
Enhancing Digital Competence Among Pre-Service Teachers: The Role of Personalized Learning Plans in Teacher Education

Norbert Beták^{1*,2}

1 Apor Vilmos Catholic College, Schuszter Konstantin tér 1-5., 2600 Vác, Hungary, betak.norbert@avkf.hu*

2 Constantine the Philosopher University in Nitra, Tr. A. Hlinku 1, 949 01 Nitra, Slovakia, nbetak@ukf.sk

Abstract

The increasing digitalisation of education necessitates a focus on developing digital competencies among pre-service teachers, a topic selected due to its relevance to 21st-century educational demands. The theoretical grounding of the paper was established through a comprehensive literature review covering digital literacy, Pedagogical Digital Competencies (PDC), and personalised learning. This study aims to explore the role of personalised learning plans in enhancing digital competencies, presenting a novel approach to curriculum design that integrates individualized development programs. A quantitative research method was employed using a structured questionnaire to assess pre-service teachers' self-perceived digital competence and attitudes toward its importance in teaching. The findings reveal a significant gap between current digital skills and expected standards, as well as key barriers to technology integration. The study concludes that personalised learning plans can effectively support digital competency development. The research offers both theoretical contributions to the discourse on digital pedagogy and practical implications for teacher education programs.

Keywords: digital literacy; 21st century skills; personalized learning plan; self-assessment

1. Introduction

One of the most acceptable ways of learning being surfaced nowadays is learning through digital technology. Technology is constantly acting as a catalyst to revolutionize the education, and for education to keep pace with the rapidly changing technology it is imperative to make technology an integral part of educational system. Individuals with a strong foundation and enhanced understanding of digital technology and innovative processes can be poised for success in 21st century global society (Srivastava & Dangwal, 2021). Teachers' digital competence is a multifaceted and essential aspect of modern education. It affects the quality of teaching and learning and shapes students' readiness for the digital world. The development and assessment of teachers' digital competence is therefore crucial to ensure the effectiveness and relevance of education in the digital age (Kiryakova & Kozhuharova, 2024).

The significance and character of digital competence are emphasised in European-level documents. The OECD programme (2005), for instance, underscores the significance of interactive tool usage as a fundamental competence for achieving a successful life and a well-functioning society. In this context, Ilomaki et al. (2011) discusses the ability to use technology with other people for communication, for working, for playing etc., which requires an

awareness of new ways in which an individual can use technologies in his/her daily life. An individual should have the ability to make use of the potential of ICT to transfer the way of working, to access information, and to interact with others. The Council of the European Union (2019) lists the digital competence among the eight key competences and mentions that it involves the confident, critical and responsible use of, and engagement with, digital technologies for learning, at work, and for participation in society. It includes information and data literacy, communication and collaboration, media literacy, digital content creation (including programming), safety (including digital well-being and competences related to cybersecurity), intellectual property related questions, problem solving and critical thinking.

The Digital Education Action Plan (2020) as a policy initiative of the European Union also fits in with the issue of the importance and development of digital competences. The Action plan sets out fourteen actions to support the following strategic priorities:

- Priority 1: Fostering the development of a high-performing digital education ecosystem
- Priority 2: Enhancing digital skills and competences for the digital transformation

The growing importance of digital literacy in education has become evident as the world of digital technology now pervades not only the workplace, but also our personal relationships, our civic and other activities, and thus our everyday lives.

For these social, economic and personal reasons students will need digital technology skills if they are to contribute successfully in a knowledge-based society and to play an effective social, economic and political role in society. Higher education institutions around the world put their efforts to restructure classroom facilities for their higher education programs (Ghayyur & Mirza 2021).

Adequate digital education is at the core of vocational training and lifelong learning. Digital competences are an essential element of the European Competence Reference Framework and one of the eight competences needed to improve personal development, active citizenship, social inclusion and employability (Tsankov & Damyanov, 2019). The digital transformation of education has brought about a pressing need for teachers to continuously develop their digital competencies. It is obvious that formal seminars, such as one-day training workshops in how to use ICT, are not sufficient and effective to develop teachers' digital competences. In order to be able to plan and design suitable education training measures for teachers initially requires a systematic approach for the professional development of teachers at vocational schools (Seufert & Scheffler, 2016).

The question arises as to whether the personalized learning plan can contribute to the development of digital literacy of pre-service teachers and thus prepare them for their future profession.

