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Higher education students' perspectives on GenAI in learning and career futures in the Visegrad countries

Laszlo Horvath[a,*], Ludvík Eger[b], Łukasz Tomczyk[c], Łukasz Szwejka[d], Dana Egerová[b], Lucie Rohlíková[e], Tomáš Kincl[f], Jan Pospíšil[f], Kristína Medeková[g], Petra Mikulcová[g], Jeyran Gasimova[a]

[a] Institute of Education ELTE Eötvös Loránd University, Budapest, Hungary
[b] University of West Bohemia in Pilsen, Faculty of Economics, Czech Republic
[c] Jagiellonian University, Poland
[d] Institute of Pedagogy, Jagiellonian University, Poland, Faculty of Psychology and Social-Political Sciences, Samarkand State University (SamSU), Samarkand, Uzbekistan
[e] University of West Bohemia in Pilsen, Faculty of Education, Czech Republic
[f] Prague University of Economics and Business, Faculty of Management, Czech Republic
[g] Slovak University of Agriculture in Nitra, Faculty of Economics and Management, Slovak Republic

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ABSTRACT

The rise of generative artificial intelligence (GenAI) in higher education has transformed how students engage with learning, prompting both enthusiasm and unease. While prior research focuses on technology acceptance using quantitative models, qualitative insights into how students interpret these tools remain limited, especially in the Visegrad Group (V4). This study employed a coordinated qualitative design, utilizing 24 focus groups with students from social sciences, education, and management programs across V4 universities.

The study aimed to map student experiences onto the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and identify necessary theoretical extensions. Inductive and axial coding was applied to analyse emerging themes. Seven thematic categories were identified: 1) AI adoption and utility; 2) output reliability concerns; 3) user skill; 4) ethical dilemmas; 5) impact on cognitive engagement; 6) the university's role; and 7) future career implications. While several UTAUT2 constructs (e.g., performance and effort expectancy) were supported, others (e.g., social influence, facilitating conditions) were largely absent or transformed. The analysis proposes four critical theoretical extensions: Contingent Performance Trust (expanding Performance Expectancy), Epistemic Vigilance (expanding simple ease of use), Identity Negotiation (internalizing social influence), and Institutional Legitimacy (validating usage norms).

Findings suggest existing models only partially capture GenAI complexity. Students view GenAI as mandatory "career capital" yet experience deep "deskilling" anxiety. The institutional context shaped interpretations, creating an "ethical vacuum." The study calls for universities to move from passive regulation to active scaffolding, implementing prompt literacy training and process-oriented assessment.

Introduction

Generative AI in higher education

The rapid diffusion of generative artificial intelligence (GenAI) technologies in higher education has brought significant changes to how students learn, engage, and prepare for future careers. GenAI tools (e.g. large language model (LLM) chatbots, and automated feedback systems) have become increasingly embedded in students' academic routines [1–4]. Initially, these tools were seen as peripheral novelties, now, they function as mainstream infrastructure. They offer perceived benefits in personalization, efficiency, and creative output. These tools are

* Corresponding author at: Hungary, 1075 Budapest, Kazinczy street 23-27. (Room 403).

E-mail addresses: horvath.laszlo@ppk.elte.hu (L. Horvath), leger@fek.zcu.cz (L. Eger), lukasz.tomczyk@uj.edu.pl (Ł. Tomczyk), lukasz.szwejka@uj.edu.pl (Ł. Szwejka), egerova@fek.zcu.cz (D. Egerová), lrohlik@kvd.zcu.cz (L. Rohlíková), kincl@vse.cz (T. Kincl), jan.pospisil@vse.cz (J. Pospíšil), xmedekovak@uniag.sk (K. Medeková), xmikulcova@uniag.sk (P. Mikulcová), jeyran.gasimova@outlook.com (J. Gasimova).

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reshaping how students search, create, communicate, and evaluate academic content, potentially augmenting autonomy, efficiency, and engagement in learning processes [2,3,5]. Empirical findings indicate that students' acceptance and usage of GenAI tools are shaped by a complex interplay of perceived usefulness, ease of use, emotional responses, prior experience and many other factors including familiarity, educational value, and ethical considerations (e.g., [6–9]).

Students' everyday interactions with AI are characterized by both enthusiasm and constraint. Many report using generative AI tools (e.g., ChatGPT, Claude) for tasks such as idea generation, paraphrasing, and time management [10,11]. These experiences often reinforce perceptions of AI as useful and supportive of academic productivity [12]. However, alongside these perceived benefits, students also report substantial concerns. Commonly cited challenges include insufficient clarity regarding AI functioning, data privacy risks, and a lack of user training [4]. Ethical uncertainties, such as algorithmic opacity, academic integrity risks, and the implications of surveillance-capable technologies, generate critical tensions in student attitudes [9,13]. These concerns are reinforcing student hesitancy and contributing to uneven usage patterns [14]. Furthermore, issues of over-reliance and questions about the authenticity of learning outcomes highlight a need for more balanced institutional discourse around AI's pedagogical role [15,16].

These tensions are further complicated by institutional context. Variability in university support and governance directly influences whether students feel confident, competent, or constrained when using GenAI tools [17]. Where universities provide clear guidelines, scaffolding, and inclusive AI strategies, students tend to report higher levels of trust, competence, and acceptance [18,19]. In contrast, ambiguous policies or underdeveloped infrastructures often correlate with confusion, skepticism, and resistance [4,20]. As such, institutional readiness, including support systems and governance frameworks, emerges as a decisive influence on student AI adoption. Consequently, students are no longer just users. They have become key stakeholders in determining the educational value and risks of AI integration [4].

Beyond the classroom, these tools are reshaping career outlooks. Economic analyses predict that AI will automate substantial routine cognitive and manual tasks [21,22]. At the same time, AI is expected to create new professional roles that require hybrid skill sets [23–25]. This dual dynamic foster both optimism and anxiety. Many anticipate that familiarity with AI will enhance their employability. Others voice concerns about skill obsolescence and their preparedness to meet new professional demands [23]. These include not only technical proficiencies but also transversal competencies (e.g. collaboration, ethical reasoning, and adaptability) which are increasingly viewed as essential in an AI-influenced economy [26]. Students' calls for the integration of future-proof skills into university curricula are therefore both timely and well-founded. Educational institutions are urged to foster AI literacy, critical data evaluation, and socio-technical awareness as integral components of career readiness education [21,27].

Therefore, students' attitudes towards AI are not just about current academic utility, they are deeply tied to their perceptions of future professional relevance. It is clear that positive attitudes can enhance awareness and understanding of AI's benefits and challenges, while negative attitudes may lead to disengagement and avoidance of AI use for future job-related activities (cf [8,28,29]).

Despite the ambivalence, student optimism regarding AI remains generally high, conditional upon the availability of adequate institutional guidance and ethical safeguards [30]. These observations emphasize the importance of a theoretically grounded and empirically supported understanding of the factors that influence AI use and acceptance among students, especially in relation to institutional strategies and evolving career expectations.

Technology-acceptance frameworks

To understand these usage patterns, researchers often rely on established adoption models. A widely accepted model to interpret individual-level technology adoption is the Technology Acceptance Model (TAM) developed by Davis [31]. TAM has been extensively applied in higher education research, especially in the context of digital and AI-based learning environments [32,33]. However, as GenAI tools become deeply embedded in epistemic and creative processes, basic utilis models are insufficient to capture the complexity of technology adoption in such contexts.

A more nuanced model is the Unified Theory of Acceptance and Use of Technology (UTAUT2) which can capture the multifactorial nature of student engagement with emerging technologies. UTAUT2 retains the core constructs of TAM: perceived usefulness (PU) as performance expectancy (PE) and perceived ease of use (PEOU) as effort expectancy (EE). Both of these factors shape users' intentions and behaviours toward technology adoption. While PE reflects the extent to which students believe AI can support their learning outcomes, EE concerns how effortless and accessible they perceive AI systems to be [34]. Empirical findings confirm the relevance of these constructs in shaping student engagement with GenAI tools: applications perceived as intuitive and beneficial to academic performance are more likely to be adopted and retained [3].

UTAUT2 extends TAM by incorporating constructs such as social influence, facilitating conditions, hedonic motivation, price value, and habit [35]. These additional factors are allowing for a more contextualized interpretation of technology use in informal and educational settings.

In alignment with technological development, UTAUT2 has been widely applied to AI adoption across highly diverse geographical and educational contexts. Recent studies focused on AI adoption by students in Saudi Arabia [36], India [37], Jordan [38], Russia [39] which provides specific insights into Global South perspectives. Besides confirming UTAUT2's baseline, they also expose its limitations when applied to GenAI.

In the context of GenAI, the new constructs proposed by the UTAUT2 model (hedonic motivation, price value, habit) prove particularly relevant, as students' experiences encompass both instrumental and affective dimensions. Additionally, these extensions support the integration of emotional and ethical dimensions (e.g. trust, risk perception, and institutional transparency) into the analysis, which is particularly crucial given the opaque logic of many GenAI tools [4].

