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EIT Higher Education Initiative

Conference Proceedings – Bridging the Knowledge Triangle for Advanced Entrepreneurship in the Era of Global Digitalization

Compiled by: V. Riashchenko (Editor)
Riga Nordic University (RNU), Latvia
14 May 2026

KIC HEI-TRAIN is supported by the European Institute of Innovation and Technology (EIT), a body of the European Union.

DOCUMENT INFORMATION

Conference Proceedings – Bridging the Knowledge Triangle for Advanced Entrepreneurship in the Era of Global Digitalization	
Project Agreement number	250749
Project title	HEI-TRAIN: HEI Transformation for Entrepreneurship and AI-Driven Innovation
Project acronym	HEI-TRAIN
Project start date	01/04/2025
Project duration	25 months
Work Package	Communication and Dissemination
Deliverable lead	Riga Nordic University (RNU)
Author(s)	Conference authors (see individual papers); compiled by V. Riashchenko
Type of deliverable* (R, DEM, DEC, other)	R
Dissemination level (PU, SEN, CI)**	PU
Date of first submission	01/08/2026
Revision n°	1
Revision date	01/08/2026

Conference "Bridging the Knowledge Triangle for Advanced Entrepreneurship in Era of Global Digitalization""

14 MAY

Location: Conference Room III

13:00 - 13:10	**Conference Opening,** **Chair: J.Mironova**
13:10 - 13:25	**Myagmarsuren Orosoo,** Associate Professor, Mongolian National University of Education, Mongolia *Strengthening the Resilience of the Higher Education System in the AI Era: A Comparative Analysis of Europe and Mongolia [ZOOM]*
13:25 - 13:40	**Zanda Vīksna,** Project Manager at Baltic Beach Hotel & SPA, Jurmala, Latvia *AI solutions in the hospitality business*
13:40 - 13:55	**Jevgenija Dehtjare,** dr.oec., as.prof., Head of the Development of the Scientific Institution and **Anna Strazda,** Ph.D. student, Head of the Science Administration Department, EKA University of Applied Sciences, Latvia *Ukrainian Universities as Third Places Bridging the Knowledge Triangle: Informal Learning and Stakeholder Co-Creation for Entrepreneurship*
13:55 - 14:10	**Anna Angena,** Ph.D. Candidate, University of Latvia, Latvia, Certified Supervisor, *Strengthening Mental Resilience and Balance for Healthcare Professionals in High-Pressure, Digitally Evolving Environments*
14:10 - 14:25	**Darya Legeza,** Doc.Ec.Sc., professor **Yana Sokil,** Cand.Ec.Sc, Associate Professor, Dmytro Motornyi Tavria State Agrotechnological University, Ukraine *Assessing AI Readiness for Marketing in Small Food Enterprises Based on Digital Skills [ZOOM]*
14:25 - 14:40	**Rudolfs Rauza,** program director of Tourism Service Organisation, Riga Nordic University, Riga, Latvia *Preserving Culinary Identity in the Era of Global Digitalization*
14:40 - 14:55	**Yevhenii Vladimirov,** PHD Student at Tavria State Agrotechnological University, Ukraine, Executive Director at International Consulting Engineers Guild *Structural Transformation of Ukraine's Flour and Cereals Market in a Crisis Environment toward Digital-Enabled Resilience*
14:55 - 15:10	**Tetiana Polupanova, Mykhailo Sulymovskyi,** Lithuanian University of Health Sciences, Lithuania; Pryazovskyi State Technical University, Ukraine Explainable Artificial Intelligence in MRI-based Diagnosis of Neurological Disorders

Wi-Fi

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INTRODUCTION

The Conference "Bridging the Knowledge Triangle for Advanced Entrepreneurship in the Era of Global Digitalization" was held on 14 May 2026 at Baltic Beach Hotel & SPA, Jurmala, Latvia, as part of RNU Science Week 2026 and the HEI-TRAIN project (EIT Higher Education Initiative, KAVA 250749).

The conference brought together researchers, educators and practitioners from Latvia, Ukraine, Mongolia and Lithuania to discuss the role of artificial intelligence in higher education, entrepreneurship and innovation. Eight presentations were delivered in a mixed in-person and online (Zoom) format. This volume compiles the full papers submitted for the conference proceedings.

FOREWORD

This volume brings together full papers presented at the international conference "Bridging the Knowledge Triangle for Advanced Entrepreneurship in the Era of Global Digitalization", held on 14 May 2026 in Jurmala, Latvia. The papers address the use of artificial intelligence and digital transformation across higher education, hospitality, healthcare diagnostics and small-business marketing, reflecting the interdisciplinary and international character of the conference.

ACKNOWLEDGEMENTS

The editors gratefully thank all authors and reviewers for their contributions, and Baltic Beach Hotel & SPA, Jurmala, for hosting the conference and providing space for the discussions that shaped these papers. The editors also thank the EIT Higher Education Initiative for its continued support of the HEI-TRAIN project (KAVA 250749).

UKRAINIAN UNIVERSITIES AS THIRD PLACES BRIDGING THE KNOWLEDGE TRIANGLE: INFORMAL LEARNING AND STAKEHOLDER CO-CREATION FOR ADVANCED ENTREPRENEURSHIP

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Abstract. This paper examines Ukrainian universities as emerging third places that can bridge the knowledge triangle of education, innovation, and societal engagement in the era of global digitalisation. The study focuses on two organisational dimensions that are particularly relevant for advanced entrepreneurship: informal learning opportunities and external stakeholder co-creation. Based on an online survey of 181 academic staff members in Ukraine, the paper analyses whether these dimensions are perceived as visible institutional practices and how they relate to the broader third-place role of universities. The results show that informal learning opportunities and stakeholder engagement are rated significantly above the neutral midpoint. Regression models indicate very strong internal coherence between both dimensions and the overall third-place construct. The findings suggest that universities can support entrepreneurship-oriented recovery and digital transformation not only through formal curricula, but also through communities, hybrid interaction spaces, networking events, competitions, and systematic collaboration with business, public institutions, NGOs, and local communities.

Keywords: advanced entrepreneurship, digitalisation, higher education, knowledge triangle, stakeholder co-creation, third place

INTRODUCTION

The conference theme, "Bridging the Knowledge Triangle for Advanced Entrepreneurship in Era of Global Digitalization", highlights the need to connect education, innovation, and engagement with society. For higher education institutions, this connection cannot be limited to formal study programmes or isolated projects. In a digital and turbulent environment, universities are expected to become active spaces where students, academic staff, entrepreneurs, public institutions, and community actors can meet, exchange knowledge, and co-create solutions.

