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AI-Supported Learning and Job Readiness in Vocational Tourism Education: A Comparative Study of Two Albanian Schools

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ABSTRACT

Artificial intelligence is entering classrooms rapidly and is increasingly promoted as a way to personalize learning and prepare young people for work. In vocational education and training (VET), where the explicit goal is employability, this promise is especially significant. Tourism and hospitality are a major employer in Albania, and the quality of vocational graduates entering this sector has direct consequences for the local labour market. Understanding whether AI-supported learning genuinely helps vocational students feel ready for work is therefore both an educational and an economic question. Despite growing enthusiasm for AI in education, it remains unclear whether AI-supported learning actually improves vocational students' perceived job readiness, and how its effect compares with that of traditional work-based learning. Even less is known about whether these relationships hold across different institutions or vary by school context. Evidence from Albanian vocational tourism education, in particular, is largely absent from the literature. The study uses a quantitative, cross-sectional design. Survey data are collected from tourism and hospitality students in two Albanian vocational schools — "Hamdi Bushati" in Shkodër and "Kolin Gjoka" in Lezhë — and analyzed using multiple linear regression. The dependent variable is self-assessed job readiness (1–5 Likert scale). The main predictors are students' use of AI-supported learning tools and the quality of their internship / work-based learning (both 1–5), together with a school dummy and a school × AI interaction term; gender, age, grade and prior work experience are included as controls. Four hypotheses test whether AI-supported learning (H1) and internship quality (H2) positively predict job readiness, whether readiness differs between the two schools (H3), and whether the effect of AI-supported learning differs by school (H4). As an ongoing study, full results are pending data collection. The analysis is expected to show that greater use of AI-supported learning tools and higher-quality work-based learning are each positively associated with perceived job readiness (H1, H2). Comparing the two schools will indicate whether readiness levels differ by institution (H3) and whether the contribution of AI-supported learning is stronger in one setting than the other (H4). Such patterns would suggest that AI tools complement, rather than replace, high-quality practical placements, and that local school context shapes how much students benefit from them. By isolating the contribution of AI-supported learning alongside work-based learning in a real VET setting, the study aims to clarify how AI can strengthen employability in vocational tourism education.

KEYWORDS vocational education and training, artificial intelligence, AI-supported learning, job readiness, employability

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Introduction

Artificial intelligence is becoming part of everyday learning. Students now use generative AI, chatbots, and other digital tools to ask questions, clarify difficult ideas, practice tasks, and receive feedback outside the traditional classroom. These tools can make learning more flexible and responsive, but their growing presence also raises a practical question for educators: does using AI actually help students feel better prepared for work? This question is especially important in vocational education and training (VET), where learning is closely tied to occupational competence and the transition from school to employment. Vocational students need more than theoretical knowledge. They are also expected to develop practical skills, digital confidence, communication abilities, and an understanding of real workplace demands. In tourism and hospitality, this combination matters greatly because the sector is becoming more digital while still depending heavily on human interaction, service quality, teamwork, and hands-on experience. Albania offers a particularly relevant setting for exploring these issues. Tourism and hospitality are important sources of employment, and vocational schools have a direct role in preparing young people for jobs in the sector. Yet there is still little evidence on how AI-supported learning relates to job readiness among Albanian vocational students. At the same time, the literature on AI in education and the literature on internships and work-based learning have often developed separately. This leaves an important question unanswered: does AI-supported learning add something to students' perceived job readiness when the value of practical workplace experience is also taken into account?

To address this question, the study compares tourism and hospitality students from "Hamdi Bushati" Vocational High School in Shkodër and "Kolin Gjoka" Vocational High School in Lezhë. It asks whether AI-supported learning predicts perceived job readiness, whether the quality of internship and work-based learning also matters, whether students at the two schools differ in their average readiness, and whether the relationship between AI-supported learning and readiness changes across school contexts.

The study makes three main contributions. First, it brings AI-supported learning into a vocational tourism context and links it directly with students' perceptions of job readiness. Second, it considers AI-supported learning together with internship quality, recognizing that digital learning and practical experience may reinforce rather than replace one another. Third, by comparing two schools, it considers whether institutional context may shape the benefits students associate with AI-supported learning.