Building on this theoretical foundation, it is essential to recognize that students' attitudes toward GenAI in academic settings are shaped by interrelated factors, including demographic characteristics, disciplinary background, prior exposure, and emotional orientation. For instance, Adžić et al. [40] demonstrate that variables such as gender, field of study, and previous experience with GenAI significantly shape attitudes and engagement. In addition, Møgelvang and Grassini [41] emphasize the moderating role of affective variables in shaping students' evaluative responses. Otermans et al. [8] further conceptualize attitudes toward AI as multifaceted, comprising affective (emotions), cognitive (beliefs), and behavioural (actions) dimensions. These components interact dynamically, influencing not only the likelihood of technology adoption but also how students understand the role of AI in their broader learning ecosystems. Emotional reactions, ranging from enthusiasm to anxiety, can mediate the perceived relevance and acceptability of AI tools in academic contexts [42,43]. Positive use experiences have also been found to strengthen student acceptance. According to Wang and Li [7], favourable outcomes associated with AI use (e.g., improved performance or feedback quality) enhance students' openness to integrating these tools into their study routines. Moreover, social background factors, such as digital resource access or career aspirations, contribute to disparities in AI engagement, as highlighted by Katsantonis and Katsantonis [9].

Besides UTAUT2, there are other validated measures of perceived utility and impact like the AI Attitude Scale (AIAS-4) developed by Grassini [44]. While these frameworks capture the mechanics of adoption (UTAUT) and the affective orientation toward AI (AIAS-4), they may not fully account for the unique epistemic struggles students face when co-creating knowledge with GenAI, nor do they typically account for long-term career imaginaries. Adoption mechanisms are not context-neutral, but embedded in assemblages of tools, policies, and assessment regimes (sociomateriality). Fenwick and Landri [45] argue that materials (e.g. software, infrastructure or assessment guidelines) are not merely “background context”, instead, they shape “epistemic agency” and determine the forms of knowledge produced. By shifting the focus from the intentional human subject, we can see that students’ decision to adopt or resist GenAI is linked to the messy “textures” of their environment. In this sense, institutional silence is not a passive void, but an active redistribution mechanism for risks and ethical ambiguity onto students [46]. This aligns well with critical data studies [47] which emphasizes that digital environments are never neutral but imbued with power relations forcing students to negotiate not just utility, but legitimacy and surveillance.

Systematic reviews increasingly show that UTAUT2 lacks the specific “epistemic” nuance required to capture how students evaluate AI hallucinations, navigate academic integrity and engage in critical thinking [48–50].

Since UTAUT2 is a well-know, general framework, this study utilises its dimensions as a complementary interpretive framework but also critically examines where student experiences extend or fall outside its boundaries.

Gaps in literature and aims of the present study

Despite the growing body of research on GenAI in higher education (e.g., Adžič et al. 2024; [8,41,44]), key gaps remain. Existing studies predominantly rely on quantitative models such as TAM to predict behavioural intentions, often overlooking the subjective and experiential dimensions of GenAI engagement and do not fully capture the fluid epistemic and ethical negotiations students need to navigate [1,33,51]. Emotional responses, institutional trust, and context-dependent barriers are underrepresented as well in empirical literature [52,53]. Emerging studies are beginning to differentiate forms of academic GenAI use, like Trejo-Trejo and Gordillo-Espinoza’s [54] validated instrument which map dimensions of integral academic use, ethical awareness and potential dependence. As evidenced by the constant need for extending and modifying the base UTAUT2 model (see for example Alkhwaldi et al. [55] for data-driven decision-making culture or Alkhwaldi [56] for perceived curiosity and hedonic gratification), GenAI would require additional considerations as noted by Nikolic et al. [49] highlighting for example the capacity of GenAI to hallucinate which creates an epistemic uncertainty that previous models didn’t address. Further extensions of the model considering GenAI included for example AI anxiety and perceived risk [37], cognitive flexibility [57] and information accuracy [38]. By shifting the focus to the underlying processes, our study aims to extend current measurement efforts.

Furthermore, there is a lack of qualitative insight into how students connect their current learning uses of GenAI with their perceptions of career futures. Although macro-level economic projections exist, we know little about how students individually make sense of these trends. Their career-related agency, anxieties, and expectations are crucial to understanding GenAI's broader educational implications. Crucially, we lack in-depth, cross-institutional accounts from the Visegrad region regarding these issues.

To address these gaps, this study investigates how students from social sciences, business and management, and education programs in Visegrad countries perceive and experience the use of GenAI tools in their academic lives, and what are their attitudes toward the role of GenAI in their future professional careers?

Specifically, this study aims to:

1. Explore how university students in Visegrad countries use and experience GenAI tools in their studies;
2. Examine how these experiences map onto existing UTAUT2 constructs;
3. Identify additional dimensions that extend or challenge the UTAUT2 framework; and
4. Analyse how current AI usage shapes students’ perceptions of their future career trajectories.

Study contributions

This research offers four distinct contributions to the literature on GenAI in higher education:

1. **Theoretical contribution:** Rather than simply applying UTAUT2, this study uses the model as a diagnostic lens to reveal its limitations. We propose that student engagement with GenAI requires extending the model to include new constructs.
2. **Methodological contribution**: Distinct from single-institution studies common in the field, this research employs a coordinated focus group design across four universities. This approach was specifically chosen to capture a broader range of student perspectives and ensure cross-national consistency in the data.
3. **Empirical contribution**: This is one of the first multi-institution, multi-country qualitative studies to examine student perspectives on GenAI specifically within the Visegrad region. It provides unique regional data that complements the predominantly Western or Asian focus of existing literature.
4. **Practical contribution**: Finally, the study grounds its recommendations for university policy and teaching practice in students’ reported tensions. By highlighting the disconnect between institutional policy and student practice, we offer concrete strategies to support AI literacy and address ethical uncertainty.

Methods

Study design

This study employed a qualitative research approach to explore university students' perceptions and experiences concerning generative artificial intelligence via focus group (FG) interviews. Qualitative research is particularly well-suited to studying underexplored or emerging social phenomena, where individual meaning-making, context, and situated interpretation are central. By utilizing a multi-site design across the Visegrad Group (V4) countries, this study moves beyond single-institution case studies to capture a broader regional perspective. The FG method allows researchers to develop an understanding about why people feel the way they do [58]. FG interviews are especially valuable when exploring topics that involve collective sense-making, contested views, or ethical ambiguity as is often the case with AI in education.

The methodology was designed to gather in-depth insights into participants' understanding, attitudes, and practical engagement with GenAI tools within diverse academic and national contexts. This approach aligns with a naturalistic ethos, seeking to understand social phenomena from the perspective of those being studied. The research is rooted in an interpretive paradigm, which seeks to understand and interpret social reality through the meanings and perspectives of individuals. Rather than aiming for objective measurement or statistical generalization, the study prioritized analytic generalization and transferability by providing rich, contextual understanding of student experiences. This qualitative inquiry focuses on answering "how" and "why" questions to achieve a clear picture of complex social processes.

A FG interview is an unstructured, free-flowing, laid-back, group interview that helps researchers define problems, reveal subconscious motivations for behaviours, and explore the research topic [59]. It usually consists of 6–12 people whose discussion is chaired by one trained moderator by means of a non-structured discussion which usually lasts 90 to 120 min. The research applied FG with an exploratory focus, emphasising the participants' experiences. This study was conducted by an international university research team, which adheres to the ethical principles set by the university's ethics committee. The research has received ethical approval from the coordinator's university [V12/2024].

Participants and recruitment

A total of 24 face-to-face FGs were carried out in April 2024 across four universities in the Visegrad Group (Czech Republic, Slovakia, Poland and Hungary) involving 225 students. To ensure a diverse sample, recruitment of students utilized a multi-channel approach consistent with the local practices of each institution, including announcements in Learning Management Systems (LMS), in-class notifications by instructors, and faculty-wide email lists. Participation was entirely voluntary, and no financial incentives or course credits were offered, ensuring that attendees were intrinsically motivated to share their experiences. A purposive sampling strategy was employed with specific inclusion criteria: participants were required to be currently enrolled students and to self-identify as having had at least some prior engagement (ranging from initial trials to regular use) with generative AI tools. While the broad reach of the recruitment announcements precludes the calculation of an exact response rate, the process was designed to meet a pre-determined quota set by the international research team. To maximize the diversity of perspectives and ensure a broad understanding of user experiences our sampling strategy was aiming for variance in participants' GenAI experience, age, gender, and study year. This approach, while not seeking statistical representativeness, aimed to gather diverse insights into the "user" perspective and support theoretical sampling by identifying different types of experiences or people. This reflects a maximum variation sampling approach aimed at capturing diverse engagement patterns across demographic and disciplinary profiles [60]. The final sample consisted of students from diverse study programs within the fields of business, management, and education. The choice of disciplinary background is appropriate since these programs usually rely on writing-intensive tasks, ethical integrity debates and professional identity questions that makes GenAI adoption a complex question. Table 1 provides a detailed breakdown of the focus groups by country and institution.

Additionally, a summary of the aggregate demographics across the full sample is provided in Table 2.

Data collection

To ensure consistency of implementation across the four national teams, a rigorous standardization process was followed. The FG protocol

Table 2
Aggregate sample characteristics.

Category	Sub-category	N	%
Gender	Female	170	75.6%
	Male	55	24.4%
Country	Czech Republic	116	51.6%
	Hungary	24	10.7%
	Slovakia	37	16.4%
	Poland	48	21.3%
Disciplines	Education (including pedagogy, psychology, teacher education)	115	51.1%
	Business and management (including international economics and development)	100	44.4%
	Other (engineering)	10	4.4%
Level of study	Bachelors	68	30.2%
	Masters	157	69.8%
Total participants		225	100%

Table 1
Characteristics of the conducted FG interviews and participants.