The development of digital skills as part of professional development is a process that has the potential to make a significant contribution to active teaching practice. The personalized approach could be essential to equip pre-service teachers with the skills, confidence, and adaptability they need to thrive in diverse educational contexts and embrace technology as an integral part of their teaching practice. Furthermore, it is essential not only to cultivate current technical knowledge and skills, but also to foster the capacity for ongoing development of digital competence, enabling future teachers to continuously adapt and expand their own digital proficiency.

The idea of personalized learning rests on the foundation that humans learn through experience and by constructing knowledge. It is heavily influenced by a learner's prior experiences and is accomplished via language and social interaction. In general, personalized-learning models seek to adapt to the pace of learning and the instructional strategies, content and activities being used to fit best each learner's strengths, weaknesses, and interests (Shemshack & Spector, 2020).

All in all, we consider the introduction of a personalised learning plan for digital competences in teacher education to be important, mainly because:

- pre-service teachers can enter teacher training program with different levels of digital literacy,
- personalization ensures that each individual's strengths and weaknesses are addressed, enabling effective skill development,
- learning plans that align with individual goals and interests encourage sustained motivation and engagement,
- technology in education is constantly evolving and personalized plans help pre-service teachers stay current and develop skills that are relevant to their unique career goals.
- the development of digital competences is also necessary in a lifelong learning perspective.

The aim of this study is to explore and introduce a way of implementing the topic of effective personalized learning plans to enhance digital competence on college education. In accordance with the aforementioned points, the article delineates the environment and the primary steps involved in upgrading the Information technology (IT) course for the Teaching for Primary

Degree programme at Apor Vilmos Catholic College in Hungary. The article expounds upon the concept of introducing the themes of self-development and self-evaluation in the process of ensuring continuous learning and development. The results of the implementation, including a critical evaluation of the benefits and shortcomings of the training course so designed, will be the subject of another article, as the implementation phase is currently still in progress.

2. Literature Review

The 21st-century educational landscape is manifested by the key concept of digital competency of professionals in the knowledge area. Education and training, therefore, need to be at a premium, and the role of teachers being very important in imparting education and constructing learning experiences need to be continuously trained and updated (Srivastava & Dangwal, 2021). The development of digital competences is necessary both for the academics to take advantage of the opportunities offered by technological advancement and to create strategies for their professional development. It is also necessary so that academics can help the improvement of the digital competence of the students themselves (Inamorato Dos Santos et al., 2023). The development of digital competences in the professional direction for future pedagogical specialists focuses on the application of digital resources and tools in the educational process, in communication and collaboration with colleagues and students, in selecting and creating learning content, working with different platforms to track student activity, achievements and commit feedback to learners, create opportunities for their active participation and increase their digital competence (Tsankov & Damyanov, 2019).

The European Union has recognized the importance of digital competence, and has developed the European Reference Framework for Key Competences for Lifelong Learning, which identifies digital competence as one of the essential skills for the 21st century (Karsenti et al., 2020). This framework provides a comprehensive guideline for the development of digital competence, and has the potential to be adapted to the specific needs of various educational settings.

Despite the growing recognition of the importance of lifelong learning, there is a significant gap in understanding how to effectively personalize learning experiences to meet the diverse and evolving needs of individuals throughout their lives. Traditional educational methods often fall short in providing the flexibility and adaptability required for lifelong learning. This gap necessitates the exploration of innovative solutions to enhance the personalization of learning experiences (Bayly-Castaneda et al., 2024). One promising approach to fostering digital skills is the implementation of personalized learning paths. In a study by Caena & Vuorikari (2021)

it is mentioned that the field of teacher education is undergoing a remarkable transformation, as educators and policymakers strive to better prepare the next generation of teachers for the evolving demands of the 21st-century classroom. One key aspect of this transformation is the growing emphasis on personalized, student-centred learning paths for aspiring teachers.

Bayly-Castaneda et al. (2024) found the research on personalization of learning and the use of AI in lifelong learning as a vital area and argues that AI offers a range of innovative tools that revolutionize the concept of personalized learning.

Personalized learning paths involve tailoring the learning experience to the unique needs, abilities, and goals of each individual student, enabling them to progress at their own pace and focus on areas of greatest need or interest.

In this context, the concept of personal learning paths has emerged as a promising approach to support teachers' self-development in digital competences. This approach recognizes that each teacher has unique learning needs, preferences, and circumstances, and therefore, a one-size-fits-all professional development program may not be effective. By adopting individual learning paths, teachers can tailor their professional growth to their specific requirements, drawing on a variety of resources and learning opportunities.

