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THE FUTURE OF WORK IN TRANSITION ECONOMIES: INTEGRATING AI, DIGITAL SKILLS, AND EMPLOYABILITY IN HIGHER EDUCATION

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Abstract

This study examines the incorporation of soft skills, digital competencies, and artificial intelligence (AI) tools in higher education to improve student employability in Bosnia and Herzegovina, with broader relevance for the South East Europe region, where similar transition economies face parallel challenges in aligning education with the demands of digitally transformed labor markets. The research utilizes a mixed-methods approach, integrating quantitative survey data from University of Sarajevo students with qualitative insights from industry professionals. Research indicates that the concurrent enhancement of soft skills (such as communication and critical thinking) and digital competencies, in conjunction with the utilization of AI tools, markedly enhances students' preparedness for the contemporary labor market. The study emphasizes the essential role of autonomy in converting AI tool utilization into academic achievement and provides practical recommendations for educators, policymakers, and employers to address the skills gap in the digital economy.

Key words: *employability, artificial intelligence, higher education*

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1. Introduction

The rapid pace of technological advancement, particularly in artificial intelligence (AI), has transformed the global business landscape. As organizations increasingly adopt AI-driven solutions, the demand for a workforce equipped with both technical and soft skills has grown exponentially (World Economic Forum 2020). However, there is a growing concern that higher education institutions are not adequately preparing students for this new reality, particularly in post-conflict and transition countries. This includes Bosnia and Herzegovina, a country where the mismatch between educational outcomes and labor market needs is a significant contributor to unemployment (Dogara et al. 2019). To uncover some of the related challenges, our main research question is: How does the integration of soft and digital skills, supported by GenAI tools, influence student employability and academic performance in higher education?

Consequently, this paper seeks to address the gap in the literature by exploring how the integration of soft and digital skills in higher education curricula, with a particular focus on the role of AI tools, might help in enhancing student employability. By combining qualitative and quantitative research methods, expert interviews, and student surveys, this study provides a comprehensive analysis of the current state of soft and digital skills among students and identify effective strategies for their development. Our findings suggests that GenAI content quality, perceived usefulness, and student autonomy are essential mediators of academic performance and loyalty to AI tools in contemporary higher education.

The paper is organized as follows. After introductory section, the next one provides literature review explaining soft skills, digital competencies, GenAI, and employability followed by research methodology. The results of SEM analysis and qualitative validation are then presented with a discussion as well as practical recommendations. Last section concludes with limitations and directions for future research.

2. Literature Review

Emerging technology, digitization, and workplace automation have revolutionized business, employment, and lifestyles. The labor market encounters substantial challenges due to the impact of technology breakthroughs on the economy, society, and quality of life in the digital era (Vasilescu et al. 2020). The rapid advancement of digital and robotic technologies is transforming and displacing human employment. Forecasts indicate that numerous corporate jobs would undergo significant transformations, necessitating contemporary capabilities (Goulart et al. 2021). Digital technologies supplant antiquated work ways, rendering straightforward activities more intricate and necessitating teamwork alongside both soft and digital competencies. Consequently, cultivating soft and digital skills is crucial for maximizing potential in the digital era and adjusting to alterations in work processes (Kelchevskaya and Shirinkina 2019).

In the contemporary technology environment, organizational skills encompass technical, methodological, social, and personal aspects, such as emotional intelligence and self-awareness. Soft and digital competencies must be cultivated alongside profession-specific technical skills. Intermittently employing both soft and digital talents facilitates network development and addresses intricate innovation challenges. Universities, as hubs of innovation, policy development, knowledge distribution, and resource generation, cultivate new professional capabilities that influence educational concepts and methodologies (Kurbanov et al. 2020). Emerging technology and innovations, sometimes absent from higher education curricula, provoke apprehensions over educational stagnation (Ilori and Ajagunna 2020). In Bosnia and Herzegovina, professionals in the real sector frequently indicate that curriculum fail to align with the requirements of employers and the labor market.

The deficiency of employable skills is a significant contributor to unemployment (Dogara et al. 2019). Consequently, higher education institutions must adapt to technology advancements to cultivate skills vital for future employability, as employment opportunities will be limited for those lacking them. In light of significant business uncertainty and escalating risks across multiple domains, including online security and environmental concerns linked to sustainable business practices, Generation Z, characterized by distinct values and traits, necessitates engagement in intricate processes of technological innovation, market development, and the modernization of decision-making within established industries. As activities grow increasingly intricate, it is essential to cultivate networks of future specialists capable of collaborating to address complicated issues. Global studies indicate that approximately 40% of worldwide employment is influenced by AI, especially cognitive-based positions in industrialized nations. Developed countries are more susceptible to AI yet are better equipped to reap its advantages (Cazzaniga et al. 2024). If individuals lack training in AI and digital transformation, the digital divide and income inequalities may exacerbate.