Country/ university	Focus group	Participants	Gender breakdown	Background
CZECH REPUBLIC				
University 1	FG1	8	1 male, 7 females	Business Economics and Management (Ing.)
	FG2	12	5 males, 7 females	
	FG3	8	1 male, 7 females	
	FG4	12	1 male, 11 females	
	FG5	8	2 males, 6 females	
	FG6	10	4 males, 6 females	
	FG7	12	1 male, 11 females	Faculty of Education
	FG8	10	10 females	
	FG9	12	7 males, 5 females	
	FG10	10	2 males, 8 females	
University 2	FG11	7	1 male, 6 females	Business Economics and Management (Ing.)
	FG12	7	3 males, 4 females	
CZ SUMMARY	**12 FGs**	**116 students**	**28 males, 88 females**	
HUNGARY				
	FG1	5	1 male, 4 females	Educational sciences MA (international students)
	FG2	9	2 males, 7 females	Various disciplines (psychology, special needs education, leadership and management)
	FG3	4	1 male, 3 females	Pedagogy BA
	FG4	6	6 females	Teacher education
HU SUMMARY	**4 FGs**	**24 students**	**4 males, 20 females**	
SLOVAKIA				
	FG1	11	5 males, 6 females	International Economics and Development (Ing.)
	FG2	10	10 males	Faculty of Engineering (Bc.)
	FG3	8	8 females	Business Management (Bc.)
	FG4	8	8 males	Business Management (Ing.)
SK SUMMARY	**4 FGs**	**37 students**	**23 males, 14 females**	
POLAND				
	FG1	8	8 females	Educational sciences MA + BA
	FG2	17	17 females	
	FG3	9	9 females	
	FG4	14	14 females	
PL SUMMARY	**4 FGs**	**48 students**	**48 females**	
TOTAL SAMPLE	**24 FGs**	**225 students**	**55 males, 170 females**	

and guiding questions were co-developed by the partners during international planning meetings in November 2024. Following a pilot FG conducted by the Czech team in December 2024, the experiences were reviewed in a joint meeting, leading to the refinement of the protocol at an international meeting in March 2025. All moderators utilized a standardized guide and a common note-taking template to ensure comparability of data. The FG discussions were captured through detailed note-taking by the moderator using this common template, emphasizing key takeaways and representative quotes, rather than verbatim recordings or transcripts. Moderators captured notes in their native languages to ensure a natural, immediate and rich description of participant insights. While verbatim transcription is common, the use of detailed field notes is a recognized and pragmatic strategy in multilingual qualitative research. While this approach limits deeper textual interpretation, likely missing micro-interactional cues (e.g. who responds to whom, interruptions, silences), it aligns with pragmatic constraints of international data collection and prioritizes shared thematic interpretation across linguistic contexts [61,62]. This approach minimizes the significant error and nuance loss associated with translating full transcripts and allows researchers to focus on shared thematic patterns rather than linguistic idiosyncrasies [63,64]. Consequently, no contextual notes (other than participants study programmes and gender) were formally recorded by the moderators during the sessions. All FGs were conducted in the local language of each country, and the resulting native language summaries were subsequently translated into English for collaborative analysis. In order to maintain conceptual equivalence, the translation process prioritized semantic equivalence over literal word-for-word translation. Ambiguities were reviewed and resolved during international team meetings to ensure that the English terminology reflected the original situated meanings [65].

The semi-structured discussion guide focused on three core areas:

- Sub-topic 1: Current Experiences with GenAI Tools
  - Q1: What are your (current) experiences with using GenAI tools?
  - Q2: Which GenAI tools are you most likely to use in the future?
  - Q3: Are there any barriers to using GenAI tools (in general)?
- Sub-topic 2: GenAI Implementation at University
  - Q4: What do you think about the implementation of GenAI at your university?
  - Q5: What is your perceived level of knowledge and competence in using GenAI tools for study purposes?
- Sub-topic 3: GenAI and Future Career
  - Q6: What do you think about GenAI and your future career?

Data analysis

The qualitative data analysis drew general inspiration from the Framework Method, which is "aptly suited for applied policy research" and allows for systematic treatment of data [62,66]. To ensure rigour and consistency, the primary analysis was led by the first author, with iterative validation by the broader research team. The analysis process involved four key stages, broadly aligning with the Framework Method's principles of sifting, charting, and sorting material according to key issues and themes:

1. **Familiarization**: Researchers immersed themselves in the collected FG summaries, gaining an overview of the breadth and diversity of the data. This allowed for identification of key ideas and recurrent themes.
2. **Inductive coding**: The first author performed inductive "open coding" to identify initial concepts and categories directly emerging from the data. This process generated a "skeleton" of the notes, classifying data systematically for comparison. These initial codes were discussed and refined in consultation with the international research team to ensure cross-cultural validity.
3. **Axial coding**: Following the refinement of codes, the first author organized them around the initial research questions. Codes were combined to explore emerging themes and identify broader patterns by comparing and contrasting data both within and between the Visegrad countries.
4. **Interpretation**: The organized themes were then mapped onto the UTAUT2 framework. Critically, this stage involved not only confirming UTAUT2 constructs but also identifying "outlier" themes that extended or challenged the model. Findings were validated through internal checks among the broader research group (peer debriefing), where regular international face-to-face project meetings and online meetings were held to discuss coding discrepancies and refine the thematic structure. Consistent with an interpretive paradigm, the team prioritized qualitative consensus through these dialogic checks.

A visual schematic of this analytic process is provided in Fig. 1. The full coding tree is available in Appendix 1, and the detailed focus group protocol is available from the corresponding author upon request. No specialized software was utilized for the analysis. The process relied on manual review and thematic organisation to maintain closeness to the data.

Results

Overview of findings

The familiarization process revealed multiple perspectives related to the sub-topics discussed in the FG interviews. Related to students' current experiences with using GenAI, codes for purpose of use were identified, where we distinguished between academic use (e.g. summarizing texts/articles) and personal use (e.g. meal planning). Related to use of GenAI further attitudes and sentiments were also identified (e.g. mistrust). We further specified use cases regarding the second subtopics based on examples mentioned during the interviews. The most commonly mentioned tool was ChatGPT. Students listed a set of benefits and challenges regarding GenAI use which were coded in a diverse set of categories. Respondents were also vocal about implementation of GenAI at their university and regarding their future career, from which two separate set of codes emerged. Finally, students' self-perception regarding their AI competencies were covered in broad topics like ethical considerations (e.g. academic integrity), impact on learning (e.g. reducing critical thinking) and self-perceived competence (e.g. difficulty with prompting).

The inductive analysis of focus group discussions across the four Visegrad universities revealed a complex landscape of student engagement with Generative AI (GenAI). While local institutional contexts varied, the core patterns of use and perception were consistent across the national datasets, suggesting shared regional experiences rather than distinct national divergences. Seven central themes emerged from the data:

1) GenAI tool adoption and utility;
2) Concerns regarding GenAI output and reliability;
3) User skill and engagement;
4) Ethical dilemmas and human element;
5) Impact on cognitive engagement and learning;
6) The university's role in GenAI integration; and
7) GenAI's double-edged sword for future careers.

There were 5 to 13 codes generated for each question, meaning altogether 100 inductive codes. The full structure of the inductive codes with comprehensive illustrative quotes is presented in Appendix 1 organized around the interview questions. Table 3 provides a summary of these themes with representative codes and illustrative quotes. The narrative results will be presented using these themes.

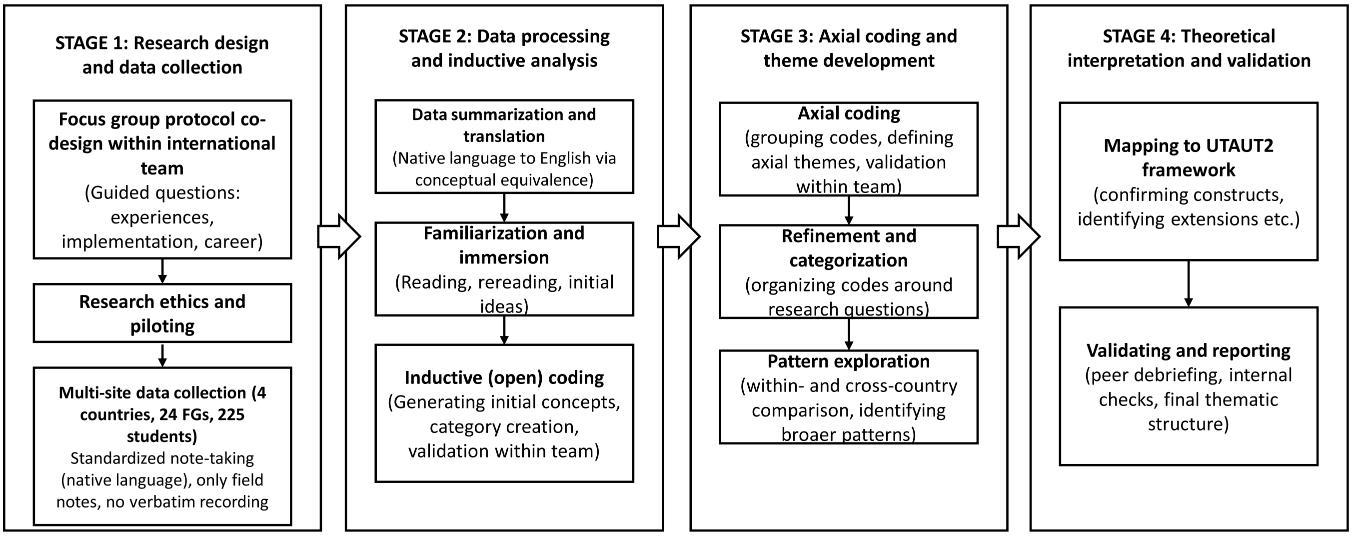

Fig. 1. Visual schematic of the research process.