Literature Review

AI-Supported Learning in Vocational Education and Training

AI is opening new possibilities for teaching and learning by making it easier to provide personalized explanations, immediate feedback, problem-solving support, and opportunities for repeated practice. These features can be especially valuable in VET, where learning is expected to lead to usable occupational skills rather than remain only theoretical. Human Capital Theory offers a useful way to understand this connection. Becker (1993) views education, training, and work experience as investments that build knowledge and skills and, in turn, improve productivity and labour-market value. From this perspective, AI-supported learning can be seen as another learning resource within the broader process of human-capital development. It may strengthen cognitive and digital skills, while internships provide the applied and occupation-specific experience that develops in real workplaces. Research on AI in education points to clear opportunities, including more personalized learning, faster access to assistance, and support for learning achievement. In vocational education, therefore, the key issue is not simply whether students have access to AI, but how they use it: for example, to understand vocational content, work through job-related problems, or practise realistic professional situations. Recent VET research similarly stresses that infrastructure, teacher capability, curriculum integration, and responsible use all influence whether AI becomes educationally meaningful (Prasetya et al., 2025).

AI-Supported Learning in Tourism and Hospitality Education

Tourism and hospitality education is being reshaped by the wider digital transformation of the sector. AI-supported customer service, recommendation systems, automated booking, data analytics, and generative AI are increasingly part of tourism workplaces. As a result, schools and universities must prepare students for two realities at once: the enduring importance of service, communication, and operational skills, and the growing need to work confidently with digital technologies. Recent studies suggest that ChatGPT and related tools can support learning in tourism education, although the benefits depend partly on students' digital literacy and on how AI is incorporated into learning activities (Dalgıç et al., 2024). Research using the Technology Acceptance Model (TAM) also shows that students' responses to ChatGPT are influenced by whether they see the technology as useful and easy to use (Zhu et al., 2024). TAM (Davis, 1989) helps explain why students adopt a technology, but adoption alone does not tell us whether meaningful learning has taken place. A student may use AI often without developing the judgement needed to evaluate its answers or apply them appropriately in a professional setting. For this reason, recent tourism and hospitality research has increasingly emphasized AI literacy, critical evaluation, and thoughtful curriculum integration rather than simple exposure to new tools (Başer et al., 2025; Fathy et al., 2025). This distinction is central to the present study, which focuses on AI use that supports vocational understanding and job-related practice.

These changes also matter for employability. As technology alters tourism jobs, graduates are likely to need a mix of digital, interpersonal, operational, and problem-solving skills. Recent work on hospitality graduates and tourism employability therefore treats technological capability as part of a broader set of competencies needed to adapt to changing workplaces (El Hajal, 2025; Ibourk & El Alami, 2026). Evidence from Albania is beginning to reflect the same concerns. Peqini, Toma, and Borici (2025), studying Tourism and Computer Science students at the University of Shkodra "Luigj Gurakuqi," examined perceptions of AI alongside labour-market readiness and career orientation. Their work draws attention to the place of AI-related competencies in

students' preparation for an increasingly digital labour market. Although their sample consists of university rather than vocational students, the study provides useful local evidence that AI is already becoming part of the conversation about employability and career preparation in Albania.

The wider Western Balkan context adds another layer to this discussion. Borici, Peqini, and Bashi (2025) review recent work on the economic, ethical, and regulatory implications of AI across the region, with particular attention to Albania. Their review stresses that technological progress needs to be accompanied by investment in workforce education, digital skills, infrastructure, and appropriate institutional frameworks. For vocational education, this matters because students are preparing to enter workplaces that are themselves changing through digitalization and AI.

Changes in the nature of work also underline the importance of preparing people to understand AI rather than simply use it. Borici and Xhaferi (2025), writing about algorithmic management and digital labour in Southeastern Europe, discuss how AI can influence task allocation, performance evaluation, surveillance, and compensation. Their analysis highlights the need for digital literacy and AI-related training, while also drawing attention to transparency, worker autonomy, and inequality. Although their focus is not vocational tourism education, the study helps place the present research within a broader regional shift toward technology-mediated work.