This study underscores the significance of

imparting soft and digital skills to university students for success in the evolving business landscape. These competencies are cultivated to enhance student employability and preparedness for the digital economy. Students will acquire communication, teamwork, critical thinking, and digital literacy skills through customized educational programs and seminars. This research recognizes AI's potential influence on labor market dynamics. The initiative suggests solutions to optimize AI's potential based on national development. Developed economies prioritize innovation, AI integration, and the oversight of regulatory frameworks to optimize the advantages of AI. Less affluent emerging countries, such as Bosnia and Herzegovina, must prioritize infrastructure and the cultivation of a digital workforce. Individuals and organizations must cultivate both soft and digital abilities concurrently to thrive in contemporary business. Communication, collaboration, and analytical reasoning are prioritized (Hurrell et al. 2013). Nonetheless, computer literacy and the utilization of digital tools are increasingly vital in the digital world (World Economic Forum 2020).

Social interest groups including educational institutions, students, alumni, and employers stress the necessity of matching soft skills for job performance (Crawford et al. 2011).

Soft skills are becoming more important in personal and professional settings. Understanding the link between AI and soft skills is vital as AI tools are integrated into more sectors. Personal and professional growth requires soft skill development. These competencies can improve efficiency, interpersonal relationships, and sustainable development, making the dynamic relationship between soft skills and AI bidirectional: AI tools automate routine tasks and provide analytical insights, while human soft skills provide an ethical framework, creativity, and emotional intelligence that AI lacks. Maximizing AI benefits while protecting and improving human-centered values requires understanding and cultivating this connection. The literature highlights the crucial soft abilities that interact with AI and they are presented in the Table 1 below.

Table 1. Soft skills

Soft Skill	Definition/Description	Key Findings and References
1. Commitment	The ability to start, manage, and finish an activity, involving keeping promises, emotional investment in work, error prevention, and goal setting.	– Escolà-Gascón and Gallifa (2022): Commitment involves analyzing mistakes and setting goals. – Faraj (2022): Dedication is crucial for AI success. – He et al. (2023): AI knowledge reduces job uncertainty and improves task execution. – Jurczuk and Florea (2022): Continuous learning is vital in AI-influenced business environments.
2. Originality	Creative thinking, inventiveness, and problem-solving for non-traditional approaches.	– El Tabal (2020): Originality enables unconventional solutions. – Baltà-Salvador et al. (2025): ChatGPT can enhance idea development and remove creative blocks. – Wingström et al. (2022) and Cascini (2022): Co-creativity (human-AI collaboration) improves idea generation. – Kim and Maher (2023): AI may reinforce established patterns rather than introduce originality. – Lee (2022): Over-reliance on AI may lead to mental laziness. – Baltà-Salvador et al. (2025): No significant difference in creativity between AI and human-generated ideas; AI should complement human creativity.
3. Integrity	Moral or ethical balance between thoughts, feelings, and actions.	– Zehr (1998): Integrity grows in importance in informational business environments. – Currie (2023): AI's potential to spread misinformation raises integrity concerns. – Jeyarani and Al-Busaidi (2023): AI does not negatively impact integrity if used responsibly.