Table 3
Summary of axial codes and their contributing inductive codes.

Axial code	Representative Inductive Codes (Selected)	Illustrative quote
Theme 1: GenAI Tool Adoption and Utility	**Use**: Text Editing/ Rephrasing, Summarizing Texts/Articles etc. **Tool**: ChatGPT, Perplexity, etc.	"I planned a hiking trip with ChatGPT and it saved me tons of time and helped coordinate with others."
Theme 2: Concerns Regarding GenAI Output and Reliability	**Barrier**: Accuracy/ Correctness Concerns, Need for Verification/Double-Checking etc.	"I asked it for sources and it gave me made-up citations."
Theme 3: User Skill and Engagement	**Barrier**: Prompting Skill Requirement **Competence**: Self-Taught/ Learned Through Practice etc.	"We figure everything out on our own, no one taught us how to actually write good prompts."
Theme 4: Ethical Dilemmas and the Human Element	**Ethical**: Dehumanization/ Loss of Human Element etc. **Attitude**: Psychological Barrier/Feels like Cheating etc.	"Using AI for creative tasks feels unethical, it takes away the human element and makes it feel manufactured."
Theme 5: Impact on Cognitive Engagement and Learning	**Impact**: Stifling Creativity, Reducing Critical Thinking etc.	"People stop thinking for themselves, ChatGPT answers everything straight away."
Theme 6: The University's Role in GenAI Integration	**University**: Desire for Clear Policies/Guidelines, Need for Training/Workshops, etc.	"Universities must adapt… banning AI is unrealistic. What we need are clear guidelines."
Theme 7: GenAI's Double-Edged Sword for Future Careers	**Future**: AI as Essential Skill, Concern about Job Displacement, etc.	"Some repetitive jobs might be replaced, but not jobs requiring creativity or empathy."

Theme 1: GenAI tool adoption and utility

Students in the Visegrad country universities have widely adopted GenAI tools, transitioning from viewing them as novelties to treating them as essential, pragmatic instruments for academic and personal efficiency. Inductive codes like "text editing," "summarizing articles," "idea generation," and "lesson planning" illustrate the breadth of academic use. While personal use ranged from "meal planning," to "travel coordination," and "casual conversation". These uses clustered around the axial theme of „GenAI tool adoption and utility."

This pragmatic stance was underpinned by a discourse of efficiency: students described AI as saving time, breaking cognitive deadlocks, and compensating for academic fatigue. *"It's like having a 24/7 assistant for my writing,"* one student reflected, while another explained, *"I planned a hiking trip with ChatGPT, it saved me tons of time and helped coordinate with others."* Efficiency was sometimes framed as a more utilitarian approach, representing unproblematic efficiency, particularly among students who prioritized time management over pedagogical concerns. As one student enthusiastically noted: *"If I have little time… I always turn to AI. It is fast, efficient… I feel day by day AI knowledge is stronger, often seems more reliable than my own fact-check."* The preference for free versions (*"I use the free version every day")* reveals both the tool's accessibility and an underlying tension: free access enables use, but limited features and reliability (explored below) restrict its full potential.

However, for the majority, this adoption is tactical rather than blind. GenAI is used when it works and discarded when it fails. This instrumental rationality frames much of the student-GenAI interaction, anchoring the broader narrative of negotiated trust where utility often competes with the reliability concerns discussed below.

Theme 2: concerns regarding GenAI output and reliability

Despite high usage rates, students frequently expressed a distinct "epistemic vigilance," [67] treating GenAI outputs with skepticism due to frequent inaccuracies. Inductive codes included "accuracy concerns," "hallucinations," and "double-checking," which formed the axial theme „Concerns regarding GenAI output and reliability". The participants' epistemic stance toward GenAI could be characterized as strategic caution. This theme highlights that acceptance in the Visegrad context is not passive but highly conditional.

Students described themselves as fact-checkers of their own tools. *"Sometimes I ask it what a document says, but I always have to double-check,"* one student noted. This was not merely anecdotal. Participants systematically described the need to triangulate GenAI output, especially in high-stakes academic tasks. *"I asked it for sources and it gave me made-up citations,"* one recalled. In certain fields, students encountered deeper mistrust: "*The values it produces are completely wrong for calculations."*

These accounts reflect a shift from blind trust to conditional acceptance, suggesting students are engaging in a form of "epistemic labour" by continuously verifying the machine's authority. GenAI is treated not as a knowledge authority but as a conversational partner whose outputs are scrutinized. This ongoing negotiation of trust suggests that student-AI interaction is not passive but cognitively engaged, albeit labour-intensive.

Theme 3: user skill and engagement

Participants repeatedly emphasized that the "digital divide" in the GenAI era is defined by prompting literacy, a skill set they felt was largely self-taught and unequally distributed. Inductive codes such as "self-taught use," "difficulty prompting," and "awareness of knowledge gaps" converged on the axial theme „User skill and engagement“.

"We figure everything out on our own," one student explained, capturing the recurring narrative of self-reliant trial-and-error learning. Another added, *"Effective use really depends on how you prompt, and many people don't know how to do that effectively."* The problem is not just skill but metacognition: students know they are underperforming. *"I know I'm just scratching the surface. I use it for basics, but I don't really know what it can do."*

Ironically, while AI offers knowledge support, its effectiveness is capped by the user's ability to interface with it. Prompting, in this sense, becomes a literacy of power. Those who master it access deeper utility, those who don't remain at the surface. Without institutional scaffolding, these skill disparities may entrench digital inequalities. This theme points to a critical pedagogical gap: while universities provide access or policies, they rarely provide the "engineering" skills required for effective use, leaving students to navigate these tools through informal peer networks.

Theme 4: ethical dilemmas and human element

Beyond functional concerns, students articulated deep ethical ambivalence, often experiencing a dissonance between the efficiency of GenAI and the perceived loss of human authorship. Inductive codes such as "feels like cheating," "loss of human element," "privacy concerns," and "potential for misuse" form the axial theme „Ethical dilemmas and the human element“.

Many students experienced a dissonance between the efficiency offered by GenAI and the moral discomfort it generates. As one participant shared, *"Inputting thesis content into AI makes me nervous, it's a privacy risk."* Others feared moral dilution: *"Using AI for creative tasks feels unethical. It takes away the human element and makes it feel manufactured."* However, voices were not uniform. Some students adopted a more pragmatic, consequentialist ethics, focusing on the result rather than the process. Yet, the dominant sentiment remained one of caution regarding identity and creativity.

Some saw AI's capability as dangerously seductive: *"It's scary how it can generate anything, even fake news. That could be really harmful."* The discourse shifted here from personal utility to social responsibility, where unchecked GenAI use risks normalizing deception, plagiarism, and loss of authorship integrity.

Theme 5: impact on cognitive engagement and learning

Closely linked to ethical concerns were profound fears about "deskilling," with students worrying that reliance on GenAI might erode their critical thinking and writing capabilities. Inductive codes such as "superficial engagement," "loss of creativity," and "over-reliance" produced the axial theme „Impact on cognitive engagement and learning“.

Students feared that GenAI, while helpful, might paradoxically deskill them. This anxiety was articulated clearly by a student who observed: *"Simply put, people don't learn to write serious texts on their own… [GenAI] saves energy, but often one doesn't master skills one should… like forming sentences or using concepts."* Another one explained, *"I don't use AI much because I feel it kills my creativity. I prefer to think and write on my own."* Another warned, *"People stop thinking for themselves, ChatGPT answers everything straight away."*

There was a sense of impending homogenization: *"If everyone uses the same tool, we'll all sound the same."* Students worried about becoming passive consumers rather than active constructors of knowledge. These insights add a critical layer to the adoption narrative: AI may help students do, but it may also weaken their capacity to learn. This theme reveals that for many students, "Ease of Use" (a UTAUT2 construct) is not always a positive. When it leads to cognitive disengagement, it can become a source of anxiety.

Theme 6: the university's role in GenAI integration

Students repeatedly voiced frustration about their universities' passive or fragmented response to AI integration, viewing the lack of clear guidance as a failure of institutional legitimacy. Inductive codes like "lack of clear policy," "inconsistent instructor approaches," and "need for training" informed the axial theme „The university's role in GenAI integration“.

"Universities must adapt. Banning GenAI is unrealistic," one participant argued. Others shared that they were *"just left to explore on [their] own,"* which resulted in unequal practices and ethical uncertainty. The call was not just for regulation but pedagogy: *"Train students in prompt engineering, nobody knows how to do this properly."*

This perceived institutional silence forces students to operate in a "grey zone," where the rules of engagement are undefined. It left them exposed to ethical ambiguity, unequal skill development, and performance anxieties. The lack of institutional guidelines, in this case, functions as both omission and complicity, exacerbating student uncertainty.