This role is especially important for Ukrainian higher education. Universities operate under wartime conditions and at the same time contribute to post-war recovery. Displacement, hybrid learning, damaged infrastructure, and the risk of talent loss create a need for flexible institutional models that support belonging, resilience, and practical innovation. In this context, the concept of the university as a "third place" is useful because it draws attention to informal interaction, accessibility, community ties, and everyday cooperation beyond the classroom.

The concept of a third place was introduced by Oldenburg, who described public places outside home and work where people come for regular informal interaction and where social ties and belonging are created [1]. Although the original concept referred mainly to civic venues, it can be adapted to higher education. Universities increasingly need to provide physical and hybrid spaces for informal learning, peer support, entrepreneurial experimentation, and stakeholder collaboration. In this way, third-place thinking can complement the knowledge triangle logic, which emphasises the interaction between universities, business, and government in innovation systems [2].

Previous studies have applied the third-place idea to campus spaces, libraries, student centres, and collaborative learning environments [3-5]. However, less attention has been paid to academic staff perceptions of organisational practices that make the third-place function visible: support for clubs, networking events, recognition of extracurricular entrepreneurship, curriculum co-design with external partners, and mechanisms for cooperation with business and community actors. The aim of this paper is therefore to examine Ukrainian universities as emerging third places by analysing academic staff perceptions of informal learning opportunities and external stakeholder engagement as foundations of entrepreneurship-oriented knowledge triangle bridging.

1. METHODS AND PROCEDURES

The empirical study used a quantitative cross-sectional survey design. Data were collected anonymously through Google Forms in February 2025. The sample consisted of 181 academic staff members working in Ukraine, mostly in public higher education institutions located in different regions and in Kyiv. The study used an adapted Faculty Members Survey with a five-point Likert scale from 1 to 5.

Three composite indicators were constructed. Informal Learning Opportunities (ILO) included four items related to access to student entrepreneurship clubs, awards and societies, networking events between students and entrepreneurs, business idea competitions, and formal recognition of entrepreneurial extracurricular activities. External Stakeholder Engagement (ESE) included four items related to involvement of stakeholders in course design and delivery, mechanisms for staff cooperation with external stakeholders, integration of external expertise into learning, and support for partnerships with communities, local and regional authorities, chambers of commerce, industry, and alumni. The Third Place composite (TP) was calculated as the mean of all eight items.

The analysis was conducted in Jamovi. One-sample t-tests compared ILO and ESE mean values with the neutral midpoint of 3. Linear regression models were then used to test whether ILO and ESE were associated with Third Place perception. Reliability was high for all scales: Cronbach's alpha was 0.927 for ILO, 0.948 for ESE, and 0.955 for TP.

2. RESULTS

The analysis indicates that academic staff generally perceive both dimensions as present in Ukrainian universities. Informal learning opportunities are viewed as visible institutional practices rather than occasional activities. External stakeholder engagement is also perceived as an established element of university work, showing that collaboration with business, public-sector, NGO, community, and alumni partners is becoming part of the organisational environment that supports entrepreneurship and innovation.

From the perspective of the conference theme, these findings show that the knowledge triangle is not only a strategic policy idea. It is reflected in everyday university practices. Clubs, networking events, business idea competitions, and recognition of extracurricular initiatives create informal pathways through which students can develop entrepreneurial competences. At the same time, curriculum co-design, collaborative teaching, and partnerships with external stakeholders connect academic knowledge with practical innovation needs in the era of global digitalisation.

The regression analysis confirms that both informal learning and stakeholder engagement are closely connected with the broader perception of the university as a third place. Where academic staff perceive stronger support for student communities, networking, and entrepreneurial initiatives, they also tend to see the university as a more inclusive and community-connected environment. Similarly, where external stakeholders are more systematically involved in learning activities and institutional partnerships, the university is perceived as better able to bridge education, innovation, and societal needs. These findings should be interpreted as evidence of coherence within the proposed conceptual model, rather than as proof of direct causality.

DISCUSSION/CONCLUSION

• The study shows that Ukrainian universities can be understood as emerging third places that bridge education, innovation, and societal engagement.

• Informal learning opportunities support advanced entrepreneurship by creating spaces for experimentation, networking, peer interaction, competitions, and recognition of student initiatives.

• External stakeholder engagement strengthens the knowledge triangle by connecting university learning with business, public-sector, NGO, community, and alumni expertise.

• In the era of global digitalisation, the third-place role should be interpreted not only as a physical campus function, but also as a hybrid and organisational function supported by digital communication, flexible collaboration, and cross-boundary interaction.

• For university leaders, the findings suggest the need to invest in entrepreneurship clubs, informal learning communities, networking events, hackathons, and mechanisms for recognising extracurricular entrepreneurial activity.

• For policymakers and institutional managers, stakeholder co-creation should become systematic through curriculum co-design, collaborative teaching, partnership mechanisms, and regular review.

• In the Ukrainian context, these practices may contribute to resilience, talent retention, innovation capacity, and recovery by helping universities act as practical bridges within the knowledge triangle.

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Accessing AI Readiness for Marketing in small Food Enterprises based on Digital Skills

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Abstract. This study provides empirical evidence on AI readiness for marketing among small food enterprises in Ukraine, with a focus on the digital skills of women agribusiness entrepreneurs. Grounded in contemporary marketing theory for SMEs, the research examines how digital skills transfer strategic intent and AI implementation outcomes into resource-constrained agri-food solutions. Survey data collected from 369 Ukrainian agrobusiness women entrepreneurs were analyzed using cross-tabulation and cluster analysis, revealing four typologically distinct and statistically significant groups that differ in their AI readiness profiles: Systemic AI Transformation Leaders, Value-Driven Operationally Restrained entrepreneurs, Adaptive Realists with Limited Potential, and Resilient AI Laggards. The findings show that food business orientation and AI readiness are mutually reinforcing constructs, that education acts as a key mediator between food business motivation and AI readiness, and that decision-making based on AI recommendations depends directly on the level of food business confidence. The results identify transferable lessons for entrepreneurship enhancement reform in the AI age, with specific relevance for women-led micro-enterprises in European countries.

Keywords: AI readiness; digital skills; small food enterprises; women entrepreneurs; cluster analysis; laggards.

Introduction

The adoption of AI remains highly unstable across companies of different sizes and regions, creating a pronounced AI gap that is particularly relevant for small food enterprises. Across OECD member economies, AI was used in 2024 by 40% of firms with 250 or more employees, 20.4% of firms with 50-249 employees, and only 11.9% of firms with 10-49 employees (OECD discussion paper for the G7, 2025). It illustrates a clear negative relationship between firm size and AI adoption. This gap is also evident at the population level: 24.7% of the working-age population in the Global North uses AI, compared with only 14.1% in the Global South (Microsoft AI diffusion report, 2025). At the same time, global AI-driven marketing revenues are projected to reach $47 billion in 2025, yet 42% of firms report lacking sufficient generative AI expertise (The Institute of Digital Marketing, New Zealand, 2025). These figures underline the urgency of understanding AI readiness in small, resource-constrained food enterprises and of identifying the digital skills that enable such businesses to close this gap, especially in businesses led by women.