4. Entrepreneurial Orientation	Traits like innovation, proactivity, risk-taking, and decision-making in uncertainty.	– Escolà-Gascón and Gallifa (2022): Entrepreneurs are self-confident and persuasive. – Hruby (2024): AI adoption is driven by entrepreneurial mindset. – Baldegger, Caon, and Sadiku (2020): Entrepreneurial firms use AI for HR and operations. – Somiá and Vecchiarini (2024): AI's impact on entrepreneurial inclination varies; some benefit in opportunity recognition, others worry about AI dependence.
5. Critical Thinking	Analyzing events from multiple perspectives to minimize losses and make informed judgments.	– QAInn et al. (2020) and Shanta and Wells (2022): Critical thinking is essential in fast-paced environments. – Darwin et al. (2024): AI aids in research and data analysis but lacks contextual nuance.
6. Thoroughness	Using rational explanations, evidence, and credible sources to justify ideas.	– Escolà-Gascón and Gallifa (2022): Involves validating information and avoiding flaws. – Ejjamija (2024): AI speeds up data extraction but lacks deep theoretical understanding. – Anis and French (2023): Human judgment remains essential for critical analysis.
7. Inefficiency	Linked to low self-esteem and difficulty learning new tasks; can be mitigated by resilience and stress management.	– Escolà-Gascón and Gallifa (2022): Resilience reduces inefficiency. – Hooda et al. (2022): AI helps via personalized feedback and early intervention but risks over-dependence.
8. Accuracy	Precision and attention to detail, crucial in fields like medicine and engineering.	– Escolà-Gascón and Gallifa (2022): Involves error prevention and critical analysis. – Russell and Norvig (2016): AI excels in pattern recognition. – Hung and Sun (2020): Human oversight ensures ethical AI use.
9. Uncertainty	Ability to function without clear guidelines; involves heuristics and intuition.	– Kahneman (2011): Humans use intuition in ambiguity. – Escolà-Gascón and Gallifa (2022): Critical thinking is key in uncertain decisions.
10. Engagement	Active participation and dedication to tasks, improving productivity and job satisfaction.	– Brynjolfsson and McAfee (2014): AI reduces cognitive load, increasing engagement. – Escolà-Gascón and Gallifa (2022): Involves responsibility and group participation.
11. Environmental Awareness	Understanding ecological and social aspects of the environment.	– Rolnick et al. (2022): AI aids in sustainability but requires human ethics. – Escolà-Gascón and Gallifa (2022): Promotes sustainability and waste reduction.
12. Teamwork	Collaboration requiring trust, communication, and shared accountability.	– Escolà-Gascón and Gallifa (2022): Adaptability is key in human-AI teamwork. – De Prada, Mareque, and Pino-Juste (2022): Higher academic years improve teamwork skills.
13. Autonomy	Independent learning and decision-making.	– Bostrom (2014): Human agency prevents over-reliance on AI. – Mulgan (2016): AI supports autonomy but critical thinking is essential. – Escolà-Gascón and Gallifa (2022): Self-motivation is crucial.
14. Honesty	Integrity and authenticity in relationships.	– Liu et al. (2012): AI sentiment analysis can enhance honest communication. – Escolà-Gascón and Gallifa (2022): Involves ethical behavior and genuine thought.

Intelligent agents that perceive and act are the hallmark of artificial intelligence (AI) (Russell and Norvig 2016). This era has arrived, and transformative AI applications for end-users like ChatGPT-3 attracted over a million users in five days (Buchholz 2023). Users' rapid adoption shows AI's transformative power (Kelly et al. 2023). AI applications, software packages, and information systems are used in medicine (Kaul et al. 2020), healthcare (Secinaro et al. 2021), and even business tasks like PowerPoint presentations (Tyagi et al. 2021). Increasing productivity in routine and complex tasks by simplifying, automating, and reducing time is possible with AI technology. In addition to these areas generative AI will impact education (Jo 2023). Generational AI helps students and teachers perform their tasks efficiently (Lim et al. 2023), and it is believed to be the next frontier that will transform education (Cooper 2023). Generative AI uses user input to generate written, visual, audio, or image data (Jo 2023). Education is increasingly using it for learning and development (Cooper 2023). Large language models (LLMs) underpin generative AI (Kasneci et al. 2023). LLMs are AI architectures trained on massive amounts of data, including images (Carlini et al. 2021). Their main goal is to mimic, understand, and generate human-like language (Wei et al. 2022). Generative AI accelerates teacher assessment (Qadir 2023), generates and simplifies student content (Lim et al. 2023), supports scientists' research, personalized tutors (Cooper 2023), and automates student tasks. Many companies and startups target educators, including teachers and students, with generative AI tools (Su and Yang 2023). These deployments let educators, especially students, choose generative AI tools for learning. AI is evaluated through following dimensions presented in Table 2 below.