Theme 7: GenAI's double-edged sword for future careers

Finally, regarding their professional futures, students expressed a dualistic vision where GenAI is perceived simultaneously as a mandatory survival skill and a threat to job security. Inductive codes like "GenAI as essential skill," "job displacement," and "human skills irreplaceable" formed the axial theme „GenAI's double-edged sword for future careers“.

"In the future, AI skills will be just as expected as knowing another language," one student asserted. Others described real-world pressures: *"Job ads are already asking for it."* This aligns with the study's objective to map career perceptions: students view GenAI competence as a new form of "career capital." Yet, this enthusiasm was undercut by displacement anxiety: *"Some repetitive jobs might be replaced, but not jobs requiring creativity or empathy."*

Students framed AI as both opportunity and threat. They anticipated needing to upskill but worried about being replaced or reduced. As one said, *"Understanding how GenAI works is now just as important as knowing how to use Word or Excel."* In the Visegrad context, where the labour market is rapidly digitizing, students view adaptation not as a choice but as a necessity for professional survival.

These seven themes illustrate students' nuanced and often ambivalent engagement with GenAI across academic, ethical, institutional, and career-related domains. The following discussion interprets these findings through both the UTAUT2 framework and its theoretical limitations.

Discussion

The integration of GenAI tools into education presents a nuanced picture of both promise and concern. Our findings reveal a landscape characterized by "conditional adoption," where high usage rates coexist with deep epistemic scepticism and ethical ambivalence. Students widely acknowledge the utility of GenAI in personalizing content and delivering timely feedback aligning with findings from Escotet [68], Marques-Cobeta [69], and Rebelo [70]. However, this study moves beyond basic acceptance to highlight that for GenAI in higher education, the core challenges are not technical but epistemic and institutional.

To interpret these findings systematically, the following discussion is organized into three sections corresponding to the study's objectives. First, we provide an integrated analysis of students' learning experiences and theoretical contributions. In this section, we examine how specific learning practices (addressing Objective 1). necessitate nuanced extensions to the core UTAUT2 constructs (addressing Objectives 2 & 3). Second, we discuss the impact of GenAI on career imaginaries within the Visegrad context (Objective 4). Finally, we outline concrete implications for university policy and practice.

Revisiting and extending the UTAUT2 framework

Addressing the second and third objectives of this study (to map student experiences onto UTAUT2 and identify necessary extensions), our findings demonstrate that while the UTAUT2 provides a useful baseline, it is insufficient to fully capture the complexity of student engagement with GenAI.

As illustrated in Fig. 2, our data confirms the relevance of functional drivers (Performance and Effort Expectancy) as students consistently valued AI for enhancing productivity and expediting writing processes, aligning with prior research [33,35]. However, the contextual drivers (Social Influence and Facilitating Conditions) require significant theoretical expansion to account for the unique ethical and cognitive landscape of GenAI. Consistent with prior studies on academic AI use [7,8], the peripheral UTAUT2 constructs (Price Value, Hedonic Motivation, and Habit) appeared less pronounced. Adoption was driven predominantly by functional and ethical considerations rather than cost or novelty, and behavioural patterns remained in flux [71]. Consequently, our theoretical focus centers on the four primary drivers where the most significant structural shifts occurred. These shifts are supported by recent empirical studies, which report anomalies when applying standard UTAUT2 for GenAI. For example, facilitating conditions exhibited a paradoxically negative influence in both Saudi Arabia [36] and Russia [39], while hedonic motivation was found not significant predictor among Jordanian students [38]. These inconsistencies suggest that GenAI adoption is mediated by localized epistemic and institutional cultures, requiring the deeper qualitative considerations provided by our V4 sample.

Performance expectancy, defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance, was clearly evident in the data, corresponding directly to Theme 1 (AI tool adoption and utility). As supported by Chan and Hu [72], students consistently valued AI for enhancing productivity, expediting writing processes, and managing both academic tasks and personal life more efficiently. This aligns with prior research indicating performance expectancy as a primary driver of technology adoption in educational contexts [3,33,35]. However, this utility was not unproblematic. A critical "paradox of efficiency" emerged in Theme 5 (Impact on cognitive engagement). While students acknowledged the pragmatic benefits of offloading tasks (aligning with Escotet [68] and Rebelo [70]), they simultaneously voiced a meta-cognitive anxiety that this offloading might lead to "deskilling" [73]. This indicates that Performance Expectancy is filtered through pedagogical values: students are not just assessing if the tool works, but whether it harms their intellectual development [74]. Furthermore, as seen in Theme 2 (Concerns regarding AI output), perceived utility was invariably conditional on verification. This suggests that in GenAI contexts, PE might be more accurately understood as **Contingent Performance Trust (CPT).** This reframing could explain the “disconfirmation effect” observed by Raffaghelli et al. [75] where high initial PE predicted lower post-usage acceptance as students encountered the tool actual limitations. Furthermore, based on Aldreabi et al.’s (2025) finding, where “information accuracy” did not significantly predict adoption intentions could signal epistemic naivety (students adopt tools without critically evaluating outputs). CPT addresses this by positioning active verification as a necessary threshold for perceived utility. This redefined construct

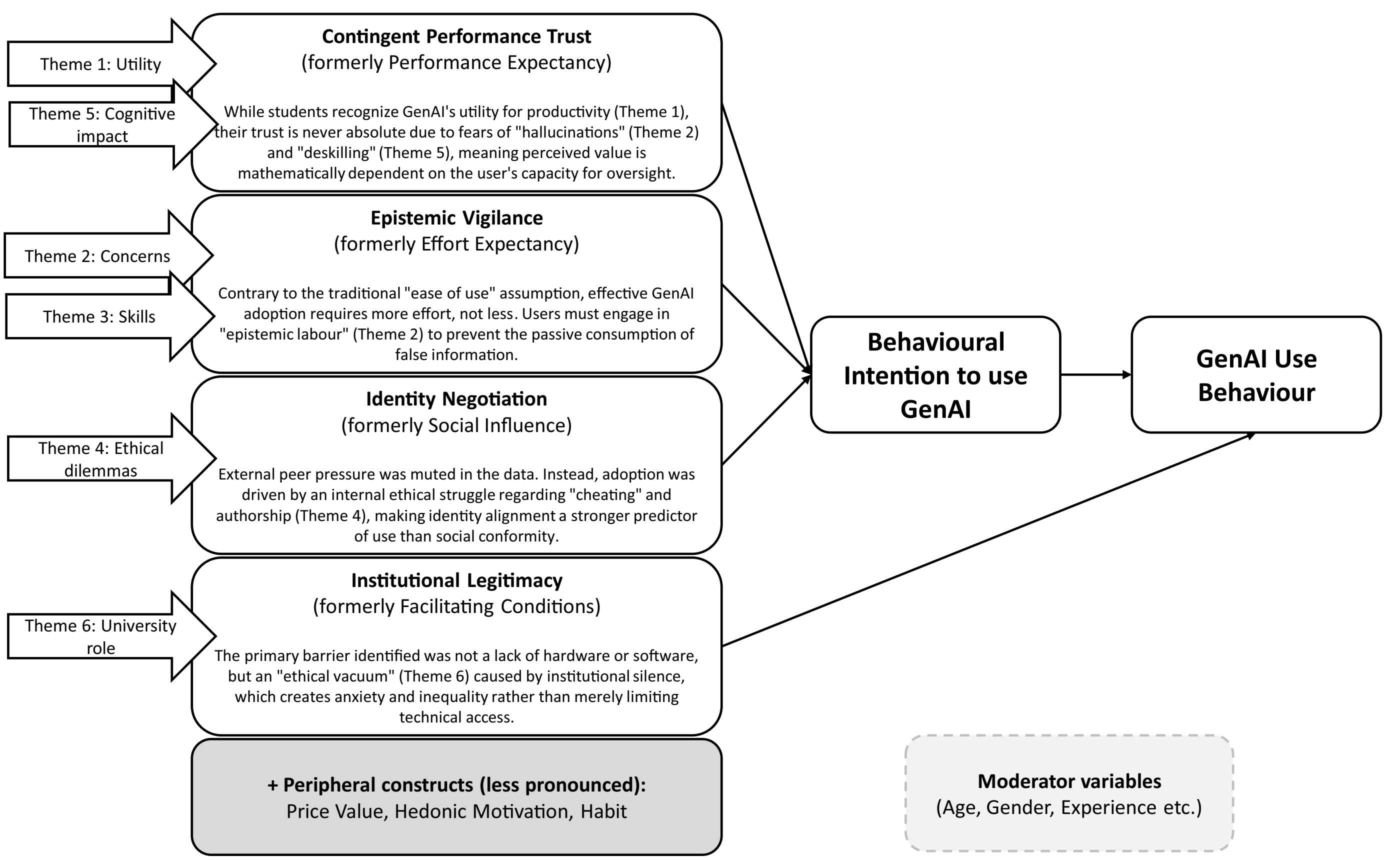

Fig. 2. Redefined UTAUT2 model for GenAI engagement in higher education. (Note: Moderator variables (e.g. age, gender, experience) are considered, but not the primary focus of this qualitative extension).

captures that in GenAI adoption, perceived usefulness is mediated by the user's active oversight and trust in their own ability to validate the machine's output. We propose the following definition: *The degree to which a user believes that using GenAI will enhance academic performance, contingent upon their active verification of its output and trust in their own ability to detect inaccuracies.*