GENERAL OBJECTIVES AND METHODOLOGY

1. Aim and objectives

The **research aims** to provide empirical evidence on AI readiness for marketing among small food enterprises in Ukraine, focusing on the digital skills of women agribusiness entrepreneurs.

Objectives of the research:

- to situate the AI readiness construct within contemporary marketing theory for SMEs, recognizing how digital skills mediate the relationship between strategic intent and AI implementation outcomes in resource-constrained agri-food contexts.
- to appraise the survey findings from Ukrainian agrobusiness women entrepreneurs, identifying critical readiness gaps and relative strengths in AI capacity-building.
- to identify transferable lessons for entrepreneurship enhancement reform in the AI age, with specific relevance for women-led micro-enterprises in European countries.

AI adoption in SMEs increasingly depends not on technology availability itself, but on managerial competencies, workforce digital capabilities, organizational acceptance of AI, ethical readiness, and the ability of resource-constrained businesses to transform marketing practices through AI-driven tools and knowledge. Cimino et al. (2025) show that organizational acceptance of AI, leadership mindset, and employee readiness are as important as technological deployment itself. Spais and Jain (2025) argue that despite AI's capacity to improve personalized marketing and customer engagement, limited managerial knowledge and underutilization of AI tools significantly constrain marketing innovation in SMEs. Kuran et al. (2025) find that women entrepreneurs can effectively leverage AI-driven social media marketing through adaptability, creativity, and relational competencies, highlighting the importance of gender-sensitive analysis in AI readiness research. Ayinaddis (2025) concludes that digital skills and operational knowledge are the primary determinants differentiating AI adoption capacity between SMEs and large firms, directly supporting a digital skill-based readiness framework. Imiren and Nicolopoulou (2025) argue that entrepreneurship education systems remain insufficiently prepared for AI-integrated business realities.

1. Methodology of the research

Cluster analysis was applied to survey responses from 369 Ukrainian agrobusiness women entrepreneurs across six AI readiness variables: AI adaptation/search, learning new AI capabilities, AI education as an investment in the future, AI-based decision-making, investing in new AI tools, and optimizing work with AI. A chi-square test was used to confirm the statistical significance of the differentiation between the resulting clusters for each of the six variables.

All six variables showed statistically significant differences across clusters ($p<0.001$), confirming that the derived typology is robust. Based on this analysis, four typologically homogeneous clusters of women in agribusiness were identified, each characterized by its size and AI readiness profile.

The centroid (mean) values on a 1–5 scale for each of the six AI readiness variables were calculated for every cluster, allowing comparison of their relative strengths and weaknesses.

The intra-cluster distribution of grades (1-5) for the composite AI readiness measure was also calculated, along with the average score for each cluster.

Table 1. Statistical significance of cluster differentiation

Variable	**χ^2**	**df**	**p-value**
AI adaptation/search	18.568	12	<0.001
Learning new AI capabilities	13.771	9	<0.001
AI education as an investment in the future	15.707	9	<0.001
AI-based decision-making	18.461	12	<0.001
Investing in new AI tools	15.303	9	<0.001
Optimizing work with AI	19.798	12	<0.001

All six variables showed statistically significant differences across clusters ($p<0.001$), confirming that the derived typology is robust. Based on this analysis, four typologically homogeneous clusters of women in agribusiness were identified, each characterized by its size and AI readiness profile.

Table 2. Clusters of Agro women: typology

Cluster	Name	n (%)	AI Readiness Profile
C1	Systemic AI Transformation Leaders	197 (53.4%)	Maximum: 4.63-4.96 across all dimensions
C2	Value-Driven, Operationally Restrained	97 (26.4%)	High value (4.76), moderate operational (3.97-4.23)
C3	Adaptive Realists with Limited Potential	50 (13.4%)	Below average: 3.20-3.88 across all dimensions
C4	Resilient AI Laggards	25 (6.8%)	High value (4.80) and decision (4.60), lower entrepreneurial activity (3.32-3.68)

The centroid (mean) values on a 1-5 scale for each of the six AI readiness variables were calculated for every cluster, allowing comparison of their relative strengths and weaknesses.

Table 3. Centroid values for each cluster (average scores on a scale of 1–5)

Variable	C1	C2	C3	C4
AI adaptation/search	4.63	3.97	3.20	4.04
Learning new AI capabilities	4.87	4.47	3.80	4.52
AI education as an investment in the future	4.96	4.76	3.88	4.80
AI-based decision-making	4.88	4.20	3.59	4.60
Investing in new AI tools	4.78	4.23	3.49	4.28
Optimizing work with AI	4.82	4.23	3.49	4.40

The intra-cluster distribution of grades (1-5) for the composite AI readiness measure was also calculated, along with the average score for each cluster.

RESULTS

The survey data show a consistent positive association between entrepreneurial attitudes and AI-related behaviors. Respondents who reported being inspired by the idea of creating something of their own, also reported trying to adapt and search for information with the help of AI, indicating a link between entrepreneurial drive and AI engagement. Cross-tabulations further confirm this pattern. Among respondents who strongly agreed (rating 5) that they see business opportunities in agriculture and food, 174 out of 217 also strongly agreed (rating 5) that they like learning about new AI capabilities and attending training events, out of a total sample of 369.Similarly, among the 299 respondents who strongly agreed (rating 5) that AI education is an investment in their future, 127 also strongly agreed (rating 5) that they are not afraid of new technologies and are motivated by them, accounting for 37% of the total sample of 369.

The cluster analysis identified four distinct typological profiles.

- Leaders (Cluster 1 – Systemic AI Transformation Leaders). The food business is perceived as a strategic platform for realizing entrepreneurial ambitions. The vision of business opportunities is directly supported by systemic AI orientation: active information search (4.63), regular attendance of educational events (4.87), and willingness to invest in AI tools (4.78). This cluster has the highest correlation between food business identification and all dimensions of AI readiness.
- Valuaders (Cluster 2 – Value-Driven, Operationally Restrained). A characteristic feature is the recognition of values with relatively cautious operational behavior. The vision of the food business as an environment of opportunities in this cluster does not automatically convert into active AI adaptation. Despite the positive food business attitude, there is a "motivational gap": the food business is attractive, but concrete steps to implement AI are lacking.
- Vrealists (Cluster 3 – Adaptive Realists with Limited Potential). The food business is not perceived as an absolutely promising environment. Opportunities are seen, but with reservations: limited resources, lower stress resistance, and technological skepticism create a cautious, hesitant stance. Entrepreneurial motivation exists, but needs external reinforcement.
- Laggards (Cluster 4 – Resilient AI Laggards). The aim of owning one's own business is the lowest among all clusters; the vision of business opportunities in the food business is also minimal. This cluster is analytically unique: despite the lowest food business orientation, women demonstrate a pronounced AI value and determination. AI readiness in this segment is formed independently of food business motivation, on the basis of personal resilience and strategic pragmatism.