A fundamental element of the proposed approach is the emphasis on the practices of self-assessment and reflection. Teachers are encouraged to regularly evaluate their own digital competencies, identify areas for improvement, and develop personalized learning plans to address their needs. As Indu (2018) also states, self-assessment promotes learning, in plain and simple manner. It gives learners training in evaluation that results in benefits to the learning process. It gives raised level of awareness of perceived levels of abilities to students as well as teachers. Training in self-assessment, motivates learners to look at course content in a more perceptive way. It motivates the teachers towards the goal-orientation. In brief, Self-evaluation can assist a teacher in many ways by.

3. The Programme of Creating Personal Development Plans for Pre-services Teachers

The topic of personal self-development plans is being introduced at the Apor Vilmos Catholic College in Hungary as part of an internal development programme. The development within the framework of the programme is intended to renew the Information technology curricula for Teacher Education (BA – Bachelor Degree). The development activities of the programme are carried out in four sections, with the current (third) section being the implementation of the pre-prepared activities into the teaching process (Figure 1). The implementation process has been

initiated during the summer semester of the school year 2024/25, with a total of 63 students taking the course, divided into 3 working groups.

The primary objective of the internal project is to initiate the development of a programme for the enhancement of digital competencies based on self-assessment and self-development. The programme is designed to facilitate the development of the digital competencies of pre-service teachers, encompassing the identification and assessment of their digital skills. Furthermore, the programme aims to assist students in the development and delineation of a personalised development plan. The successful completion of this pathway is expected to empower students to engage in their future pedagogical work in the context of digital education.

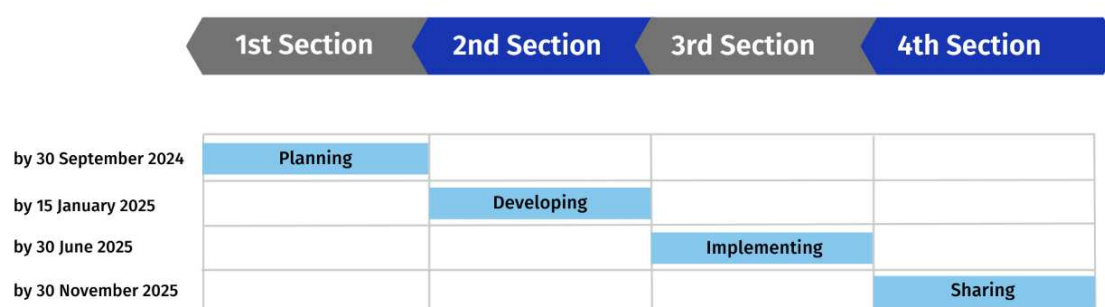


Figure 1. Timeline of the development programme

As a fundamental research and development objective, a complex programme plan for self-development is to be implemented. This programme is based on a self-reflective digital competence assessment of pre-service teachers. During the available research and development period, a number of activities will be implemented to support the self-assessment and self-development of pre-service teachers' digital competence skills.

A further objective is to emphasise the significance of self-reflection and the identification of individual self-development pathways in the context of digital competences, and along this line, to prepare student teachers to assess, identify and develop their individual needs as they arise.

The programme is predicated on the European Framework for Digital Competences for Educators (DigCompEdu), with a focus on the 22 competences delineated as the foundation for the project's implementation phases, namely the self-assessment of students. This is followed by a phase of identification and interpretation of the results achieved, also within the framework of the subject innovation, which will serve as a basis for the implementation of the subsequent phases, in particular the elaboration of the self-development plan. The aim of the self-development plan is to provide teachers with a structured framework for assessing their own digital competences and concrete steps for their future development. The plan will take into

account the individual needs of the teacher-educator candidates, thus ensuring continuous professional development in the field of digital education.

Consequently, the following principal five activities will be undertaken in the context of the programme within the Information technology course:

1. Self-assessment of students' digital competences;
2. Definition of individual self-assessment levels and evaluation of the results achieved;
3. Development of an individual self-development plan;
4. Identification and selection of supporting materials and tools;
5. Presentation of an individual self-development plan.

The activities listed above and illustrated on the Table 1 are preceded by a session on the concept, role and development potential of digital competences, which introduces and provides a grounding in the field and the topic.