Traditionally, Effort expectancy focuses on "ease of use," assuming that lower effort leads to higher adoption [76]. Our findings challenge this premise. As detailed in Theme 3 (User skill and engagement), while the chat interface is technically "easy," effective use requires significant "prompting literacy" As noted in the theoretical background, prompt literacy and AI self-efficacy are emerging as critical differentiators of student experience [8,18]. In this study, prompt literacy emerged as an unforeseen yet significant barrier and a source of potential skill disparity among students. More critically, the "effort" required for successful GenAI use is not just technical but cognitive. As highlighted in Theme 2 (Concerns regarding GenAI output and reliability), students who engaged in active "epistemic labour" (fact-checking, triangulating, and correcting hallucinations) reported a deeper understanding of content. Conversely, those who sought to minimize effort ("passive consumption") reported superficial engagement and anxiety. Therefore, we propose transforming this construct into **Epistemic Vigilance (EV)**. This extension argues that for GenAI, the "effort" construct must measure the user's willingness to engage in the rigorous verification work (or "vigilance") required to transform raw AI output into valid learning outcomes. We propose the following definition: *The degree of cognitive effort and "prompting literacy" a user is willing to invest in rigorously fact-checking, triangulating, and refining GenAI outputs to ensure epistemic validity*. To establish conceptual boundaries distinguishing EV from CPT (as both concern conditions under which outputs become usable knowledge) we should consider the two concepts as sequential phases of engagement rather than overlapping states where CPT precedes and enables EV. CPT functions as a threshold judgement (students' belief that GenAI output is worth engaging at all), while EV focuses on the ongoing cognitive process of executing that verification labour.

Some UTAUT2 constructs were found to be minimally supported or notably absent in this specific context. Facilitating conditions (defined as the availability of resources and support) were largely undeveloped, a gap explicitly highlighted in Theme 6 (The university's role in AI integration). Most institutions lacked clear policies, formal training initiatives, or consistent instructional frameworks. While UTAUT2 presupposes a basic level of enabling infrastructure, our findings demonstrate that this institutional vacuum itself constituted a structural barrier, inadvertently fostering anxiety, inequity in access, and an ethical drift among students. This aligns with the claim that institutional ambiguity plays a decisive role in student hesitancy [4,17]. We propose shifting this construct to **Institutional Legitimacy (IL).** We can distinguish two underlying subcomponents: 1) normative permission (unambiguous, task-specific rules regarding what AI use is permissible or prohibited) and 2) pedagogical scaffolding (active provision of training, exemplars, and assessment redesign that integrates AI skills into the curriculum). While our participants experienced the absence of both aspects, analytically they are distinct. An institution may provide policy guidance (permission) without providing necessary training (scaffolding) or vica versa (Theme 3 – User skill and engagement). This extension highlights that students require ethical permission and normative clarity just as much as they require technical infrastructure and training [4]. We propose the following definition: *The degree to which a user perceives that the institution provides both normative permission (clear rules, ethical guidelines), and pedagogical scaffolding (training and assessment integration) that legitimize the use of GenAI.*

In the standard model, Social Influence is often interpreted as external peer pressure or faculty recommendation. It also conflates positive peer pressure with epistemic resistance, failing to capture student concerns regarding the dehumanisation of learning and the erosion of critical thinking [49]. Our data suggests this was muted. Instead, the primary social pressure was internal. There was little evidence of strong normative peer pressure or consistent modeled behavior from authority figures. Instead, students largely navigated AI adoption independently or within fragmented social cues. This divergence from UTAUT2 assumptions may be characteristic of the early, decentralized stage of GenAI adoption, where institutional culture has yet to establish clear normative expectations. Yusuf et al. [77] further demonstrate that GenAI adoption is heavily entangled with moral disengagement and academic misconduct. We propose transforming this construct into **Identity Negotiation (IN).** As seen in Theme 4 (Ethical dilemmas and human element), participants' experiences were deeply intertwined with affective dimensions (guilt, mistrust, and alienation) [41,52]. The pervasive sentiment of "it feels like cheating" represents a form of epistemic ambivalence [42]. The decision to use GenAI is filtered through the student's self-concept: they must negotiate the efficiency of the tool against their identity as an honest learner and an original author [30,78]. This internal value conflict seems to be a far stronger regulator of behavior than external norms. Our data suggests that this negotiation operates as a state-like construct which is activated situationally depending on task stakes (e.g., discomfort was higher in "production" tasks than in "ideation"). By redefining this construct as IN, we capture the internal ethical-epistemic struggle and effectively integrate Perceived Ethics (as suggested by [48]) into AI adoption frameworks. Future scale development should operationalise IN as context-specific, allowing for pedagogical design to modulate this ethical reasoning rather than treating it as a fixed trait. We propose the following definition: *The extent to which a user's decision to adopt GenAI is regulated by an internal negotiation between the pragmatic benefits of the tool and their self-concept as an honest, original learner.*

Price value, Hedonic motivation, and Habit appeared marginally. Adoption was driven more by functional relevance than by entertainment or novelty, consistent with prior studies on academic AI use [7,8]. The lack of habitual use suggests that behavioral patterns are still in flux, similar to cases reported by Oliveira et al. [71].

The following Table 4 summarises the proposed extended interpretation of UTAUT2 constructs compared to their original definitions.

Our theoretical extensions serve to deepen the nomological net surrounding GenAI adoption which moves beyond measurement of behavioral frequency to cognitive and ethical engagement. Recent validation efforts like Trejo-Trejo and Gordillo-Espinoza [54] have successfully mapped the forms of academic use (e.g., integral academic use, creation and editing) and their barriers (e.g., ethical use, dependence). Our findings are complementary as it operationalise the conditional mechanisms that governs these behaviors. While Trejo-Trejo and Gordillo-Espinoza [54] quantifies what students do, our proposed constructs explain under what conditions they choose to do it. This frameworks is also different from existing attitudes scales (e.g., AIAS-4) which usually measure general affective orientation as our constructs are orthogonal to these dispositions. We propose to measure the process of epistemic and ethical engagement, rather than the attitude towards the technology. Our study offers a theoretical infrastructure for future measurement tools.

Career futures and labour-market imaginaries

With regard to the fourth objective (analysing how AI usage shapes perceptions of future career trajectories) our findings in Theme 7 reveal that GenAI serves as a powerful "career imaginary" for students in the Visegrad region. Reflecting future-oriented attitudes found in broader literature [23,26], students view GenAI competence as a mandatory survival skill.

The Double-Edged Sword Student perspectives on AI's job-related impacts were distinctly dual. Optimistically, participants viewed AI as creating new roles and demanding new hybrid skills [79]. Yet, contrasting this optimism was a pervasive fear of job displacement, particularly in intellectual and traditional fields. This reflects the tension

Table 4
Comparison of original UTAUT2 constructs and proposed GenAI extensions.

UTAUT2 original construct (based on Venkatesh et al. [35])	Proposed extension	Mechanism of extension	Example student quotes
Performance Expectancy (PE): The degree to which an individual believes that using the system will help him or her to attain gains in job performance	**Contingent Performance Trust (CPT):** The degree to which a user believes that using GenAI will enhance academic performance, contingent upon their active verification of its output and trust in their own ability to detect inaccuracies.	Conditional Utility: Shifts from viewing utility as an absolute gain to a conditional one. Usefulness is mediated by the user's active oversight and the "threshold judgment" that they possess the skills to validate the machine's output.	*"Sometimes I ask it what a document says, but I always have to double-check."*
Effort Expectancy (EE): The degree of ease associated with the use of the system.	**Epistemic Vigilance (EV):** The degree of cognitive effort and "prompting literacy" a user is willing to invest in rigorously fact-checking, triangulating, and refining GenAI outputs to ensure epistemic validity.	Cognitive labor vs. technical ease: Effective GenAI use requires increased cognitive effort (epistemic labor). It measures the willingness to perform rigorous verification rather than just the technical ease of the interface.	*"Effective use really depends on how you prompt, and many people don't know how to do that effectively."*
Social Influence (SI): The degree to which an individual perceives that important others believe he or she should use the new system.	**Identity Negotiation (IN):** The extent to which a user's decision to adopt GenAI is regulated by an internal negotiation between the pragmatic benefits of the tool and their self-concept as an honest, original learner.	Internal vs. external regulation: Moves from external peer/authority pressure (which was muted) to an internal value conflict. Adoption is regulated by the struggle to reconcile tool efficiency with the student's identity as an authentic learner (e.g., navigating feelings of guilt).	*"Using AI for creative tasks feels unethical, it takes away the human element and makes it feel manufactured."*
Facilitating Conditions (FC): The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system.	**Institutional Legitimacy (IL):** The degree to which a user perceives that the institution provides both normative permission (clear rules, ethical guidelines), and pedagogical scaffolding (training and assessment integration) that legitimize the use of GenAI..	Normative sanctioning vs. infrastructure: Shifts focus from physical resources to ethical permission. The barrier is not a lack of tools, but a lack of "normative clarity." Students require institutional scaffolding to feel "authorized" and confident in using the technology ethically.	*"Universities must adapt... banning AI is unrealistic. What we need are clear guidelines."*

highlighted in the literature between automation threats and the rise of new professional competencies [21,24]. Consequently, adoption is often driven by a defensive necessity: students recognize the crucial need to develop future skills not because they trust the technology, but to remain competitive in an AI-driven economy.

