path through career adaptability. The equation is career competencies (direct) = .366 AI literacy + .028 STARA awareness + .258 AI literacy × STARA awareness.

The second-stage path does not vary with STARA awareness, so the conditional indirect effects follow the conditional first-stage slopes. At high STARA awareness the indirect effect was .149, t = 3.698, p < .001, 95% CI [.083, .247]. At the mean it was .091, t = 3.260, p = .001, 95% CI [.050, .164]. At low STARA awareness it was .033, t = 1.594, p = .111, 95% CI [.012, .086]. Figure 5 plots these three estimates. At low STARA awareness the percentile interval excludes zero, and the normal-theory p value is above .05. Under the pre-specified rule, the interval is the criterion, so the estimate is retained as positive. The coefficient is small, and the p value of .111 means that this particular indirect effect is statistically uncertain. The indirect effects at the mean and at high STARA awareness are significant. H6 concerns the index, which tests whether the indirect effect is larger at higher STARA awareness.

A separate check used equally weighted composite scores and ordinary least squares. Gender, age band, and hotel brand were entered as covariates. The estimates corresponding to H1 through H6 stayed within .004 of Table 4. Gender and age were nonsignificant. Students in local brand hotels scored .141 standard deviations higher on career adaptability than students in international brand hotels, p = .032. Prior experience and digital skills were not measured. Tables 4 and 5 remain the estimates for the hypotheses.

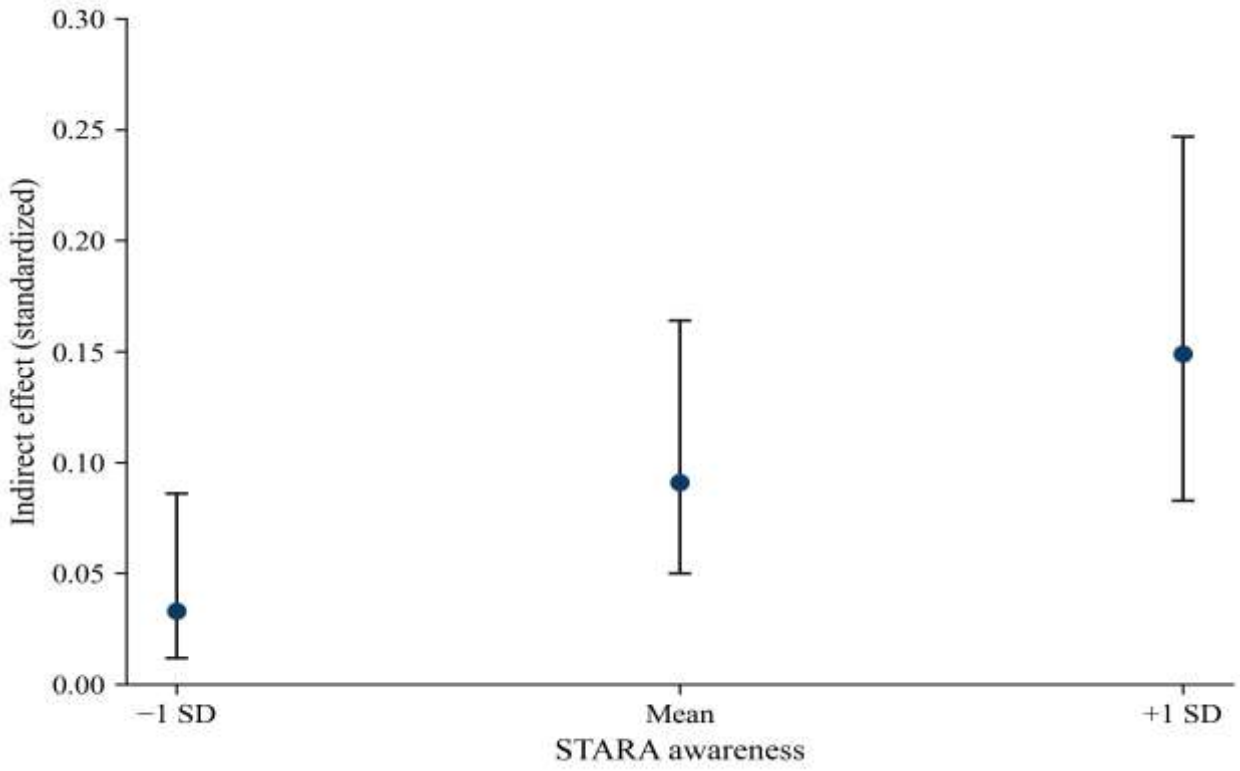

Figure 5. Conditional indirect effect of AI literacy on career competencies through career adaptability.