Table 1. Course-innovation activities

Activity	Title	Duration (min)
1	Digital competencies - Introduction	1x45 in-person, 1x45 distance
2	Self-Assessment	1x45 in-person
3	Identifying individual self-assessment levels	1x45 in-person
4	Developing individual self-development plan	1x45 in-person, 2x45 distance
5	Identifying supporting materials and tools	1x45 in-person, 1x45 distance
6	Presenting individual self-development plan	2x45 in-person

4. Research Methodology and Results

Prior to the introduction of the course innovations, we mapped the current status of the course and at the same time prepared a structured questionnaire for pre-service teachers. The main objective of the research, which involved data collection through a questionnaire, is to analyse the level of digital skills of pre-service teachers and to identify the differences between the current level of digital skills and their own self-reflection, thus contributing to the development of digital skills through the creation of an individual learning development plan.

The structured questionnaire was divided into two sections: a) self-reflection on digital skills; b) the role of digital skills in teaching practice.

In the aforementioned sections, respondents were invited to respond to questions that reflected the specific objectives of the questionnaire. These objectives were as follows:

1. To ascertain the expected level of digital competences

2. To encourage pre-service teachers to engage in self-reflection with regard to their digital competence
3. To explore the views of pre-service teachers on the need to develop digital competencies
4. To explore which digital competencies pre-service teachers consider most relevant to their future practice

The questionnaire was conducted in the 2024/2025 school year and a total of 206 students of Apor Vilmos Catholic College participated.

The collected data were analysed using descriptive statistics to determine the distribution of responses, mean values, and median scores. Specifically:

- **Frequency and percentage distributions** were used to assess overall trends.
- **Mean (M), median, and mode** provided insight into the central tendency of responses.
- A **comparative analysis** was conducted between self-assessment scores and the perceived importance of digital competencies to identify competency gaps.
- The relationship between self-perceived digital competence and concerns about digital technologies was examined to detect potential barriers to digital readiness.

The majority of the sample was female (93.7%), which is in line with the typical gender structure observed in the teaching profession. As demonstrated in the table 2 and figure 2, the majority of respondents were from the field of elementary education (40.3%), while the least were from the field of preschool education (10.7%).

Table 2. The study programme of the respondents

Study program	Number of respondents	Frequency (%)
Elementary pedagogy	83	40,3
Social pedagogy	49	23,8
Preschool pedagogy	22	10,7
Early Childhood Education	52	25,2
Total	206	100

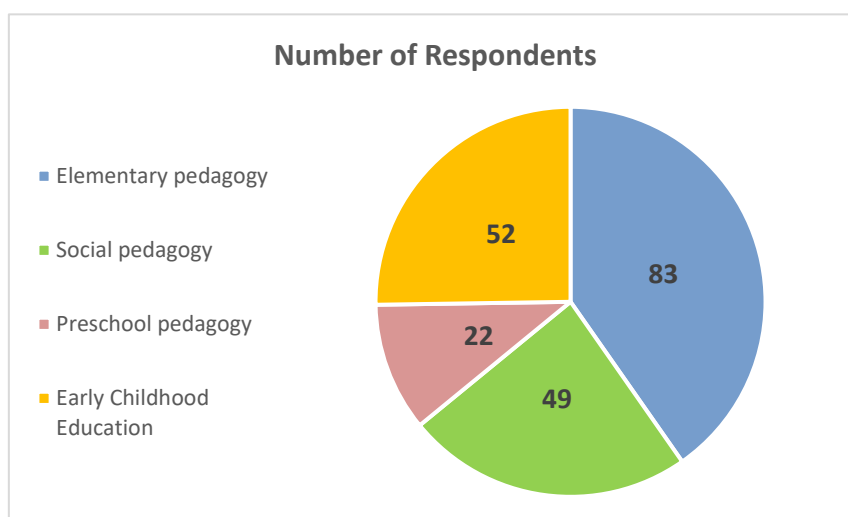


Figure 2. Study programmes and number of respondents

The vast majority of respondents were external students (90.8%), and at the higher education institution where the research was carried out, the number of external students is considerably larger than the number of full-time students. However, it should be noted that the tertiary ratio may also reflect practitioners' interest in upskilling within the educational sciences, and that it may also influence access to digital technologies and education in general, and thus have an impact on the research findings.

In the subsequent section, an analysis of the results obtained from the questionnaire research is presented.

The majority of respondents (84.5%) perceived the necessary level of digital competences as high (4 or according to the Likert scale). The results demonstrate that none of the respondents considered a very low level (1 or 2 according to the Likert scale) to be sufficient in terms of teaching practice.