Regional context: visegrad nuances

Although this study did not adopt a systematic comparative cross-country design, the qualitative data revealed notable divergences in how this "career anxiety" was framed across the Visegrad sample, enriching the broad claims of Theme 7:

- Pragmatic Efficiency (Czechia & Slovakia): Czech and Slovak participants tended to approach AI use in a highly pragmatic manner, focusing on efficiency, task completion, and time-saving. Their career discourse centered on the need to acquire AI-related skills to remain competitive. Concerns focused on tool functionality and institutional inaction, with repeated calls for clear guidelines and training.
- Ethical and Existential Reflection (Hungary & Poland): In contrast, students in Hungary and Poland more frequently reflected on the ethical and epistemic implications of AI. Hungarian participants, in particular, raised concerns about authorship and data security, framing AI use in relation to broader questions of integrity and identity. Polish students, especially those in education programs, emphasized the human dimension of teaching and learning, expressing mixed feelings about the growing role of automation in knowledge work.

These contrasts reflect contextual texture emerging from a non-comparative qualitative design, rather than systematic claims about national academic cultures. While Czech and Slovak students focused on competitiveness, some Hungarian participants expressed deeper anxiety about displacement and a perceived lack of institutional preparation. These tentative observations highlight context-sensitive factors that were previously highlighted as well. For example collective cultures like Saudi Arabia showed dominant influence of SI [36], while digitally mature contexts, like Norway [80] or Poland [81] highlighted the role of habit. The V4 perspectives show a highly instrumental and epistemically anxious form of adoption. Our results reflects that the V4 perspectives show pragmatic efficiency paired with existential reflection showing that post-transition economies could view GenAI less as a socially mandated norm and more as an individualised, high-stakes tool for navigating a digitally transforming labour market. These assumptions would require further systemic investigation in future comparative research to better understand the specific context-sensitive experiences of the Central European region looking beyond global trends [15,82].

Implications for universities

From "Institutional silence" to active scaffolding

Finally, translating these empirical and theoretical insights into practice, we propose concrete strategies for universities to address the gaps identified in our analysis. The findings regarding Theme 6 (The university's role) suggest that the current "laissez-faire" approach of many institutions is untenable. Our analysis supports the claim that institutional ambiguity plays a decisive role in student hesitancy and fragmented engagement [4,17]. The "institutional vacuum" observed in this study (where policies are absent or inconsistent) does not merely reduce access. It constitutes a structural barrier that fosters anxiety and "ethical drift." As argued in our theoretical analysis, institutions are not neutral enablers but co-constructors of AI legitimacy and norms. When universities remain silent, they inadvertently signal that AI use is either illicit or unimportant, forcing students to navigate complex ethical landscapes without guidance.

To counter this, universities must move from being passive observers to active shapers of student trust and competence [16]. We propose three levels to consider which operationalises the two subcomponents of Institutional Legitimacy defined earlier:

- Macro-level (administration): To establish normative permissions, administration must define policies that clearly states what are prohibited and permitted AI use cases. Further support would require institutionally subscribed and endorsed AI tools that offer transparent audit trials for regular policy updates.
- Meso-level (faculty and support services): The main role of this level is to bridge permission and scaffolding. Under this tier universities should consider the creation of faculty playbooks with discipline-specific guidance and peer learning communities. Collaborating with writing centres and libraries are essential to formalize prompt and verification literacy trainings.
- Micro-level (course, instructor): To support pedagogical scaffolding, instructors should redesign their assessment to also capture and reflect on the process of AI use (not just the output). In addition, it should also support the implementation if instructors would establish assignment-level disclosure forms and provide task-specific examples of appropriate and inappropriate AI use.

Addressing all three levels would allow institutions to offer a coherent infrastructure that legitimizes ethical AI engagement.

Developing AI literacy and prompt engineering

Addressing the "prompt literacy gap" identified in Theme 3 (User skill and engagement) requires a shift from restricting access to scaffolding competence. Our findings support arguments that effort expectancy must be contextualized within users' evolving literacies [76]. As noted in the original text, prompt literacy and AI self-efficacy are emerging as critical differentiators of student experience, especially where formal institutional scaffolding is absent [8,18]. Therefore, universities should implement specific "Prompt Engineering and AI Literacy" workshops. These initiatives must go beyond technical mechanics to include epistemic training: teaching students how to verify, critique, and edit AI outputs. This training should be anchored in recognized competency frameworks (e.g. DigComp 3.0 or UNESCO's AI Competency Framework). Specifically, modules focusing on verification, source-tracing, and error-typology recognition would foster Epistemic Vigilance, while those addressing ethical reasoning and authorship attribution would help navigating Identity Negotiation. By formalizing this training, institutions can mitigate the "skill disparity" observed in our sample, where only those self-taught students could access the tool's full potential.

Redesigning assessment and ethical frameworks

Finally, the deep-seated fears regarding "deskilling" (Theme 5) and "cheating" (Theme 4) require a fundamental redesign of assessment and governance. The sentiment of "it feels like cheating" reflects earlier theoretical insights that student discomfort is not simply technological but epistemological and ethical [13,16]. To resolve this value conflict, universities must provide unified guidelines that distinguish between "ideation" (permitted) and "production" (restricted), clarifying the boundaries of integrity. Furthermore, institutions should shift toward process-oriented assessment. Instead of grading final outputs, evaluative frameworks should mandate specific evidences. For example an AI use disclosure and an AI trace (prompt iterations and manual edits) can operationalise Epistemic Vigilance. A verification commentary along with authorship reflection can help scaffold Identity Negotiation. Solutions can focus on the student's ability to critique AI generations, integrate tools into a transparent workflow, and demonstrate cognitive agency. This aligns with the literature emphasizing the importance of socio-technical awareness in shaping student trust [4], ensuring that AI adoption is driven by pedagogical goals rather than mere convenience.

Limitations and future research

While this study offers valuable insights into student engagement with GenAI in the Visegrad region, several limitations should be considered when interpreting the findings.

First, regarding sampling and generalisability, the study relied on a non-probability convenience sample drawn primarily from business, management, and education programs. While the sample reflected the gender and demographic characteristics of these specific faculties and provided robust insights into these specific text-base disciplines, it establishes a clear boundary condition for the study. The findings cannot be transferred to STEM (where verification norms differ), creative arts (where authorship debates take different forms), and health sciences. Exploring these different disciplinary cultures are critical agendas for future research.

Second, a self-selection bias is likely present. Although the focus groups included sceptical voices, students who volunteered were likely more interested in AI, more engaged with university life, or more confident discussing technology than the average student. Consequently, the data may under-represent the perspectives of disengaged, highly anxious, or strictly non-digital students.

Third, regarding data capture, the decision to rely on structured moderator notes rather than audio recordings imposes constraints. While this was a pragmatic necessity for a multi-lingual study, it limits the richness of the analysis; micro-linguistic nuances, specific interactional dynamics, and the exact wording of the original languages were inevitably lost in the summarization and translation process. To mitigate selective salience the team employed immediate post-session debriefs and a structured note-taking template to constrain moderator discretion. While these debriefings provided a check on thematic interpretation, no further inter-coder reliability procedures were applied to the note-taking stage. Acknowledging the potential loss of these micro-interactional aspects or affective and paralinguistic cues, the applied method helped comparability across languages. In addition, translation ads an additional interpretative layer that could reshape meaning. Therefore, the quotes presented are illustrative of thematic meaning and patterns rather than verbatim linguistic data or micro-level discourse.

Fourth, regarding cross-country comparability, although a standardized protocol was strictly followed, differences in moderator styles and national discourses may have influenced the discussions. The analysis prioritized shared regional themes; therefore, observations regarding specific cross-country contrasts should be interpreted as contextual coloration rather than systematic claims about national academic cultures. These distinctions reflect context-sensitive factors rather than established causal differences.

Fifth, the study represents a cross-sectional snapshot in a fast-moving field. Data were collected at a single point in time during a rapidly evolving phase of GenAI adoption. Given the speed of technological updates and policy responses, the specific tools and institutional gaps reported here may quickly change, limiting temporal generalisability.

Sixth, the study relies on self-reported perceptions. We did not triangulate student claims with behavioural data (e.g., actual AI usage logs), teacher perspectives, or analysis of institutional documents. Future research should employ mixed-methods designs to contrast what students say they do with their actual digital behaviours.

Finally, the application of UTAUT2 constitutes a specific, selective interpretive lens. While useful for mapping adoption drivers, alternative theoretical frameworks (such as critical data studies or sociomaterial perspectives) might yield different insights regarding power dynamics, data commodification, or the agency of the algorithm itself.

Future research should address these limitations by employing longitudinal designs to track how "conditional adoption" evolves. Furthermore, expanding the scope to include faculty perspectives and utilizing full-transcript analysis would provide a more holistic view of the educational ecosystem. Building on existing measurement work (e.g., [54]) a next step could be to operationalize the proposed constructs into validated scales measuring depth of verification (Epistemic Vigilance), the situational ethical tension (Identity Negotiation) and the distinct between normative permission and pedagogical scaffolding (Institutional Legitimacy). The proposed instrument would be best implemented as a mixed-methods tool to pair self-reported scores with behavioral data (e.g. AI usage logs) to triangulate perceptions with actual epistemic labor.

Conclusion

This study explored how university students in the Visegrad countries perceive and engage with GenAI tools in their academic and professional trajectories. The findings reveal a nuanced mix of pragmatic adoption, epistemic caution, and ethical ambivalence. By synthesizing these insights, the study offers four distinct contributions to the literature on GenAI in higher education.