SUMMARY

- Food business orientation and AI readiness are mutually reinforcing constructs: clusters with higher management motivation (C1, C2) demonstrate higher readiness to use AI tools in business activities.
- The most “critical” is Cluster 3 (“Adaptive Realists”): a neutral or moderately positive attitude towards the food business correlates with general AI passivity. Without targeted external intervention, this segment risks being left out of the technological transformation of agribusiness.
- The most anomalous is Cluster 4 (“Resilient Pragmatists”): high AI competence and low food business identification indicate the potential for cross-sectoral skill transfer. This segment is a potential source of cross-sectoral innovators.
- Decision-making based on AI recommendations depends directly on the level of agrosphere confidence: “Leaders” are significantly more willing to delegate decisions to AI than “Realists”.
- Education is a key mediator between business motivation and AI readiness: the higher the level of food business identification, the higher the subjective value of AI education.

Acknowledgment

This work has been supported by the EIT Higher Education Initiative within the project “HEI Transformation for Entrepreneurship and AI-Driven Innovation (HEI-TRAIN)” No. 24225

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STRENGTHENING THE RESILIENCE OF HIGHER EDUCATION SYSTEMS IN THE AI ERA: A COMPARATIVE ANALYSIS OF EUROPE AND MONGOLIA

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Abstract. Artificial intelligence (AI) is reshaping higher education by transforming teaching, learning, research, and institutional governance. Although AI has the potential to improve educational quality, personalization, and institutional efficiency, it also presents challenges related to ethics, digital inequality, academic integrity, and governance. This study investigates how higher education systems can strengthen institutional resilience in the AI era through a comparative analysis of Europe and Mongolia. Drawing on resilience theory, the Technology Acceptance Model (TAM), the DigCompEdu framework, and emerging AI governance literature, the study employs a qualitative comparative policy analysis based on international policy documents, scholarly literature, and empirical evidence from Mongolia. The findings indicate that European higher education institutions are generally better prepared for AI integration due to more mature policy frameworks, stronger digital infrastructure, and coordinated governance mechanisms. In contrast, Mongolia continues to face challenges related to uneven digital infrastructure, limited policy implementation, and insufficient pedagogical readiness for AI integration. The study argues that resilience should be understood not only as technological adaptation but also as the capacity of higher education institutions to respond to AI-driven change in ethical, inclusive, and sustainable ways. It proposes a multidimensional framework that integrates governance, digital competence, pedagogy, and ethical responsibility, offering practical policy recommendations for strengthening AI-enabled resilience, particularly in emerging and developing higher education systems.

Keywords: AI governance, artificial intelligence, digital competence, higher education, institutional resilience, Mongolia

Introduction

Artificial intelligence (AI) has become a major force driving change in higher education, reshaping teaching, learning, research, assessment, and institutional governance. Universities are increasingly adopting AI-powered technologies, including intelligent tutoring systems, automated assessment tools, learning analytics, and generative AI applications such as ChatGPT, to enhance educational quality, personalize learning experiences, and improve institutional efficiency (UNESCO, 2023). As AI becomes more deeply embedded in academic practice, it is fundamentally changing how knowledge is created, accessed, and evaluated.

The adoption of AI accelerated considerably following the COVID-19 pandemic, which exposed vulnerabilities in higher education systems while highlighting the importance of digital readiness and institutional adaptability. The rapid transition to online and hybrid learning demonstrated that technological capacity alone is insufficient; universities must also possess the organizational flexibility and governance structures needed to respond effectively to disruption (Crawford et al., 2020). In this context, resilience extends beyond the ability to recover from crises and encompasses the capacity of institutions to adapt, innovate, and sustain educational quality in the face of continuous technological change (Holling, 1973). Despite the growing global adoption of AI, substantial disparities remain in institutional preparedness, digital infrastructure, policy development, and digital competence. Across Europe, coordinated initiatives such as the Digital Education Action Plan, the AI Act, and the DigCompEdu framework have established a relatively comprehensive foundation for integrating AI into higher education while promoting ethical governance and digital competence development (European Commission, 2020). In contrast, many emerging higher education systems continue to face challenges related to limited digital infrastructure, uneven access to technology, insufficient professional development, and the absence of coherent AI governance policies.

Mongolia provides a valuable context for examining these challenges. As a developing country undergoing rapid digital transformation, it is seeking to modernize its higher education system while addressing persistent issues of digital inequality, rural–urban disparities, and limited institutional capacity. Although universities are increasingly recognizing the importance of AI literacy, digital competence, and international collaboration, the integration of AI into teaching and institutional practice remains uneven and constrained by policy and resource limitations. Against this background, this study examines how higher education systems can strengthen institutional resilience in the AI era through a comparative analysis of Europe and Mongolia. Specifically, it addresses the following research questions:

1. How is AI transforming higher education systems in Europe and Mongolia?
2. What factors contribute to institutional resilience in AI-enabled higher education?
3. What ethical and governance challenges accompany the adoption of AI in universities?
4. Which policy strategies can promote resilient, inclusive, and responsible AI integration in higher education?

By integrating comparative policy analysis with resilience theory, the Technology Acceptance Model (TAM), the DigCompEdu framework, and empirical evidence from Mongolia, this study contributes to the growing literature on AI in higher education. It offers a theoretically informed and policy-oriented perspective on institutional resilience and provides practical recommendations to support responsible AI adoption, particularly in emerging and developing higher education systems.

Literature Review

Artificial intelligence in higher education

Artificial intelligence (AI) is rapidly reshaping higher education by influencing teaching, learning, assessment, research, and institutional management. Universities increasingly employ AI-powered applications—including adaptive learning systems, intelligent tutoring systems, predictive analytics, automated assessment, virtual assistants, plagiarism detection, and generative AI—to enhance educational quality, personalize learning experiences, and support evidence-based decision-making (Zawacki-Richter et al., 2019). These technologies have shifted AI from a specialized innovation to an integral component of digital transformation across higher education. The emergence of generative AI has further accelerated institutional interest in AI adoption. Applications such as ChatGPT, Gemini, and Claude have transformed academic writing, content creation, and access to information, while also challenging traditional approaches to teaching, assessment, and knowledge production (Kasneci et al., 2023). Although these technologies offer considerable opportunities to improve accessibility, learner support, and academic productivity, they have also raised concerns regarding academic integrity, misinformation, overreliance on AI-generated content, and the potential erosion of critical thinking and independent learning. Recognizing both the opportunities and risks associated with AI, UNESCO (2023) advocates a human-centered approach that prioritizes ethical responsibility, transparency, inclusiveness, and learner empowerment. Consequently, effective AI integration requires more than technological adoption; it also depends on institutional policies, governance structures, and pedagogical strategies that ensure AI is used responsibly and in ways that enhance, rather than replace, human learning.