In response to the invitation to engage in self-reflection, the majority of respondents (43.7%) indicated a medium level of agreement (3 on a Likert scale) in terms of their self-estimated digital competencies (Table 3 and Figure 3). A mere 5.3% of respondents attributed themselves to the highest level of digital competence, a proportion that aligns with the 34.5% of respondents who deemed this level to be essential. The mean self-assessment score (3.42) falls short of the expected level (4.19), thereby pointing to an evident competence gap.

As for other statistical indicators, the mean for expected competences is 4.19, while for current competences it is only 3.42. Both the median and the mode were one number higher (4) for the expected competencies compared to the actual competencies.

Table 3. Comparison of the expected and current levels of digital competences

Level on the Likert scale	Expected competencies (%)	Current competencies (%)	Difference
1 (Very poor)	0	1,9	+1,9
2 (Below average)	0	7,8	+7,8
3 (Average)	15,5	43,7	+28,2
4 (Above average)	50	41,3	-8,7
5 (Excellent)	34,5	5,3	-29,2

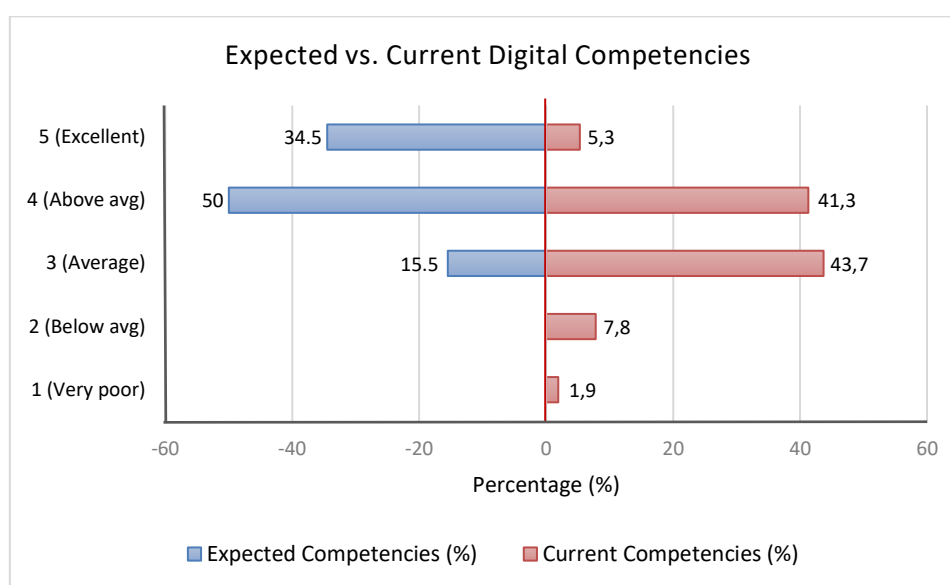


Figure 3. Data visualisation – Competency gap

The data presented in the table indicates a substantial deficit at level 5 (-29.2%), suggesting that only a limited proportion of respondents perceive themselves to be adequately prepared to address the challenges associated with digital learning. Additionally, the findings reveal that a significant proportion of respondents regard their state digital competencies as average, despite the expectation being that they should be higher. This finding is further corroborated by the fact that the self-assessment at level 3 (43.7%) is significantly higher than the expected level 3 (15.5%), with up to 84.5% of respondents expressing the opinion that digital competences should be at level 4 or level 5.

In accordance with another specific objective of the questionnaire (To explore views on the need to develop digital competences), respondents were invited to express their opinions on the importance of enhancing the emphasis placed on cultivating digital competencies within higher education programmes. The analysis of the responses reveals a predominant sentiment in favour of such an emphasis, with 73.8% of respondents (calculated as the sum of responses 4 and 5 on

the Likert scale) expressing agreement with the statement that higher education programmes should place greater emphasis on digital competences. The results also demonstrate a significant degree of uncertainty among the respondents (Table 4 and Figure 4), with 20.4% expressing a neutral stance on this issue. This finding may also indicate a necessity for a more comprehensive awareness campaign emphasising the importance of digital skills in pedagogical practice.

Table 4. The need for greater emphasis on the development of digital competences.