Internship and Work-Based Learning as Drivers of Job Readiness

Even as AI becomes more prominent, practical workplace experience remains one of the defining features of vocational education. Internships and other forms of work-based learning give students the chance to apply what they have learned, deal with real problems, develop professional routines, and interact with supervisors, colleagues, and customers. In tourism and hospitality, where service and practical performance are central, these experiences are difficult to reproduce fully in a classroom.

Kolb's (1984) Experiential Learning Theory helps explain why these experiences matter. Learning develops through a cycle of concrete experience, reflection, conceptual understanding, and active experimentation. A good internship can bring these stages together: students perform real tasks, receive feedback, reflect on what happened, and adjust their behaviour. However, simply having an internship is not enough. What students are asked to do, the guidance they receive, and the relevance of the placement to their field can determine how much they actually learn.

This distinction is supported by previous research. Pianda et al. (2024), in a bibliometric and systematic review, identify internship experience as an important contributor to vocational students' employability. In hospitality education, Alharethi et al. (2025) likewise report a positive relationship between internship experience and work readiness. Together, these studies suggest that the quality of workplace learning deserves attention in its own right rather than being reduced to a simple yes-or-no measure of internship participation.

Evidence from Northern Albania points in the same direction. Borici, Selimi, and Shkambi (2026), studying 96 students, examined work experience, work-study compatibility, and institutional integration as predictors of competency development. Work experience emerged as the strongest positive predictor, followed by institutional integration, while work-study compatibility was not significant once the other factors were considered. The finding is relevant here because it suggests that direct engagement with work and structured institutional support may matter more for competency development than perceived alignment alone.

Taken together, the international and Albanian evidence suggests that work-based learning is most useful when it is a meaningful educational experience: students need relevant tasks, opportunities to practise, mentoring, and institutional support (Alharethi et al., 2025; Borici et al., 2026; Pianda et al., 2024).

Seen in this way, AI-supported learning and work-based learning do not need to compete for space in vocational education. They can serve different but complementary purposes. AI can help students explore ideas, obtain explanations, and practise digitally, while internships expose them to the pace, expectations, relationships, and practical demands of real work. The empirical question is whether each makes an independent contribution to how ready students feel for employment.

Perceived Job Readiness, Employability, and Self-Efficacy

In this study, job readiness refers to students' own perceptions of how prepared they are to enter employment; it is not an objective measure of workplace performance. The construct captures confidence in finding a job, beliefs about possessing labour-market-relevant skills, the perceived value of schooling for employment, expectations that employers will value those skills, and an overall sense of preparedness for work.

This emphasis on perceived readiness connects closely with self-efficacy. Bandura (1997) describes self-efficacy as people's beliefs about their ability to organize and carry out the actions needed to achieve particular outcomes. Such beliefs can grow through successful experience, observation, feedback, and social interaction. Social Cognitive Career Theory (SCCT) extends this idea to educational and career choices by linking learning experiences with career self-efficacy and outcome expectations (Lent et al., 1994). Lent et al. (1999) further show how this perspective can help explain the transition from school to work. Both AI-supported learning and internships may strengthen perceived readiness through these pathways. AI can give students repeated opportunities to solve problems and receive feedback, while internships offer direct experience of performing tasks in authentic workplaces. Still, confidence should not be confused with demonstrated employability. Students may feel ready without yet possessing all skill employers expect, and the reverse may also be true. This distinction is particularly important in research on generative AI, where ease of access to answers can increase confidence without necessarily producing equivalent gains in professional judgement.

Institutional Context and the AI-Readiness Relationship

AI does not enter every school in the same way. Access to technology, teacher confidence, curriculum design, industry links, pedagogical practice, and local norms around AI use can all shape students' experiences. TAM suggests that perceived usefulness and ease of use influence adoption (Davis, 1989), but the educational value of adoption is also likely to depend on the environment in which it occurs. This means that two schools could report similar average levels of job readiness while arriving there through different pathways. In one school, structured use of AI may be closely connected with students' confidence; in another, teacher support, workplace partnerships, or other learning experiences may matter more. This possibility motivates the study's comparison of average readiness as well as its test of the AI × School interaction.