Note. Points are standardized indirect effects. Error bars are percentile 95% confidence intervals from 5,000 bootstrap samples. At -1 SD the interval excludes zero and the normal-theory p value is .111.

Table 5 Conditional Direct and Indirect Effects

Effect	**STARA awareness**	**β**	**t**	**p**	**95% CI**
AI literacy → adaptability	-1 SD	.178	3.154	.002	[.083, .297]
AI literacy → adaptability	Mean	.487	14.862	< .001	[.423, .550]
AI literacy → adaptability	+1 SD	.797	17.189	< .001	[.699, .863]
AI literacy → competencies (direct)	-1 SD	.108	2.651	.008	[.029, .186]
AI literacy → competencies (direct)	Mean	.366	8.565	< .001	[.268, .439]
AI literacy → competencies (direct)	+1 SD	.624	8.600	< .001	[.431, .725]
AI literacy → adaptability → competencies	-1 SD	.033	1.594	.111	[.012, .086]
AI literacy → adaptability → competencies	Mean	.091	3.260	.001	[.050, .164]
AI literacy → adaptability → competencies	+1 SD	.149	3.698	< .001	[.083, .247]

Note. Coefficients are standardized. Confidence intervals are percentile intervals. Effects at the mean of STARA awareness equal the corresponding estimates in Table 4. The direct effects do not include the path through career adaptability.

DISCUSSION

What the Estimates Show

Three results organize the discussion. First, AI literacy had a large positive association with career adaptability and a medium direct association with career competencies. The direct association was larger than the indirect

association. Second, the path from career adaptability to career competencies was positive, small, and imprecisely estimated. Third, the main effects of STARA awareness were nonsignificant, and both interactions were positive. In Figures 2 and 3, the lowest plotted values occur when STARA awareness is high and AI literacy is low. The highest plotted values occur when both are high. The indirect effect increased with STARA awareness. At low STARA awareness it was small, and its normal-theory p value was .111, although the percentile interval excluded zero.

The relationship between AI literacy and career competencies is partial mediation. Both the direct path and the indirect path were positive, and the direct path was larger. Career adaptability accounts for part of the association. An internship activity that addressed only concern and confidence would correspond to the smaller coefficient. An activity that taught AI literacy without any practice of looking ahead, choosing what to learn, or attempting an unfamiliar task would omit the path that is larger when STARA awareness is high.

Comparison With Hotel Employee Research

In full-service hotels in China, AI awareness had no significant direct relationship with career competencies, and it had a positive relationship with job burnout (Kong et al., 2021). The main effect of STARA awareness on career competencies in the present model was also nonsignificant, and the direct path from AI literacy was positive. Job burnout was not measured here. The employee study used organizational commitment as the intervening variable. This study uses career adaptability. The additional result is the interaction: STARA awareness had no significant association with the mean of career competencies, and it had a positive association with the slope of AI literacy.

Employee research on leaving reports a different outcome. Among full-time hotel employees in Guangzhou, awareness of artificial intelligence and robotics was positively associated with turnover intention (Li et al., 2019). Turnover intention refers to leaving a current job. The nonsignificant main effects in this study are coefficients for career adaptability and career competencies among students who were learning hotel work. The two sets of coefficients refer to different outcomes and different samples. The intern results add a condition. Across the sample, STARA awareness had no significant linear association with the two career variables. In Figures 2 and 3, high STARA awareness is associated with lower predicted values when AI literacy is low, and with higher predicted values when AI literacy is high. That pattern comes from the interaction and from main effects close to zero.

AI awareness has also been examined as having both favorable and unfavorable associations with employees' service innovative behavior (Liang et al., 2022). This study did not measure service innovative behavior or challenge and hindrance appraisals. In the present estimates, STARA awareness alone had nonsignificant main effects on career adaptability and career competencies. The positive slopes of AI literacy were steeper when STARA awareness was higher. The difference between high and low AI literacy, at high STARA awareness, is the pattern in Figures 2 and 3.

Implications for the Hotel Internship

The practical implication follows the relative size of the paths. The direct path from AI literacy to career competencies is larger than the indirect path, so instruction in AI literacy has a direct association with reflection, self-profiling, work exploration, and career control. A placement that practices only concern and confidence, and does not ask students to evaluate an artificial-intelligence output, addresses the smaller coefficient. The slopes are larger when STARA awareness is high, so the association is strongest among students who already judge that the job they are preparing to enter could be affected by replacement. The nonsignificant main effect describes the average association. Figure 3 shows a separate result: at high STARA awareness, low AI literacy corresponds to the lowest predicted career adaptability.