Level on the Likert Scale	Frequency (%)
1 (Strongly disagree)	1,0
2 (Disagree)	4,9
3 (Undecided)	20,4
4 (Agree)	43,2
5 (Strongly agree)	30,6

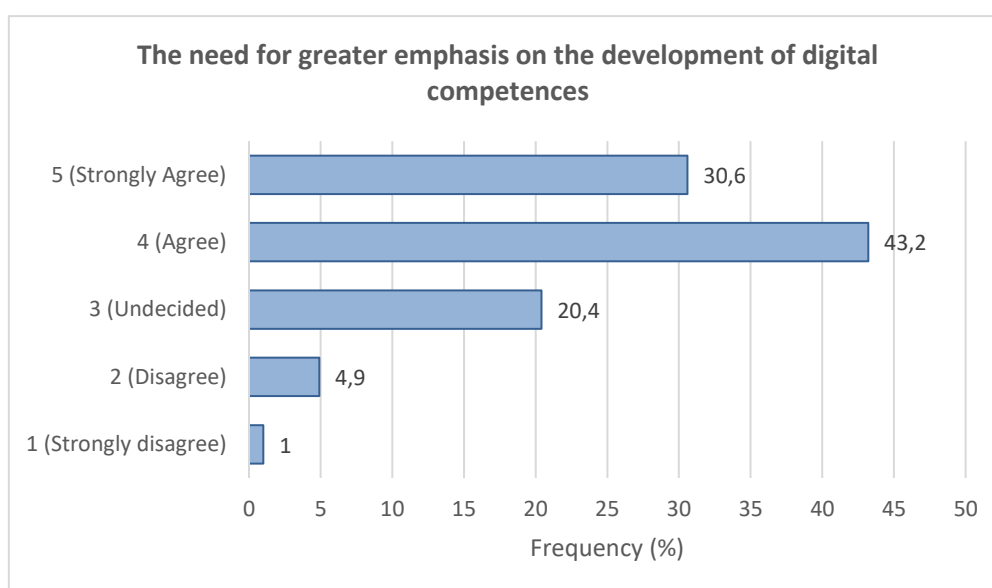


Figure 4. Data visualisation – Emphasis

In the course of the questionnaire, respondents were also invited to express their concerns regarding the integration of digital technologies within conventional teaching practices (Table 5 and Figure 5). This particular inquiry is intricately linked to the preceding question, thereby providing a more comprehensive representation of respondents' perspectives on the digital competencies of educators. The distribution of respondents' answers to this question is relatively even, with 27.7% (levels 1 and 2) expressing low levels of concern, while 47.1%

(levels 4 and 5) report higher levels of concern. A neutral response (level 3) was chosen by 25.2% of respondents, indicating uncertainty or mixed feelings towards the topic.

However, a significant proportion of the student body (47.1%) has expressed concerns regarding the integration of digital technologies in teaching methodologies. This observation is of considerable significance for the enhancement of innovation in teacher training programmes, as it may be indicative of a paucity of practical experience and/or a deficiency in the confidence to utilise digital technologies in pedagogical contexts.

In previous analyses, it was ascertained that respondents acknowledged the significance of digital competencies; nevertheless, their self-perceived levels of digital proficiency were found to be suboptimal. This incongruity may manifest in feelings of insecurity and apprehension about the future use of digital technologies in teaching practice.

Table 5. Barriers in the use of digital technologies

Level on the Likert Scale	Frequency (%)
1 (Strongly disagree)	16,5
2 (Disagree)	11,2
3 (Undecided)	25,2
4 (Agree)	25,7
5 (Strongly agree)	21,4