Resilience theory and higher education

The concept of resilience, originally developed within ecological systems theory, describes the capacity of a system to adapt to change while maintaining its essential functions (Holling, 1973). In higher education, resilience has evolved into a framework for understanding how institutions respond to crises, technological disruption, and long-term organizational change. The COVID-19 pandemic demonstrated the importance of institutional resilience by exposing significant differences in universities' capacity to sustain educational continuity during large-scale disruption. Institutions with robust digital infrastructure, flexible governance, and digitally competent faculty were generally better positioned to adapt to emergency remote teaching and maintain educational quality (Crawford et al., 2020).

In the context of AI-driven transformation, resilience extends beyond crisis recovery. It reflects an institution's ability to continuously adapt to technological innovation while safeguarding educational quality, equity, and ethical responsibility. Building resilient higher education systems therefore requires adaptive leadership, effective governance, ongoing professional development, and institutional cultures that encourage innovation without compromising academic values.

Technology acceptance model (TAM)

The Technology Acceptance Model (TAM), proposed by Davis (1989), remains one of the most widely applied theoretical frameworks for explaining technology adoption. The model suggests that individuals' intentions to use new technologies are primarily influenced by two factors: perceived usefulness and perceived ease of use. Within higher education, TAM provides a useful lens for understanding educators' and students' willingness to adopt AI-supported technologies. Faculty members are more likely to integrate AI into teaching when they perceive these technologies as beneficial for improving learning outcomes and sufficiently accessible for everyday practice. Likewise, students' engagement with AI is influenced by their confidence in the technology's effectiveness and usability.

The model is particularly relevant in the Mongolian context, where variations in digital competence, technological infrastructure, and institutional support may shape the adoption of AI across universities. Examining AI acceptance through TAM therefore provides valuable insights into the human factors that influence successful digital transformation.

Digital competence and DigCompEdu

Digital competence has become a prerequisite for the effective integration of AI in higher education. Recognizing this need, the European Commission developed the DigCompEdu framework, which identifies six interrelated areas of educators' digital competence: professional engagement, digital resources, teaching and learning, assessment, empowering learners, and facilitating learners' digital competence (Redecker, 2017). Rather than focusing solely on technical skills, DigCompEdu emphasizes the pedagogically meaningful use of digital technologies and continuous professional development. Research consistently demonstrates that educators' digital competence plays a central role in determining whether AI technologies are integrated in ways that genuinely enhance teaching and learning.

An important distinction within the literature is between operational digital competence and pedagogical digital competence. While many educators possess the technical skills needed to use digital tools, they often experience difficulties incorporating these technologies into learner-centered instructional practices (Howard et al., 2021). As AI becomes increasingly embedded in educational practice, this distinction becomes even more significant. Recent developments have further broadened the concept of digital competence. UNESCO's AI Competency Framework (2024) argues that educators should develop not only technical proficiency but also ethical awareness, critical thinking, and the pedagogical knowledge required to use AI responsibly. Consequently, digital competence in the AI era should be viewed as a combination of technological capability, pedagogical expertise, and ethical judgment.

AI governance and ethics

As AI becomes more deeply integrated into higher education, governance and ethical considerations have become central to institutional decision-making. Universities must address complex issues related to algorithmic bias, data privacy, transparency, accountability, intellectual property, and the responsible use of AI-generated content. Recent research emphasizes that effective AI governance requires coordinated action at institutional, national, and international levels to ensure that technological innovation aligns with educational values and societal expectations (Batool et al., 2025). The European Union has established one of the most comprehensive regulatory approaches through initiatives such as the AI Act, which promotes a risk-based framework emphasizing transparency, accountability, human oversight, and fundamental rights (European Parliament, 2024). Similarly, Floridi et al. (2018) argue that ethical AI should be guided by principles of fairness, explainability, accountability, and human-centered design.

Beyond governance frameworks, AI ethics education has emerged as an increasingly important area of scholarship. Wiese et al. (2025) emphasize that universities should equip learners with the knowledge and critical skills necessary to engage responsibly with AI, while Abbas et al. (2025) highlight persistent governance gaps related to institutional policy, data protection, and regulatory readiness. These challenges are particularly evident in developing countries, where AI governance frameworks are often still evolving. In Mongolia, institutional policies and regulatory mechanisms for AI in higher education remain at an early stage of development. Strengthening governance capacity, establishing clear ethical guidelines, and investing in institutional readiness will therefore be essential to ensuring that AI supports equitable, responsible, and sustainable educational development.

Methodology

Research Design

This study adopts a qualitative comparative research design to examine institutional resilience in AI-integrated higher education systems in Europe and Mongolia. A comparative policy analysis was chosen because it enables a systematic examination of how different higher education systems respond to the opportunities and challenges associated with AI adoption within their respective policy, institutional, and socio-economic contexts. Given the exploratory nature of the research, an interpretive qualitative approach was considered appropriate for understanding the complex interactions between technological change, educational policy, and institutional resilience. The analytical framework is informed by resilience theory, the Technology Acceptance Model (TAM), the DigCompEdu framework, and the emerging literature on AI governance. These theoretical perspectives guided the deductive analysis, while themes specific to the European and Mongolian contexts were identified inductively. The analysis focused on five key dimensions: policy readiness, digital infrastructure, faculty competence, ethical governance, and institutional resilience.

Data Sources

The study draws on multiple sources of secondary data to ensure a comprehensive understanding of AI integration in higher education. These sources include peer-reviewed articles indexed in **Scopus** and Web of Science, reports published by UNESCO, the European Commission, and the OECD, European digital education policy frameworks, and national higher education policy documents from Mongolia. Using diverse sources enabled the triangulation of evidence and strengthened the credibility of the comparative analysis. To enrich the contextual interpretation, the study also incorporates empirical evidence from a DigCompEdu-based assessment of pre-service teachers in Mongolia. The assessment employed the **S**ELFIEforTEACHERS instrument, which is aligned with the European Framework for the Digital Competence of Educators (DigCompEdu), and involved 55 graduating pre-service primary teachers. The instrument demonstrated high internal consistency, with a Cronbach's alpha coefficient of 0.905, indicating strong reliability.

Data Analysis

The collected data were analysed using thematic analysis to identify recurring patterns related to AI adoption, institutional resilience, digital competence, governance, and educational transformation. The findings were subsequently interpreted through a comparative lens to examine similarities and differences between Europe and Mongolia in terms of policy development, institutional preparedness, and approaches to AI integration. Rather than seeking statistical generalisation, this study aims to generate context-sensitive insights into how higher education institutions respond to AI-driven transformation. The findings are intended to contribute to theory development and inform policy and institutional strategies, particularly in emerging and developing higher education systems.