Research Gap and Hypotheses

Taken together, the literature leaves a clear opening for the present study. Research on AI-supported learning is expanding quickly, tourism and hospitality education is paying greater attention to digital competencies, and a substantial body of work already demonstrates the value of internships and work-based learning. Yet these strands are not often examined together. Much of the recent AI literature also concentrates on higher education, leaving secondary-level vocational students comparatively underrepresented. Albanian and regional research has started to address pieces of this picture. Peqini et al. (2025) connect AI perceptions with labour-market readiness and career orientation among university students. Borici, Peqini, and Bashi (2025) place AI within the wider Western Balkan discussion of skills, infrastructure, ethics, and regulation. Borici and Xhaferi (2025) examine the changing nature of AI-mediated work, while Borici et al. (2026) show the importance of work experience and institutional integration for competency development. What remains largely unexplored is how AI-supported learning and work-based learning operate together in shaping perceived job readiness among secondary-level vocational tourism students. The present study brings these strands together. It treats AI-supported learning and internship quality as complementary learning experiences, examines their relationships with perceived job readiness in the same model, and asks whether the AI-readiness relationship differs across two vocational-school contexts.

H1. AI-supported learning use positively predicts vocational students' perceived job readiness.

H2. Internship/work-based learning quality positively predicts vocational students' perceived job readiness.

H3. Perceived job readiness differs between "Hamdi Bushati" and "Kolin Gjoka" students.

H4. The relationship between AI-supported learning and perceived job readiness differs by school.

Research methodology

Research Design, Sample, and Data Status

This study uses a quantitative, cross-sectional comparative design. The analytic dataset contains 316 observations, divided equally between "Hamdi Bushati" Vocational High School in Shkodër (n = 158) and "Kolin Gjoka" Vocational High School in Lezhë (n = 158). The model examines perceived job readiness as the dependent variable, AI-supported learning and internship/work-based learning quality as the principal predictors, school as a contextual variable, and an AI × School interaction. Gender, age, grade, and prior work/internship experience are included as controls. An important data-status qualification must accompany the current analysis. Participants were recruited from all the classes except the first year, because the first year students are not registered in vocational practices. The Hamdi Bushati subsample contains real responses for demographics and job-readiness items from the original school survey; the AI-supported learning and internship-quality items were not included in that original instrument and were therefore modelled synthetically for pilot-testing the analysis. The current Kolin Gjoka subsample is also simulated pilot data. Accordingly, the statistical results in this manuscript demonstrate the planned analytical structure and should not be interpreted as final empirical evidence from both schools. Further empirical validation would require administering the finalised questionnaire at both institutions and conducting the corresponding analyses using the primary data collected.

Respondent Profile

Table 1 summarizes the characteristics of the analytic sample. The sample is predominantly male (76.3%). Most respondents are aged 17–18 years (60.8%), and 80.4% report prior work or internship experience.

Table 1. Profile of respondents

Variable	n	%
School: Hamdi Bushati (Shkodër)	158	50.0
School: Kolin Gjoka (Lezhë)	158	50.0
Gender: Male	241	76.3
Gender: Female	75	23.7
Age: 15–16	47	14.9
Age: 17–18	192	60.8
Age: 19+	77	24.4
Grade: Class 11	134	42.4
Grade: Class 12	60	19.0
Grade: Class 13	122	38.6
Prior work/internship experience: Yes	254	80.4
Prior work/internship experience: No	62	19.6

Measures

AI-supported learning use was measured using three five-point Likert items (1 = strongly disagree; 5 = strongly agree): use of AI tools/apps to learn vocational content, AI tools helping students understand difficult concepts, and use of AI to practise job-related scenarios. Internship/work-based learning quality was measured with three five-point items addressing mentor guidance, relevance of tasks to the student's professional profile, and real opportunities to develop practical skills. Perceived job readiness was measured with five five-point items covering confidence in finding a job, possession of skills required by the market, perceived labour-market advantage from schooling, belief that employers would value the student's skills, and overall

preparedness for work. School was dummy-coded with Kolin Gjoka = 1. The interaction term AI × School was included to test whether the relationship between AI-supported learning and perceived job readiness differed by institution. Gender, age, grade, and prior work/internship experience were included as controls.