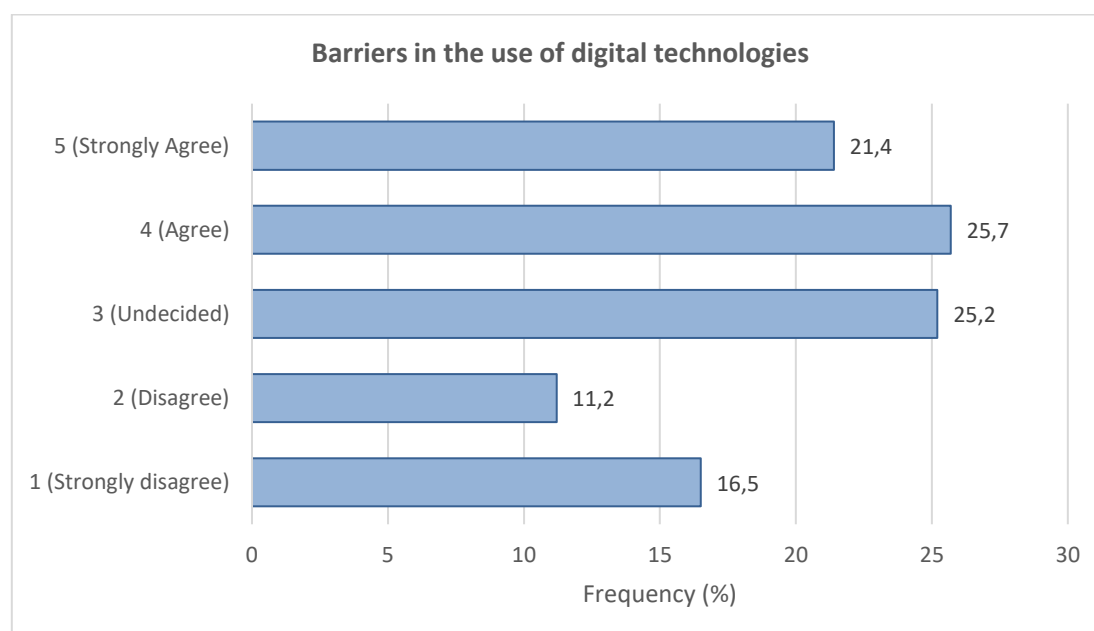


Figure 5. Data visualisation – Barriers

5. Discussion

The findings of this study reveal a significant relationship between pre-service teachers' perceptions of digital competencies and their actual proficiency in this domain. The majority of respondents recognize digital competencies as essential for effective teaching and advocate for their more systematic integration into undergraduate education. However, nearly half of the participants expressed concerns about their ability to apply these skills in practice, highlighting a gap between the perceived necessity of digital competencies and the technological preparedness of future educators.

A particularly notable finding is that many respondents acknowledge deficiencies in their own digital competencies, likely due to limited hands-on experience with digital technologies during their academic studies. This observation is supported by the high proportion of students who rate their digital proficiency as average or below. The discrepancy between expected and actual competencies may contribute to uncertainty and apprehension when transitioning into professional teaching roles.

From the perspective of curriculum innovation in teacher education, these findings emphasize the need for a comprehensive re-evaluation of current training programs. A key challenge is ensuring that strategies for developing digital competencies effectively align with the needs of pre-service teachers, equipping them for a rapidly evolving educational landscape.

The results of this study align with previous research. For instance, Amir (2023) found that teachers' professional preparation experiences significantly influenced their perceptions of ICT use in classrooms and helped overcome disciplinary barriers. Additionally, Dinc (2019) identified that pre-service teachers face both external and internal barriers to technology integration, with internal barriers—such as lack of knowledge and lack of confidence—having a particularly negative impact. These findings further underscore the importance of addressing both skill development and psychological readiness in teacher training programs.

When designing innovations in digital education courses, particularly in IT related courses and educational technology, it is crucial to identify both strengths and weaknesses in digital competencies to support continuous professional development. Based on our findings, we recommend the implementation of a structured development plan that provides pre-service teachers with extended practical training in digital technologies, ensuring their integration into everyday teaching practice.

Future research should focus on exploring how pre-service teachers perceive digital technologies in teaching and what barriers hinder their effective use. A deeper understanding of these challenges will contribute to the development of evidence-based strategies that better prepare teachers for the demands of digital education. A potential future research area could also be the identification of the role and possible applications of AI within the context of individual development pathways.

6. Conclusion and Recommendation

In modern educational systems, the role of pedagogical assessment is undergoing a fundamental transformation. The continuous monitoring and evaluation of the teaching-learning process are essential for the effective operation of education and training systems (Karl, 2024). Teachers' self-evaluation plays a crucial role in their professional development, particularly in the domain of digital literacy, which has become an integral aspect of contemporary teaching. Developing digital competencies within teacher education is not only a means to enhance current knowledge and skills but also an opportunity for professional growth, renewal, and lifelong learning.

This study introduced a program for personalized digital competency development, implemented through an internal call at the Apor Vilmos Catholic College. Currently, we are in the third phase of this initiative, where course innovations are being applied in practice based on the initial planning. The development of personalized learning plans for digital competencies is a gradual process, but initial implementations within course structures indicate promising potential for enhancing students' digital skills.

To further advance the digital competence development of pre-service teachers, we propose two key curricular innovations in IT-related courses:

1. Integration of digital competencies into the course's core topics, ensuring that digital literacy becomes an essential component of teacher education.
2. Implementation of a personalized self-development plan, enabling students to assess their competencies and tailor their learning trajectories accordingly.