Table 2. AI dimensions/factors

Factor	Definition/Description	Key Findings and References
1. Content Quality	Generative AI's ability to produce diverse, high-quality content (text, images, music, etc.) that meets user needs.	– Epstein and Hertzmann (2023): AI can generate high-quality music, videos, and images. – Ahmad et al. (2023): AI-written content impacts student experience. – Louie et al. (2020): Content should be useful, relevant, and appealing. – Kim et al. (2022): Quality depends on coherence, creativity, accuracy, and relevance. – Liu et al. (2023): Accurate AI content aids exam success. – Pavlik (2023): Relevant content reduces student effort. – Muller et al. (2022): Creative AI content supports skill development.
2. Distrust	Users perceive GenAI as unreliable, non-transparent, or harmful due to inaccuracies, misinformation, privacy risks, or lack of regulation.	– Shin (2021): Mistrust stems from response inaccuracy. – Zhou et al. (2023): Fear of misinformation. – Awad and Kröger (2020): Privacy/data security concerns. – McKnight et al. (2002): Distrust leads to cautious AI use. – Langer and Landers (2021): Distrust is higher in education, medicine, and finance.
3. Adoption	User integration of GenAI into education/careers, driven by perceived usefulness, ease of use, and trust.	– Davis (1989) and Venkatesh and Davis (2000): TAM model highlights usefulness and ease of use. – Dwivedi et al. (2023): Adoption increases if AI boosts productivity. – Selwyn (2022): Institutional integration shapes attitudes. – Dzindolet et al. (2002): Usefulness is key for adoption. – Vert (2023): AI's immediate utility drives adoption. – Weisz et al. (2021): Subjective/objective assessments determine usefulness. – Castelli and Manzoni (2022): Functionality, reliability, and adaptability increase usefulness. – Lodge et al. (2023): Students evaluate content relevance for learning.

4. Usefulness	Generative AI's perceived value in meeting user needs (e.g., skill development, exam prep).	– Lv (2023): Functionality impacts usefulness. – Dwivedi et al. (2023): Reliability and adaptability boost satisfaction. – Castelli and Manzoni (2022): AI aids skill development and exam prep.
5. Loyalty	User commitment to AI products, influenced by trust, product quality, and privacy.	– Gul (2014): Trust precedes loyalty. – McMullan and Gilmore (2003): Consistency builds loyalty. – Siau and Wang (2018): Positive experiences foster loyalty. – Carvalho and de Oliveira Mota (2010): Trust is key in education. – Kim and Frick (2011): Attractiveness encourages use. – Fogel and Kvedar (2018) and Manheim and Kaplan (2019): Privacy concerns affect loyalty. – Kirienko et al. (2021): Privacy protections are critical. – McClure (2018): AI should assist, not replace, humans.
6. Satisfaction	Psychological state from meeting needs via AI's shortand long-term benefits.	– Giese and Cote (2000): Widely studied in marketing/IS. – Geyskens et al. (1999): Driven by need fulfillment. – Khalifa and Liu (2004): Systems must meet needs for sustained use. – Ouyang et al. (2022) and Xia et al. (2023): AI meets learning needs. – Malakul and Park (2023): AI supports academic and career goals. – Yilmaz and Yilmaz (2023): Subjective assessment matters. – Bozkurt (2023): AI differs from traditional IS.

Recent interest in employability has grown due to unfavorable labor market conditions in many economies. An extensive body of literature on this topic can be divided into three slightly overlapping research areas, each of which is relevant and has improved employability understanding. The first area of research examines national workforce employability, including government policies and skills strategies, and industrial sector employability. This approach, which emerged from changes in work and employment at the end of the 20th century, has helped define employability as a concept with "internal" (e.g., individual skills, internal labor market) and "external" (demand for certain occupations, external labor market) dimensions (Hillage and Pollard 1998).

Employability in HRM and work and career psychology is the second research area (Baruch 2001; Forrier and Sels 2003). Employability is the ability to retain or find work, and work experience gives skills and flexibility. Employers often promote this type of employability over job security. This research includes individuals' perceptions of their ability to find or retain desired employment, employees' willingness to develop their skills within the organization (Van Dam 2004), self-confidence and work relationships (Schyns et al. 2007), re-engagement in work, and obesity's impact on employability. These studies have helped define employability as a multidimensional construct (Fugate et al. 2004; Thijssen et al. 2008) and develop models to assess professional workers' perceptions.

In the third area of research, academics are increasingly involved in employability, particularly by integrating skills into teaching curricula (Gedye et al. 2004; Rothwell 2008). The initial fragmented application of skills in educational modules has evolved into comprehensive learning and teaching strategies, including students' expectations of employability before graduation, skill integration into curricula, and graduate employment analysis. There are a few studies on postgraduate employability (Hay and Hodgkinson 2006; Morse 2006) and national contexts (Tomé 2007; Zhiwen 2008), but they are often country-specific and have limited generalizability. For business management students, employability is "the perceived ability to gain sustainable employment that matches the level of qualifications" (Rothwell et al. 2008). Research shows that undergraduates have modest expectations due to a realistic view of the labor market. The employability scale was studied to create a career counseling and professional guidance diagnostic tool. Employability is a popular concept, but empirical studies on what it means to people—their experiences, aspirations, and perception of their ability to compete in the labor market—are scarce. This study builds on previous research on professional worker employability (Rothwell and Arnold 2007) to examine individual employability.