Analytical Strategy

The analysis proceeded in four stages. First, the sample profile was summarized descriptively. Second, exploratory factor analysis and Cronbach's alpha were used to assess the structure and internal consistency of the three multi-item constructs. Third, simple regressions tested H1 and H2, and an independent-samples comparison tested H3. Fourth, a hierarchical multiple regression including AI-supported learning, internship quality, school, the AI × School interaction, and the control variables tested H4. School-specific regressions were used to interpret the interaction.

Results

Factor Analysis and Reliability

Exploratory factor analysis using principal-axis extraction with varimax rotation indicated that the eleven Likert items were suitable for factor analysis. The Kaiser-Meyer-Olkin measure was .873 and Bartlett's test of sphericity was significant, χ^2 = 1815.2, $p < .001$. A three-factor structure corresponding to AI-supported learning, internship quality, and perceived job readiness emerged, with all reported primary loadings above .70. Internal consistency was good to excellent: α = .834 for AI-supported learning, α = .851 for internship quality, and α = .902 for perceived job readiness.

Table 2: Measurement-scale summary

Construct	Item	Loading	Cronbach's α
AI-supported learning	AI1. Use AI tools/apps to learn vocational content	.745	.834
	AI2. AI tools help understand difficult concepts	.774	
	AI3. Use AI to practise job-related scenarios	.725	
Internship/work-based learning quality	IQ1. Mentor guided me well	.782	.851
	IQ2. Tasks relevant to my profile	.771	
	IQ3. Real opportunities to develop skills	.797	
Perceived job readiness	WR1. Confident I can find a job	.799	.902
	WR2. Have the skills the market requires	.800	
	WR3. School gives me an advantage	.720	
	WR4. Employers would value my skills	.753	
	WR5. I feel prepared for work	.779	

Hypothesis Tests

To test H1, perceived job readiness was regressed on AI-supported learning. The relationship was positive and statistically significant, $F(1, 314) = 73.611$, $p < .001$, $b = 0.359$, $r = .436$, $R^2 = .190$. Thus, greater AI-supported learning use was associated with higher perceived job readiness, supporting H1. To test H2, perceived job readiness was regressed on internship/work-based learning quality. The relationship was also positive and significant, $F(1, 314) = 41.243$, $p < .001$, $b = 0.277$, $r = .341$, $R^2 = .116$. H2 was therefore supported. For H3, mean perceived job readiness was compared between schools. Hamdi Bushati students reported M = 4.02 (SD = 0.86), while Kolin Gjoka students reported M = 4.10 (SD = 0.61). The difference was not statistically significant ($p = .390$). Accordingly, H3 was not supported. Because the current dataset is partly simulated, this school comparison remains provisional and must be re-estimated using complete primary data. To test H4, a hierarchical multiple regression was estimated with perceived job readiness as the outcome and AI-supported learning, internship quality, school, AI × School, gender, age, grade, and prior work experience as predictors. The full model was significant, $F(8, 307) = 30.81$, $p < .001$, $R^2 = .445$, adjusted $R^2 = .431$. AI-supported learning ($b = 0.645$, $p < .001$) and internship quality ($b = 0.331$, $p < .001$) remained positive predictors. The AI × School interaction was negative and significant ($b = -0.273$, $p = .002$), supporting H4. School-specific regressions clarified the interaction. The AI-readiness slope was stronger at Hamdi Bushati ($b = 0.745$, $R^2 = .341$, $p < .001$) than at Kolin Gjoka ($b = 0.356$, $R^2 = .270$, $p < .001$). None of the demographic or experience controls reached statistical significance.