Table 1. Conceptual Framework for Resilient AI-Integrated Higher Education

Dimension	**Europe**	**Mongolia**	**Resilience Implication**
Policy and Governance	Strong EU-level AI regulation and digital education frameworks	Emerging National AI Vision and Strategy	Mongolia requires clearer higher education-specific AI governance
Digital Infrastructure	Advanced institutional digital ecosystems	Uneven infrastructure and rural–urban digital disparities	Infrastructure equity is central to resilience
Faculty Competence	DigCompEdu-aligned professional development	Developing but uneven AI and digital competence	Faculty training should be prioritized
Ethics and Regulation	Risk-based AI governance, transparency, accountability	Early-stage AI ethics and governance mechanisms	Need for institutional AI ethics committees
Pedagogy	AI-supported adaptive learning and analytics	Growing use of LMS and AI-supported learning	Human-centered pedagogy must guide AI adoption

Developed by the authors based on resilience theory, the Technology Acceptance Model (TAM), DigCompEdu, AI governance literature, and the comparative analysis conducted in this study.

Comparative Analysis: Europe and Mongolia

Europe

European higher education institutions are generally better positioned to integrate AI due to well-established digital policies, advanced technological infrastructure, and coordinated governance. Initiatives such as the Digital Education Action Plan (2021–2027) and the EU AI Act provide a comprehensive policy framework that promotes digital competence, ethical AI adoption, transparency, and risk management (European Commission, 2020; European Parliament, 2024). Universities have increasingly embedded AI into teaching, assessment, learning analytics, and administrative processes while investing in faculty development through frameworks such as DigCompEdu. Nevertheless, challenges remain, including algorithmic bias, data privacy concerns, academic integrity, and unequal institutional capacity to adopt AI effectively.

Mongolia

Mongolia has made notable progress toward digital transformation, with universities increasingly adopting learning management systems and AI-supported educational technologies. However, institutional resilience remains constrained by uneven digital infrastructure, limited faculty preparedness, and the absence of a comprehensive AI governance framework for higher education. Recent initiatives, including the National AI Vision and Strategy developed in partnership with UNDP, reflect growing national commitment to responsible AI development. Despite these advances, strengthening institutional resilience will require sustained investment in digital infrastructure, professional development, governance, and international collaboration.

Teacher Digital Competence and AI Readiness in Mongolia

Empirical evidence from a DigCompEdu-based assessment of 55 pre-service primary teachers highlights significant gaps in AI readiness and pedagogical digital competence. Most participants demonstrated foundational to intermediate competence (A2–B1), with no participants reaching advanced (C-level) competence. While digital communication and professional engagement emerged as relative strengths, competencies related to teaching, assessment, learner empowerment, and AI-supported pedagogy remained limited. The findings also revealed a gap between participants' operational digital skills and their ability to integrate technology into meaningful, learner-centered teaching. Furthermore, many participants underestimated their own competence, suggesting limited confidence despite moderate digital capability. These findings indicate that strengthening resilience in Mongolian higher education requires more than expanding technological access; it also depends on developing educators' pedagogical competence, ethical awareness, and institutional capacity to integrate AI effectively into teaching and learning.

Table 2. Digital Competence Readiness of Pre-Service Teachers in Mongolia

Competence Domain	Dominant Level	Key Finding
Professional Engagement	B1	Strongest competence area; effective digital communication and collaboration
Digital Resources	B1	Functional use of digital resources but limited advanced innovation
Teaching and Learning	A2–B1	Weak pedagogical integration of digital technologies
Assessment	A2	Limited strategic use of digital assessment tools
Empowering Learners	A2	Limited learner-centered and inclusive digital pedagogy
Facilitating Learners' Digital Competence	B1	Moderate support for learners' digital skill development
Overall Competence	B1–B2	Functional competence present, but advanced digital leadership lacking

Source: Adapted from DigCompEdu-based assessment of pre-service teachers in Mongolia.

Conclusion

Artificial intelligence is transforming higher education by creating new opportunities for innovation while introducing significant challenges related to governance, ethics, digital competence, and institutional capacity. Through a comparative analysis of Europe and Mongolia, this study demonstrates that institutional resilience extends beyond the adoption of AI technologies. Rather, it depends on the ability of higher education institutions to integrate AI within coherent governance frameworks, develop educators' digital competence, ensure equitable access to digital infrastructure, and uphold ethical and human-centered educational practices.

The comparison highlights that European higher education institutions benefit from more mature policy frameworks, coordinated governance, and stronger digital ecosystems. In contrast, Mongolia is making important progress through national AI initiatives and digital transformation efforts but continues to face challenges associated with infrastructure, faculty preparedness, and AI governance. The findings also underscore the need to strengthen pedagogical digital competence and AI readiness among future educators as a prerequisite for sustainable institutional resilience.

Overall, this study argues that resilient higher education systems must balance technological innovation with educational quality, ethical responsibility, and social inclusion. By integrating comparative policy analysis with resilience theory, TAM, DigCompEdu, and AI governance perspectives, the study provides a conceptual framework and practical policy recommendations that can inform AI integration in emerging and developing higher education systems.

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Funded by the European Union

EXPLAINABLE ARTIFICIAL INTELLIGENCE IN MRI-BASED DIAGNOSIS OF NEUROLOGICAL DISORDERS

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Abstract. Deep learning has significantly improved magnetic resonance imaging diagnostics of neurological disorders. Because conventional deep learning techniques function as ‘black boxes’, its usage is limiting clinicians trust in artificial intelligence. This paper reviews the main approaches in MRI diagnosis of neurological disorders by Gradient-weighted Class Activation Mapping (Grad-CAM), Saliency Maps, SHAP, and Local Interpretable Model-agnostic Explanations (LIME), their applications, clinical benefits, limitations and future research directions. Explainable artificial intelligence improves transparency, supports clinical decision-making and increases clinicians’ reliability on AI-assisted diagnosis, but it also needs to improve its standardized validation frameworks and develop collaboration between AI researchers and clinitians to facilitate integration into routine diagnostics.

Keywords: Deep learning, Explainable artificial intelligence, Magnetic resonance imaging, Neurological disorders

INTRODUCTION

Deep learning Artificial Intelligence model has shown high success in analysing large amounts of data to work out patterns across many disciplines and fields including medicine, however the problem of such models is that, while being able to propose solutions, it may not always be able to explain the ‘thought process’ behind it, creating the ‘black box’ phenomenon- because the link to the physical environment of the learned data is very hard to isolate, it is not possible for the AI model to interpret the reasoning in between input and output, which is problematic in healthcare as it is a highly sensitive topic[1].