3. Methodology

This study adopted a mixed-methods approach, combining an online quantitative survey with structural equation modeling (SEM) and a qualitative validation phase. Data were collected via LimeSurvey among students at the University of Sarajevo who had experience using GenAI tools (n=218; 32.4% response rate). Survey items were based on TAM, TPB, and trust-based models. SEM analysis was conducted using SmartPLS 4.0, including bootstrapping (5,000 resamples) and CFA. Expert interviews were conducted with professionals from education and industry to validate survey findings. This methodology was chosen for its robustness in handling latent variables composed of multiple measurement items and its capability to analyze complex mediating and serial mediation effects (Kline 2015; Hair et al. 2022).

4. Results and Discussion

Reliability and validity tests

Using Hair et al. (2010) guidelines, construct dimensionality was assessed before hypotheses testing. The measurement model's goodness-of-fit indices, shown in Table 1, indicate good data fit. The chi-square to degrees of freedom ratio (χ^2/df) is 2.294, which is within the acceptable range (< 3). The Root Mean Square Error of Approximation (RMSEA) is 0.077 and the Standardized Root Mean Square Residual (SRMR) is 0.062, both below 0.08. The Further Comparative Fit Index (CFI) is 0.909, above the 0.90 threshold, confirming model fit. Several reliability and internal consistency measures were taken. Cronbach's alpha (α) coefficients, both standardized and unstandardized, exceed the minimum threshold of 0.70 (Hair et al. 2010) with values ranging from 0.846 to 0.952 and 0.841 to 0.952, respectively. These findings show high internal consistency and reliability for all latent constructs. Cronbach's alpha, a standard measure of scale reliability, indicates that construct items measure the same concept. All constructs have Composite Reliability (CR) values between 0.833 and 0.952, exceeding the recommended 0.70. This shows that each construct accurately represents its indicators. The constructs' convergent validity is confirmed by Average Variance Extracted (AVE) values between 0.502 and 0.800, which exceed the 0.50 threshold (Hair et al. 2010). Discriminant validity was assessed using the Fornell-Larcker criterion (Fornell and Larcker 1981). This criterion requires each construct's square root of the AVE to be greater than its correlation with any other construct. In Panel B of Table 3, all constructs meet this condition, indicating that each construct is distinct and shares more variance with its own indicators than with other model constructs.

Table 3. CFA results of measurement model (DFL)

PANEL A: Model fit of measurement model

	ChiSqr	df	ChiSqr/df	RMSEA	SRMR	CFI
Goodness of fit stats	830.249	362.000	2.294	0.077	0.062	0.909

PANEL B: Results of reliability and validity tests of measurement model

Dimensions	CR	AVE	α (standardized)	α (unstandardized)	AP	USF	QLT	LOY	AUT	SAT
ACADEMIC PERFORMANCE (AP)	0.862	0.508	0.860	0.860	0.713					
USEFULENESS (USF)	0.874	0.587	0.876	0.874	0.216	0.766				
QUALITY (QLT)	0.833	0.502	0.846	0.841	0.200	0.821	0.709			
LOYALTY(LOY)	0.912	0.729	0.917	0.915	0.258	0.835	0.774	0.854		
AUTONOMY (AUT)	0.898	0.687	0.897	0.896	0.616	0.240	0.223	0.288	0.829	
SATISFACTION (SAT)	0.952	0.800	0.952	0.952	0.206	0.653	0.796	0.798	0.230	0.894

PANEL A: the observed norm (χ 2 /df should be less than 3), RMSEA (should be less than 0.08), SRMR (should be less than 0.08), and CFI (should be greater than 0.9) (Hair et al. 2010).

PANEL B: Fornell-Larcker criterion: Squared-Root of AVE in diagonal (cursive) and factors correlations below the diagonal.

Hypotheses testing

After establishing the reliability and validity of the measurement model, the proposed structural models were evaluated using the Structural Equation Modeling (SEM) approach with the Maximum Likelihood (ML) estimation method. The overall model fit was also assessed by examining key goodness-of-fit (GoF) indices. Results are presented in Table 4.

The model fit indices showed a good fit to the observed data (χ^2 = 865.981; df = 369; χ^2/df = 2.347; RMSEA = 0.079; SRMR = 0.070; CFI = 0.909). These findings confirm the structural paths' robustness and enable further interpretation of the hypothesized relationships. The structural model analysis shows several significant and theoretically grounded relationships that explain how students' perceptions of GenAI-generated content's accuracy, objectivity, relevance, and usefulness for task execution and learning affect satisfaction, loyalty, autonomy, and academic performance. Usefulness (USF) and Loyalty (LOY) have a significant relationship (H1: β = 0.611, t = 5.110, p < 0.001). GenAI analysis showed that student engagement, reliance, and continued use of digital learning tools will improve when students' opinions are assessed on learning improvement, faster task execution, or exam preparation.