This practice can be included in the placement itself. Hospitality internship practice has been studied as a question of what the hours contain and how they are supervised (Zopiatis & Theocharous, 2013). The internship has also been described as a stage before students form career intentions (Farmaki, 2018). Where a hotel uses artificial intelligence, the placement can include that technology. One suitable task is to use a tool already in

operation at the property, such as a draft reply to a guest, a translation, a staffing suggestion, or a demand forecast. The intern can then identify an error in the output and state what the error would mean for a guest or a department. If the error concerns privacy or fairness, the task also covers the ethical component of AI literacy. The task can be completed within the supervision the hotel already provides.

Career adaptability can be practiced on the same task. Concern is the question of what the tool implies for the job the student is preparing to enter. Control is a decision about what to learn before the placement ends. Curiosity is a question put to the supervisor and a question about how the system produced the output. Confidence is a second attempt at a task the student could not complete in the first week. The association between career adaptability and career competencies is small. The indirect association of AI literacy with career competencies is larger when students report higher STARA awareness.

Limitations and Future Research

The mediation is statistical. AI literacy, career adaptability, and career competencies were measured at one time. Their order follows career construction theory. Measures at the start, middle, and end of the placement would be needed to test that order. The interactions are conditional associations in a cross-sectional survey. They do not show that an increase in AI literacy would change the outcomes by the amounts in Table 5. An intervention using the task described above could examine change. The moderator is the student's judgment, which is the variable specified in the model. An inventory of the systems used by the property was not collected. The sample does not include permanent employees, students in other tourism sectors, or students who had not started a placement. Internship duration, department, star rating, and hotel size were not recorded. Prior experience and digital skills were not measured and were not controlled. No interviews were collected. The sample is from one country.

The checks for common method variance were anonymity, the variance inflation factors reported above, and the principal component analysis of the 61 items. No marker variable was included. Career competencies were measured by self-report. Supervisor ratings of performance were not collected. At low STARA awareness, the percentile interval for the indirect effect excludes zero and the normal-theory p value is .111. The analysis uses the interval, as specified in advance, and the coefficient remains small and uncertain. A replication can show whether this indirect effect is a small association or a chance result.

Artificial intelligence and robotics are expected to continue to change tourism work (Samala et al., 2022). If later cohorts report higher AI literacy, the means and slopes may change. The model that can be tested again is the same set of relations: AI literacy as a knowledge resource, career adaptability as the psychosocial process, career competencies as the outcome, and STARA awareness as a moderator of the AI literacy paths. The coefficients in Tables 4 and 5 are estimates for this sample. The same relations can be tested in other countries, with measures at the start, middle, and end of the placement, with supervisor ratings, and with interviews about how interns meet artificial intelligence at the property.

CONCLUSION

In a sample of students interning in hotels in mainland China, AI literacy was positively related to career adaptability and to career competencies. The direct path was larger than the indirect path, so the mediation was partial. STARA awareness referred to the hospitality and tourism job the student was preparing to enter, and the instrument definition used automation. Its main effects on career adaptability and career competencies were nonsignificant. The associations of AI literacy with career adaptability and with career competencies were stronger at higher STARA awareness, and the index of moderated mediation was positive. The indirect effect was significant at the mean and at high STARA awareness. At low STARA awareness it was small and statistically uncertain. The simple slopes intersected near the mean of AI literacy. High STARA awareness with low AI literacy had the lowest predicted values, and high STARA awareness with high AI literacy had the highest predicted values.

For hotel internship practice, the results point to two activities used together. One is instruction and practice in using and evaluating artificial intelligence, including ethical judgment. The other is an explicit discussion of

possible replacement in the hospitality and tourism job the student is preparing to enter. The university is the more suitable place for the broader literacy curriculum. The hotel is the more suitable place for practice on an output the property already uses. Career adaptability remains part of the placement. Its association with career competencies is small, and the indirect association from AI literacy is larger when STARA awareness is higher. AI literacy can be embedded in the hospitality curriculum at the university. During the placement, questions to the supervisor can be arranged as structured mentoring. A workshop on concern, control, curiosity, and confidence can accompany the placement task. The workshop addresses the smaller coefficient, from career adaptability to career competencies.

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