Deep learning is now widely used to interpret Magnetic Resonance Imaging results- from segmentation to disease prediction [2] as it is famous for its ability to give accurate decisions based on high amounts of accumulated complicated data sets, which is especially important in diagnosis of neurological disorders which highly rely on MRI.

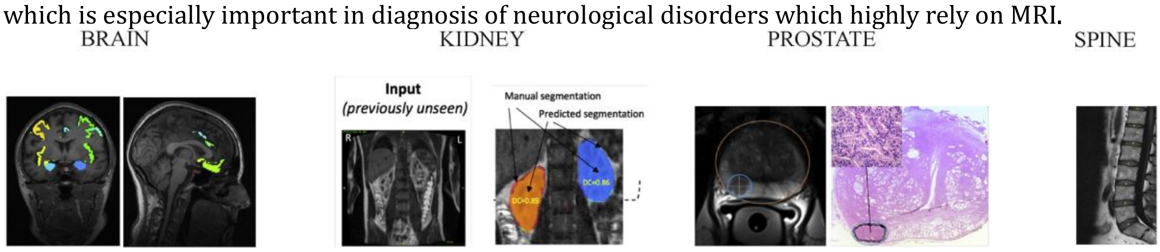

Fig.1 Deep learning for magnetic image analysis in selected organs. [2]

1 EXPLAINABLE ARTIFICIAL INTELLIGENCE IN NEUROLOGICAL DIAGNOSIS

As deep learning is able to analyse big data and notice subtle changes and discrepancies, it finds it’s application in neurology, where delicacy and complexity of structures give birth to bias and limitations of human perception, as well as high time and

effort demand when it comes to human-operated analysis [3]. Therefore, several major approaches have been developed in order to perform neurological MRI-based diagnosis of such major diseases as Alzheimer’s disease, Parkinson’s disease, Multiple sclerosis, brain tumours, stroke, epilepsy, etc. Major common methods include Grad-CAM, Saliency maps, SHAP and LIME.

Gradient-weighed Class Activation Mapping (Grad-CAM) is one of the most widely used convolutional neural networks techniques which is able to detect increasingly abstract features of the MR image automatically, to make best possible decisions based on the unique feature patterns learned from input data. It has been shown to be useful in multiple sclerosis diagnosis by localising heat map patterns, which highlight the regions of the image that contribute to models' prediction in disease progression. [4]

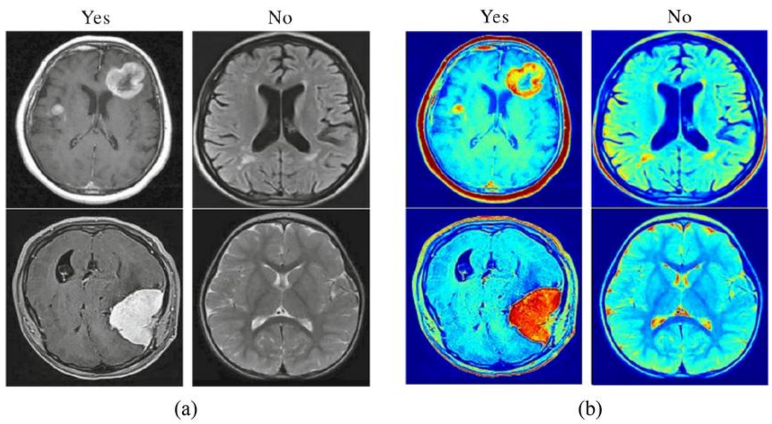

Fig. 2. (a). Sample of MRI brain images and (b) Sample of Grad-CAM result of MRI Brain images. [5]

Saliency maps are graident-based visualisation methods which help identify individual pixels on the MR image which greater contribute to the model's prediction, making them helpful in identifying subtle abnormalities associated with neurological diseases such as Alzheimer's disease. Visual saliency maps extract relevant disease regions and have shown to outperform other methods (such as state-of-art) in assisting physicians to effectively evaluate the diagnosis and extract useful information out of the image. [6]

Shapley Additive explanations (SHAP) calculate how much each image feature changes the prediction by considering all possible combinations of input feature. Experimental data shows that when applied to experimental MRI data in mild cognitive impairment and Alzheimer's disease, SHAP showed that insula, lateral occipital, medial frontal, temporal pole, and occipital fusiform gurus were the primary contributors to global cognitive decline, offering the insights into the multivariative nature of the relationship between brain regions and cognition. [7]

Local Interpretable Model-agnostic Explanations (LIME) is another method that explains individual predictions by creating a single surrogate model around a single prediction to see how the prediction changes. It is widely used to facilitate precise diagnoses and transparent decision-making in early brain tumour identification. [8]

In conclusion, explainable artificial intelligence methods are widely used to increase the transparency and interpretability of deep learning- assisted Magnetic Resonance Imaging diagnosis of neugologic diseases through various ways, thus enhancing the trust in artificial intelligence- assisted diagnosing and increasing explanation accuracy, aiming to reduce the 'black box' effect.

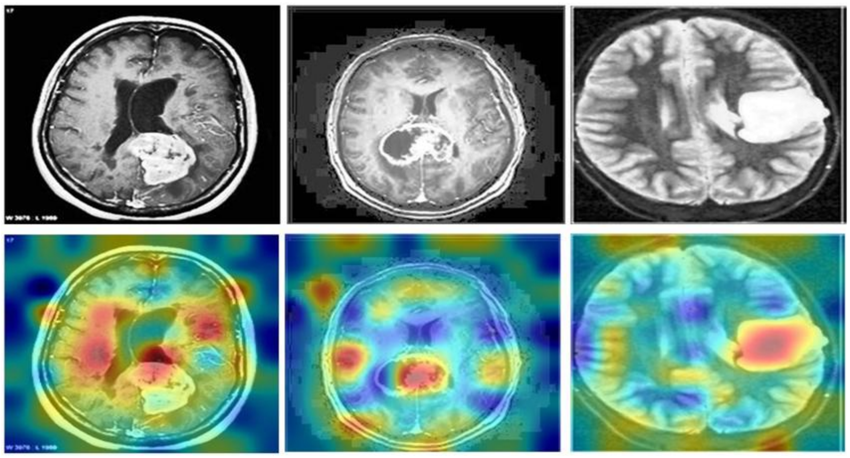

Fig. 3 Sample images of LIME base analysis; the first row has brain tumor MRI images, and the second row has LIME analysis results of that brain tumor MRI image. [9]

2 CLINICAL BENEFITS, CHALLENGES AND FURTHER DIRECTIONS

While explainable artificial intelligence generally maintains similar predictive performance to competing deep learning models, its main characteristic that makes it more advantageous in medical field is transparency- by validating that the model focuses on the right brain regions and not on artefacts and facilitating clinical decision support through explanations of artificial intelligence predictions, explainable artificial intelligence improves clinical trust in AI-assisted diagnoses.[10]