The correlation between Quality (QLT) and Usefulness (USF) was significant (H2: β = 0.821, t = 16.574, p < 0.001). GenAI outputs were evaluated by students for accuracy, objectivity, clarity, and relevance. These dimensions directly affect the tool's academic usefulness. As previously found, content quality drives perceived usefulness and trust in digital tools, as students are more likely to value and rely on AI tools that consistently deliver reliable and meaningful results. Quality (QLT) did not significantly impact Loyalty (LOY) (H3: β = -0.122, p = 0.405), indicating that good GenAI outputs alone are not enough to build user loyalty. According to the literature, AI tool loyalty requires trust, which is built through consistent, reliable, and problem-free user experiences (Gul 2014; Siau and Wang 2018). Students' loyalty is also influenced by privacy, usability, and AI's perceived ability to meet their learning needs, not just technical accuracy (Carvalho and de Oliveira Mota 2010; Kirienko et al. 2021).

Quality (QLT) significantly impacts Satisfaction (SAT) (H4: β = 0.796, t = 19.172, p < 0.001), indicating that students who view GenAI outputs as accurate, clear, and relevant report higher tool satisfaction. The literature suggests that satisfaction arises when an information system meets short-term academic needs and long-term development goals (Ouyang et al. 2022; Malakul and Park 2023). Geyskens et al. (1999) and Khalifa and Liu (2004) also note that satisfaction is a subjective psychological state based on how well GenAI meets user needs, which include task completion, learning support, and skill-building.

The relationship between Loyalty (LOY) and Academic Performance (AP) is not significant (H5: β = 0.089, p = 0.200), indicating that affective commitment to GenAI alone is not enough to improve academic outcomes. Instead, students' ability to autonomously apply AI tools to their learning appears to determine such outcomes. This supports literature warning that loyalty without internalised self-regulatory

Table 4. Direct effects and fit indices

Test	Path	β	SE	t	p	Result
Direct effects						
H1	Usefulness (USF) → Loyalty (LOY)	0.611	0.119	5.110	0.000	Supported
H2	Quality (QLT) → Usefulness (USF)	0.821	0.050	16.574	0.000	Supported
H3	Quality (QLT) → Loyalty (LOY)	-0.122	0.147	0.832	0.405	Not significant
H4	Quality (QLT) → Satisfaction (SAT)	0.796	0.041	19.172	0.000	Supported
H5	Loyalty (LOY) → Academic performance (AP)	0.089	0.069	1.281	0.200	Not significant
H6	Loyalty (LOY) → Autonomy (AUT)	0.288	0.085	3.377	0.001	Supported
H7	Autonomy (AUT) → Academic performance (AP)	0.590	0.069	8.562	0.000	Supported
H8	Satisfaction (SAT) → Loyalty (LOY)	0.497	0.096	5.179	0.000	Supported

Standardized betas, standard errors and t-statistics reported.

R^2 (AP) = 0.386; R^2 (USF) = 0.673; R^2 (LOY) = 0.812; R^2 (AUT) = 0.083; R^2 (SAT) = 0.633

Model fit: df = 369, χ2 = 865.981, χ2/df = 2.347; RMSEA = 0.079; GFI: 0.779; SRMR = 0.070

[a] p < 0.01. [b] p < 0.05. [ns] Not significant.

competencies may lead to dependency rather than empowerment and improved student performance (Escolà-Gascón and Gallifa 2022; Faraj 2022). Loyalty (LOY) significantly impacts Autonomy (AUT) (H6: β = 0.288, t = 3.377, p = 0.001), indicating that students who use GenAI tools more are more capable of independent learning. This is important because it shows that trust in AI can improve but not replace human engagement (Bostrom 2014; Mulgan 2016). According to Escolà-Gascón and Gallifa (2022), autonomy is a key competence in AI-supported learning because it allows students to make informed choices and avoid passive technology use.