Table 3: Hierarchical regression predicting perceived job readiness

Predictor	b	SE	t	p
Intercept	-0.218	0.507	-0.43	.668
AI-supported learning	0.645	0.068	9.45	< .001
Internship quality	0.331	0.041	8.05	< .001
School (Kolin Gjoka = 1)	1.755	0.305	5.75	< .001
AI × School	-0.273	0.085	-3.20	.002
Gender (male = 1)	0.083	0.076	1.09	.276
Age (ordinal)	-0.034	0.053	-0.64	.526
Grade (ordinal)	0.040	0.037	1.09	.279
Work experience (yes = 1)	-0.020	0.080	-0.25	.800

Discussion

The findings offer provisional support for three of the four hypotheses and, more importantly, suggest that digital and experiential learning may both matter for how vocational students see their transition into work. AI-supported learning was positively associated with perceived job readiness. This is consistent with research showing that AI tools can provide individualized explanations, feedback, and learning support (Labadze et al., 2023), as well as tourism-education evidence linking ChatGPT-supported learning with educational outcomes (Dalgıç et al., 2024). It also fits with TAM: students

are more likely to engage with technologies they consider useful and manageable (Davis, 1989; Zhu et al., 2024).

Internship quality also showed an independent positive relationship with readiness. This result is consistent with Experiential Learning Theory (Kolb, 1984) and with studies showing that authentic workplace experience, relevant tasks, and mentoring can strengthen employability and work readiness (Alharethi et al., 2025; Pianda et al., 2024). It also echoes evidence from Northern Albania, where work experience and institutional integration were important predictors of competency development (Borici et al., 2026). The fact that AI-supported learning and internship quality remain relevant in the same model supports a complementary view: technology may enrich learning, but it does not remove the need for meaningful contact with real workplaces. The absence of a significant difference in average readiness between the two schools is also informative. Students can arrive at similar levels of confidence through different educational experiences. The significant AI × School interaction points to this possibility: the association between AI-supported learning and readiness was stronger at Hamdi Bushati than at Kolin Gjoka. Rather than suggesting that one school is simply 'better,' the result raises questions about what may differ behind the averages—such as teacher guidance, access to technology, curriculum integration, or the way students are encouraged to use AI. Those explanations remain hypotheses rather than findings from the present data. The study does not directly measure teacher AI competence, digital infrastructure, school-industry partnerships, or institutional policies on AI. Future research should measure these features explicitly before attributing the interaction to any particular school characteristic.

Limitations and future research

The most important limitation concerns the status of the data. The AI-supported learning and internship-quality variables for the Hamdi Bushati subsample were synthetically modelled because they were absent from the original survey, and the current Kolin Gjoka subsample is simulated pilot data. The reported coefficients, factor structure, and hypothesis tests therefore represent a rehearsal of the planned analytical pipeline rather than final evidence from fully observed primary data. This limitation must be resolved before the study is presented as a completed empirical comparison. After full primary data collection, the same measurement and regression procedures should be repeated and the stability of the three-factor structure should be reassessed. If sample size permits, confirmatory factor analysis could provide a stronger test of construct validity. Additional limitations will remain even with complete primary data. The cross-sectional design cannot establish causality; self-reported measures are vulnerable to common-method bias and social-desirability effects; and perceived readiness is not equivalent to employment outcomes. Future research should follow graduates longitudinally, incorporate employer assessments or objective competency measures, distinguish among specific AI applications, and examine institutional moderators such as teacher AI competence, infrastructure, and curriculum integration.

Conclusion

This study brings together three issues that are becoming increasingly important in vocational tourism education: AI-supported learning, the quality of workplace experience, and students' confidence about entering employment. Within the current pilot analytic dataset, both AI-supported learning and internship quality are positively associated with perceived job readiness. Average readiness is similar across the two schools, but the strength of the AI-readiness relationship differs between them, suggesting that institutional context may matter. The practical message is not that AI should replace traditional vocational training. The more useful interpretation is that the two forms of learning can complement one another. AI can give students additional opportunities to ask questions, practise, and develop digital confidence; high-quality internships place them in real situations where they must apply knowledge, communicate, adapt, and learn from others. Preparing students for a changing tourism labour market is likely to require both. At the same time, the present conclusions must remain provisional. The finalized questionnaire needs to be administered in full at both schools, and the analyses should then be repeated using complete primary data. That step is essential before the reported relationships are used to draw firm institutional or policy conclusions.

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Declaration

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