While Explainable artificial intelligence seems like a flawless instrument perfect for medical setting, it does have limitations- for instance, saliency maps are susceptible to adversarial attacks (a small input perturbation generates a large salience map variation, however not changing the output prediction), additionally, gradient-based methods heavily depend on a reference point, or a baseline image, so it is important to aim research at converting the reference point to a hyper-parameter. Additionally, these methods have reproducibility and repeatability issues, as well as high realisation costs and necessary human involvement, [11] so the research should aim at the development of collaboration with clinicians for model training, as well as producing standardised methods for increasing quality, reliability and effectiveness for lower cost.[12]

CONCLUSION

To summarise, explainable artificial intelligence is a powerful deep learning model, which uses Grad-CAM, Saliency maps, SHAP and LIME to increase transparency behind artificial intelligence's data processing and output generation. It is very sensible to implement explainable artificial intelligence into medical field, particularly neurological Magnetic resonance imaging, as neurological disorders produce very subtle and heterogenous effect, which requires big data to be analysed in order to produce the correct diagnosis. Through increasing explanation accuracy and reducing the 'black box' effect, it increases clinitians trust making it more widely used in medicine. Although explainable artificial intelligence is a very effective instrument, it still requires further development and research to make it a useful integral part of routine MRI neurological diagnostics.

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ARTIFICIAL INTELLIGENCE (AI) IN HOSPITALITY

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ABSTRACT

The study was carried out as part of the project investigating the application of artificial intelligence in the hospitality industry.

Artificial intelligence (AI) is transforming the hospitality industry by improving operational efficiency, enhancing customer experiences, and supporting data-driven decision-making. The research examined the role of AI in hospitality, focusing on its applications in customer service, hotel operations, and personalized guest experiences. The study aimed to evaluate the benefits, challenges, and future potential of AI technologies in the industry. A qualitative literature review was conducted using peer-reviewed articles and industry reports to identify key trends and findings. The results indicate that AI-powered tools, such as chatbots, virtual assistants, predictive analytics, and automated management systems, contribute to increased efficiency, reduced operational costs, and higher customer satisfaction. However, challenges related to data privacy, implementation costs, employee adaptation, and ethical considerations remain significant. The study concludes that AI should complement rather than replace human interaction, as personalized service remains essential in hospitality. It is recommended that hospitality organizations adopt AI strategically, invest in employee training, and establish clear data governance practices to maximize the benefits of AI while maintaining high service quality and guest trust.

Keywords: Artificial Intelligence (AI), Customer Experience, Data Analytics, Hospitality Industry, Personalisation

RESEARCH METHOD

This study employed a qualitative research approach to examine the use of artificial intelligence (AI) in the hospitality industry. The research consisted of two complementary methods: a review of existing literature and semi-structured employee interviews.

The literature review examined peer-reviewed articles and industry reports to explore current AI applications, benefits, challenges, and emerging trends in the hospitality sector. This provided the theoretical foundation for the study and helped identify key themes discussed in research.

To complement the literature review, semi-structured interviews were conducted with employees of Baltic Beach Hotel & SPA representing sales, reservations, marketing and operations departments. The interviews aimed to gain practical insights into employees' experiences and perceptions of AI technologies in their workplace, as well as their views on the opportunities and challenges associated with AI adoption. This approach enabled the collection of in-depth qualitative data while allowing participants to discuss their experiences openly. Interview participants believe AI helps to improve the response times while emphasizing that human interaction remain essential for guest satisfaction.

The findings from the literature review and employee interviews were analysed using thematic analysis. Common themes, patterns, and differences were identified and compared to provide a comprehensive understanding of the role of AI in the hospitality industry and its impact on hotel operations and employees.

CONCLUSION

• AI is transforming the hospitality industry by improving operational efficiency, streamlining processes, and enhancing guest experiences.

• AI technologies, including chatbots, virtual assistants, predictive analytics, and personalized recommendation systems, enable hospitality businesses to deliver faster and more tailored services. AI improves response time but human interaction remains essential for guest satisfaction.

• The successful adoption of AI can lead to increased customer satisfaction, cost savings, and improved decision-making through data-driven insights.

• Despite these benefits, challenges such as implementation costs, data privacy and security concerns, ethical considerations, and employee adaptation continue to affect AI adoption.

• Human interaction remains a fundamental aspect of hospitality, and AI should be used to complement—not replace—the personal service that guests value.

• Hospitality companies should implement AI strategically, ensuring that technological innovation is balanced with employee training, ethical practices, and a strong focus on customer trust.

• Future research should examine the long-term impact of AI on employee roles, guest satisfaction, and sustainable business performance as AI technologies continue to evolve.

RECOMMENDATIONS

• **Adopt AI strategically:** Hospitality businesses should implement AI technologies gradually, focusing on areas where they provide the greatest value, such as customer service, reservations, and operational management.

• **Maintain a balance between AI and human interaction:** AI should enhance, rather than replace, personal customer service. Employees should continue to play a central role in delivering empathy, problem-solving, and personalized guest experiences.

• **Invest in employee training:** Organizations should provide continuous training to help employees develop the digital skills needed to work effectively alongside AI technologies.

• **Prioritize data privacy and security:** Hospitality businesses should establish robust data governance policies and comply with relevant data protection regulations to safeguard customer information and maintain trust.

• **Use AI to personalize guest experiences:** Hotels and other hospitality providers should leverage AI-driven analytics to better understand customer preferences and offer tailored recommendations, services, and promotions.

• **Evaluate AI performance regularly:** Hospitality companies should continuously monitor the effectiveness of AI systems, gather guest feedback, and update technologies to ensure they continue to meet customer expectations and business objectives.

• **Encourage further research:** Future studies should investigate the long-term impact of AI on employee satisfaction, customer loyalty, ethical considerations, and sustainability within the hospitality industry.

ACKNOWLEDGEMENT

This work has been supported by the European Union project
HEI-TRAIN: HEI Transformation for Entrepreneurship and AI-Driven Innovation.
Project (KAVA) Number 250749
The project is implemented within the framework of
EIT HEI Initiative Call for Proposals 2024 – Strand A
Implementation period: April 2025 – April 2027

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CONCLUSION

The papers collected in this volume illustrate the breadth of the knowledge triangle in practice — linking education, research and enterprise through the shared theme of artificial intelligence. Together they show AI reshaping institutional resilience in higher education, informal learning and stakeholder engagement at Ukrainian universities, AI readiness among women-led food enterprises, explainable AI in clinical diagnosis, and AI adoption in hospitality management. The editors hope this collection will support continued collaboration across the HEI-TRAIN partner network and inform future editions of the conference.