Moreover, Autonomy (AUT) significantly predicted Academic Performance (AP) (H7: β = 0.590, t = 8.562, p < 0.001), highlighting its crucial role in AI-enhanced education Students who reported higher GenAI independence also performed better, supporting the idea that students with better soft skills are better positioned to benefit from AI systems (Cazzaniga et al. 2024; Crawford et al. 2011) than those who only develop digital skills. The study found a significant relationship between Satisfaction and Loyalty (H8: β = 0.497, t = 5.179, p < 0.001), indicating that students who found GenAI enjoyable and useful were more likely to continue using it. According to research, academic satisfaction forms the emotional basis for trust, which is necessary for AI tool loyalty (Geyskens et al. 1999; Gul 2014).

We tested indirect effect statistical significance with bootstrapping with 5,000 resamples. Unstandardized coefficients and 95% bias-corrected confidence intervals were calculated using this method, improving indirect pathway evaluation accuracy and reliability. Multiple indirect and serial mediation effects were statistically significant. These findings explain how students' perceptions of GenAI tool content quality, satisfaction, and usefulness affect academic performance, with a focus on autonomy, a key soft skill. Results are in Table 5.

In H9 (QLT → SAT → LOY; β = 0.395, t = 4.714), students who view GenAI content as accurate, relevant, and clear are more satisfied, leading to increased loyalty to GenAI. This supports literature that states satisfaction is a psychological state resulting from the fulfillment of academic and developmental needs and that information systems like GenAI support both short-term goals (e.g., exam preparation) and long-term learning development. According to H10 (QLT → USF → LOY; β = 0.501, t = 4.521), the perception of GEN AI usefulness (defined as value, reliability, and adaptability of AI-generated output) positively affects loyalty. According to the literature, students value content that supports learning, saves time, and adapts to their goals, so perceived usefulness is a key factor in GenAI adoption and use. Again, H11 (LOY → AUT → AP; β = 0.170, t = 2.907) confirms that loyalty alone is insufficient to impact academic performance without promoting autonomy. The literature defines autonomy as self-motivation, independent learning, and decision-making (Escolà-Gascón and Gallifa, 2022). Again, AI can provide support through personalized recommendations, but autonomy is necessary to avoid over-reliance on AI and preserve critical thinking (Bostrom 2014; Mulgan 2016). H12 (QLT → SAT → LOY → AUT → AP; β = 0.067, t = 2.586) confirms a full serial mediation pathway, linking perceived quality to academic performance via satisfaction, loyalty, and autonomy. In AI-supported environments that require self-regulation, autonomy is needed to turn engagement into meaningful learning outcomes (Escolà-Gascón and Gallifa 2022). Conversely, H13 (QLT → USF → LOY → AP; β = 0.044, t = 1.233) was not statistically significant. This confirms previous findings that usefulness and loyalty do not affect academic performance without autonomy. AI tools may improve procedural

Table 5. Indirect effects and serial mediations (CB-SEM bootstrapping results)

Test	Path	β	SE	t	LLCI	ULCI	Results
Indirect effects							
H9	QLT → SAT → LOY	0.395	0.084	4.714	0.249	0.573	Supported
H10	QLT → USF → LOY	0.501	0.111	4.521	0.308	0.741	Supported
H11	LOY → AUT → AP	0.170	0.058	2.907	0.061	0.286	Supported
H12	QLT → SAT → LOY→AUT→ AP	0.067	0.026	2.586	0.023	0.123	Supported
H13	QLT→USF→ LOY→AP	0.044	0.036	1.233	-0.022	0.124	Not supported
H14	QLT→USF→ LOY→AUT → AP	0.085	0.040	2.142	0.025	0.178	Supported

Standardized betas, standard errors and t-statistics reported. LLCI represents 5.0% confidence interval, ULCI represents 95% confidence interval; 5,000 bootstrapped samples.

[a] p < 0.01. [b] p < 0.05. [ns] Not significant.

learning, but they cannot improve understanding without internalized soft skills and independent learning strategies that allow tailoring outputs to specific needs (Lee, 2022). Finally, H14 (QLT → USF → LOY → AUT → AP; $\beta = 0.085$, $t = 2.142$) confirms that reintroducing autonomy in mediation restores significance. The literature emphasizes that autonomy as a soft skill is essential to transforming digital engagement into academic achievement and that self-directed AI tool use is more effective than passively relying on outputs. This emphasises human-led approach again (Escolà-Gascón and Gallifa 2022; Bostrom 2014).

Findings show that GenAI content's perceived quality and usefulness promote satisfaction and loyalty, but only autonomy can translate these perceptions into academic success. This emphasises the need for educational programmes that actively promote autonomy and other soft skills needed for digital learning environments as well as AI tools.