Theoretical Contribution: Rather than simply applying UTAUT2, this study used the model as a diagnostic lens to reveal its limitations in the context of GenAI. While constructs such as performance and effort expectancy proved relevant, our analysis demonstrates that student engagement requires extending the model. We propose that Epistemic Vigilance, Identity Negotiation, and Institutional Legitimacy be treated as central constructs in future models. Considering a sociomaterial perspective, this study highlights how AI adoption is not a context-neutral individual choice, but the result of broader assemblages where institutional silence redistributes epistemic risk onto the student. This response aligns with recent calls for more ecologically valid and context-sensitive frameworks (cf [8,83]), shifting the focus from simple utility to cognitive agency and normative alignment.

Methodological Contribution: Distinct from the single-institution case studies common in the field, this research employed a coordinated focus group design across four universities. This approach allowed us to capture a broader range of student perspectives and ensure cross-national consistency in the data. By synthesizing qualitative accounts across borders, the study validates that key challenges (such as the "paradox of efficiency") are structural features of the student experience rather than isolated local phenomena.

Empirical Contribution: Empirically, this is one of the first multi-institution studies to examine student perspectives on GenAI specifically within the Visegrad region. It provides unique regional data that complements the predominantly Western or Asian focus of existing literature. Specifically, it highlights how students in these post-transition economies view GenAI competence as mandatory "career capital" necessary for survival in a digitizing market [84,85].

Practical Contribution: Finally, the study grounds its recommendations for university policy in students' reported tensions. By highlighting the disconnect between rigid institutional policies and actual student practice, we argue that the current "laissez-faire" approach fosters ethical drift. Universities must move from being passive enablers to active shapers of student trust. This requires implementing specific training in prompt literacy, shifting toward process-oriented assessment, and creating ethical guidelines that explicitly address authorship.

As generative AI becomes increasingly integrated into education and work, understanding students' perspectives (not just as users but as active sense-makers) will remain essential for responsible, inclusive, and pedagogically grounded AI implementation in higher education.

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CRediT authorship contribution statement

Laszlo Horvath: Writing – review & editing, Methodology, Formal analysis. **Ludvík Eger:** Writing – original draft, Supervision, Funding acquisition, Data curation, Conceptualization. **Łukasz Tomczyk:** Writing – review & editing, Validation, Data curation. **Łukasz Szwejka:** Writing – review & editing, Validation, Data curation. **Dana Egerová:** Writing – review & editing, Validation, Data curation, Conceptualization. **Lucie Rohlíková:** Writing – review & editing, Validation, Data curation. **Tomáš Kincl:** Writing – review & editing, Validation, Data curation. **Jan Pospíšil:** Writing – review & editing, Validation, Data curation. **Kristína Medeková:** Writing – review & editing, Validation, Data curation. **Petra Mikulcová:** Writing – review & editing, Validation, Data curation. **Jeyran Gasimova:** Writing – review & editing, Validation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.caeo.2026.100357.

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László Horváth, is an economist-andragogue, currently working as an Associate Professor at the Institute of Education, ELTE Eötvös Loránd University. He defended his PhD (2019) in higher education management, focusing on higher education institutions as learning organisations and received his habilitation in 2025. His research interests focus on how educational institutions and teaching professionals adapt and learn in response to digital transformation (especially artificial intelligence). He worked in various national (e.g. postdoctoral research grant focusing on digital transformation in education) and international research, development, and consultancy projects (e.g. supporting the OECD in their study of labour market outcomes of Hungarian doctoral education or exploring quality assurance of digital teaching and learning in Hungarian higher education). He teaches in teacher education and continuous professional development, pedagogy BA, educational sciences MA, and human resources counselling MA programmes focusing on organizational/school development, development of entrepreneurial competencies, educational technology and policy. Currently, he is the coordinator for the educational development and management specialization of the educational sciences MA programme, head of the Digital Transformation in Education Research Group and director of the Illyés Sándor College for Advanced Studies.

Ludvík Eger is Associate Professor at the University of West Bohemia in Pilsen and the author or co-author of a variety of books focused on school management and marketing and ICT in education. His research concentrates on subjects related to research methodology, ICT in education, management and marketing, and digital marketing. He is particularly focused on researching communication through social media.

Łukasz Tomczyk is top 2% of the world's most influential scientists in 2022 and 2023 (Stanford University and Elsevier ranking). Professor at the Institute of Pedagogy (Jagiellonian University, Poland). He received his doctorate in philosophy (PhDr) from Charles University in Prague - Czech Republic and PhD in social sciences in the field of pedagogy (media education, social pedagogy) from the Pedagogical University in Krakow. He is also a computer science engineer. Author of 7 monographs and over 220 scientific articles, editor of 15 collective monographs. Researcher and manager in several international projects financed from sources: NCBiR, NCN, Erasmus+, NAWA, Visegrad Fund, Mundus Penta. He has lectured students in the Czech Republic, Slovakia, Macedonia, Bosnia and Herzegovina, Serbia, Germany, Croatia, Brazil, Uruguay, Dominican Republic, Italy, Indonesia, Hungary and Greece. His research interests are in media and information education, information society and lifelong learning. Reviewer of textbooks at the Ministry of Education. Fellow of the Ministry of Science and Higher Education (outstanding young researchers). Member of the research network: EU KIDS Online and COST Action CA16207 European Network for Problematic Usage of the Internet. Deputy Editor in the journal Education and Information Technologies (Springer, IF=4.8). He works as a reviewer for a number of foreign research agencies, including the European Commission. He has currently completed an 18-months research project on digital competences of teachers of the future at the Italian University of Macerata, funded by a Mieczyslaw Bekker scholarship (National Agency for Academic Exchange).

Dr Łukasz Szwejka is an assistant professor at the Department of Social Prevention and Resocialisation at the Jagiellonian University. He graduated in resocialisation pedagogy from the Gdańsk University of Humanities (bachelor's degree) and the Jagiellonian University (master's degree), where he subsequently obtained a doctorate in humanities. In addition, he completed postgraduate studies in statistical data analysis at the AGH University of Science and Technology. His research interests focus on quantitative research on the effectiveness of therapeutic, social rehabilitation and preventive measures, as well as on the analysis of the aetiology of social problems. He is the author and co-author of numerous research projects, including those devoted to the prevention of behavioural addictions, the evaluation of therapy effectiveness, and the development of diagnostic and evaluation tools. He carries out projects both within the university and in cooperation with public institutions, including the Ministry of Health and the Central Board of Prison Service.

Dana Egerova is Associate Professor at the University of West Bohemia in Pilsen, Faculty of Economics. Her main research interests encompass various topics within human resource management and organizational behavior. Another significant research activity includes the application of new technologies in employee training and development and digital transformation in a range of different contexts. She has experience in leading national and international projects.

Lucie Rohlíková is an associate professor in the field of Pedagogy at the University of West Bohemia in Pilsen, currently serving as Vice-Dean and teacher at the Faculty of Education of the University of West Bohemia in Pilsen. She has long been involved in the training of future teachers and the coordination of university-wide and nationwide activities in the Czech Republic to support e-learning and university pedagogy (administration of university e-learning systems, training of authors of e-learning courses and study materials, training in the development of pedagogical and psychological skills of teachers, leadership of a team of university pedagogy, implementation of university and national development projects). She is the author of numerous publications and has received many awards for her work, including the Minister of Education, Youth and Sports Award for outstanding educational activities at a university. She currently leads a group at the University of West Bohemia in Pilsen that focuses on artificial intelligence in education.

Tomáš Kincl is an associate Professor at the Faculty of Management, Prague University of Economics and Business, Czech Republic. He received his doctorate in Management from the Faculty of Management, Prague University of Economics and Business. His research spans multiple domains, including online consumer behaviour, corporate social responsibility, social media marketing, and AI adoption in various settings. He is a member of the American Marketing Association, the Academy of International Business, and the European Academy of Management. He serves as Vice Dean for Research and PhD Studies and a study programme director. He serves as a reviewer for multiple top-tier journals, such as the International Journal of Advertising, and his studies have been published in numerous international journals. He is currently a co-investigator of the Visegrad Fund project on the application of AI in higher education.

Jan Pospíšil is an assistant Professor at the Faculty of Management, Prague University of Economics and Business, Czech Republic. He received his doctorate in Economics and Management from the Tomas Bata University in Zlín, Czech Republic. His research focus lies in brand management, marketing and social communication, media, and consumer behavior. He has been awarded Best Educator Award several times, and actively participates in the implementation of AI technologies in an educational context and is an AI enthusiast.

Kristína Medeková is a PhD student at the Slovak University of Agriculture in Nitra, Faculty of Economics and Management. Her research focuses on the impact of global crises, such as the ongoing pandemic, the war in Ukraine and the energy crisis, on sustainable consumer behaviour. She is particularly interested in consumer decision-making processes, behavioural change and the factors that influence responsible consumption during times of crisis.

Petra Mikulcová is a PhD student at the Slovak University of Agriculture in Nitra, Faculty of Economics and Management. Her research explores the integration of artificial intelligence into strategic human resource management, particularly in relation to talent acquisition, development, and retention. She is interested in how digital transformation and AI tools can improve decision-making processes and encourage innovation within organisations.

Jeyran Gasimova is a master student at the Eötvös Loránd University Faculty of Education and Psychology. Her major is in educational sciences, focusing on educational development and management. She acts as a project assistant and her research focus is on acceptance and use of AI in higher education.