The use of AI in education raises ethical and practical issues. Responsible and transparent use of AI tools with clear ethical guidelines is essential. In order to prepare students for the digital economy, educational programs must be constantly updated to meet labor market demands. Although insightful, the findings have several limitations. First, the study only included University of Sarajevo students, which may limit its applicability to other regions or educational institutions. A more diverse sample of Bosnia and Herzegovina and international organizations would improve knowledge. Second, self-reported statistics may be biased since students may overestimate their AI skills and utilization. To improve dependability, future studies may use longitudinal or direct observational data.

5. Conclusion

This study examined how the integration of soft skills, digital competencies, and generative AI (GenAI) tools can enhance student employability in higher education, with a particular focus on the context of Bosnia and Herzegovina. Using a mixed-methods approach that combined quantitative surveys and qualitative interviews with experts, the research uncovered several important insights about the factors influencing student engagement with AI tools and their overall academic development. Notably, the study found that content quality, perceived usefulness, student autonomy, and satisfaction all play significant roles in shaping academic performance and fostering loyalty toward AI applications.

One of the key findings was the importance of high-quality AI-generated content. When the content produced by GenAI tools is accurate, relevant, and creatively structured, it significantly boosts student satisfaction and enhances perceptions of usefulness, thereby contributing to improved learning outcomes. However, the benefits of these tools are not automatic. The study emphasized that students' ability to use AI autonomously is crucial. While AI increases efficiency and streamlines academic tasks, true educational value emerges only when students engage with these tools through self-regulated learning. Without this autonomy, there is a risk that AI loyalty could result in dependency rather than genuine academic growth.

Trust remains another critical factor. Despite increasing exposure to GenAI, many students still harbor concerns about the accuracy of AI outputs, data privacy, and ethical implications, especially in high-stakes educational environments. Nevertheless, the study found that these concerns can be partially mitigated when students perceive the tools as useful and feel satisfied with their outputs, which in turn encourages broader adoption.

Importantly, the study also addressed the intersection between education and the labor market. It found that developing both soft skills—such as critical thinking, collaboration, and adaptability—and digital competencies is essential for preparing students for modern workplace demands. These capabilities not only complement AI use but also close the gap between academic training and employer expectations. Ultimately, the research underscores that AI should not be viewed as a standalone solution in education. Rather, it must be integrated into a balanced and human-centered learning environment. Educational institutions have a responsibility to design curricula that foster both AI literacy and the essential soft skills needed to navigate an increasingly digital economy.

Beyond the national context, these findings carry important implications for the wider South East Europe region, where many countries share comparable socio-economic structures, educational system legacies, and labor market dynamics shaped by post-transition reforms. The demonstrated link between AI tool integration, soft skill development, and employability suggests a scalable framework for regional adoption, particularly in addressing skill mismatches and preparing graduates for cross-border mobility within an increasingly digitalized European economy. By fostering collaborative higher education–industry partnerships, harmonizing AI literacy and soft skills training across curricula, and investing in digital infrastructure, policymakers and universities across South East Europe can collectively strengthen their human capital competitiveness. This regional alignment would not only reduce the digital divide but also

position the region as a proactive participant in the evolving global knowledge economy.

To build on these findings, several practical recommendations are proposed for key stakeholders. For educators, there is a clear need to integrate AI tools meaningfully within pedagogical frameworks. This can involve designing assignments that use GenAI for initial brainstorming or drafting phases, followed by student-led critical analysis and revision. Educators should also offer AI literacy workshops that address ethical use, bias awareness, and source validation. Promoting student autonomy is equally important, and instructors should teach strategies for self-regulated learning, such as goal-setting and reflective practices. Personalized AI feedback can be beneficial, but students must be encouraged to actively shape their own educational journeys. Policymakers have a role to play in reforming curricula across disciplines to include modules focused on both soft skills and digital competencies. These efforts should align closely with the needs of the labor market.

Stronger partnerships between universities and industries can help co-develop learning pathways that reflect real-world applications of AI. Addressing the digital divide is also essential. Employers should improve higher education collaboration. Internships or real-world initiatives where students apply AI to business problems can bridge theory and practice. Along with technical talents, hiring should prioritize soft skills like adaptability and ethics. This study should be expanded using a number of methods, including comparative cross-national investigations of AI's impact on education. Investigating AI in vocational education and lifelong learning could enrich the discipline. Additionally, ethical frameworks are needed, especially for academic plagiarism, algorithmic transparency, and data protection. Students learn that while AI can improve efficiency and assistance, long-term competitiveness depends on critical thinking, creativity, and multidisciplinary approaches. Engaging in technical and humanistic subjects will help students adjust to a changing workforce worldwide.

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