Looking ahead, we plan to analyze the outcomes of these innovations, evaluate their effectiveness, and refine the framework for developing personalized digital competency plans. Additionally, we recognize the potential of artificial intelligence (AI) in personalized learning and assessment, a topic already explored by several researchers (Zhang et al., 2023; Holman et al., 2024; Nyaaba et al., 2024; Karataş & Yüce, 2024). As noted by Katonáné Gyöngyörű

(2024), Intelligent Learning Pathways (ILP) – powered by AI and data analytics – can dynamically adapt content, pacing, and learning styles to optimize educational outcomes. Such AI-driven personalized learning approaches have significant potential for improving engagement and effectiveness in both educational and professional training environments.

Furthermore, it is also necessary to mention dilemmas that are relevant to the findings and themes of the study. One central dilemma lies in the discrepancy between perception and proficiency; while pre-service teachers recognize digital competencies as essential, many report a lack of confidence in their actual skills. It is evident, that pre-service teachers enter programs with varying levels of access to and familiarity with digital tools as a result of which inequalities are created. Additionally, regarding to the topic of implementation of digital tools in pedagogy, many pre-service teachers face psychological barriers such as low confidence and fear of failure. In addition to the above, in line with the principle of lifelong learning, it is desirable that the current level of digital competence is verified and opportunities for further development are subsequently identified. These dilemmas underscore the complexity of fostering digital competence in teacher education and highlight the potential of personalized learning plans as a strategic response to these multifaceted challenges.

In conclusion, fostering digital competencies in teacher education requires a structured, individualized approach that aligns with the evolving demands of the digital age. By integrating personalized learning pathways, AI-driven assessment tools, and targeted curriculum innovations, teacher education programs can better equip future educators with the necessary skills to confidently integrate digital technologies into their teaching practice.

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About Authors

Norbert BETÁK is an Associate Professor at Apor Vilmos Catholic College (Hungary) and Constantine the Philosopher University in Nitra (Slovakia). He obtained his PhD in Disciplinary Didactics from the Slovak University of Technology in Bratislava in 2014. His academic research is focused on two principal areas. Firstly, the integration of emerging digital technologies in education. And secondly, the development of digital competencies.

Appendix A

DIGITAL COMPETENCE LEVEL - SELF-ASSESSMENT

1. How do you rate your own digital competences in general?

- 1 (Lowest level) – 5 (Highest level)

2. I am satisfied with my own level of digital competence.

- 1 (I totally disagree) – 5 (I totally agree)

3. I am ... in creating digital learning materials.

- a. very poor
- b. poor
- c. average/fair
- d. good
- e. very good

4. I am ... in using digital tools in the classroom (*e.g. interactive whiteboard, robots, tablets, etc.*)

- a. very poor
- b. poor
- c. average/fair
- d. good
- e. very good

5. I am ... in digital communication (*e.g. digital communication with parents, students, online meetings, etc.*)

- a. very poor
- b. poor
- c. average/fair
- d. good
- e. very good

6. My knowledge of digital security issues is ... (*e.g. virus protection, data safety, etc.*)

- a. very poor
- b. poor
- c. average/fair
- d. good
- e. very good

7. I am ... with digital information issues (*e.g. searching, identifying, information processing, etc.*)

- a. very poor

-
- b. poor
 - c. average/fair
 - d. good
 - e. very good

8. Most of my digital literacy development has taken place at ...

- a. elementary school
- b. secondary school
- c. College/University
- d. outside an educational institution
- e. workplace
- f. further education/training
- g. other

9. In the future, I would like to seek employment in a position that aligns with my academic background.

- 1 (I totally disagree) – 5 (I totally agree)

10. What do you think are the most important areas for the labour market? (Please select at least 1 and up to 3 options)

- a. Quick information search
- b. Digital materials - storing and organising learning materials
- c. Using digital technologies for collaboration
- d. Communicating effectively across social platforms
- e. Digital curriculum development and content creation
- f. Knowledge of new digital tools
- g. Protecting data and information online
- h. Ergonomic use of digital tools
- i. Other:

THE ROLE OF DIGITAL LITERACY IN PEDAGOGY

1. The knowledge of the professional use of digital tools is essential in modern pedagogy.

- 1 (I totally disagree) – 5 (I totally agree)

2. Digital literacy development is a key element in education.

- 1 (I totally disagree) – 5 (I totally agree)

3. What comes to mind when you hear the term "digital pedagogy"?

4. Digital technologies are expected to have an even greater impact on education in the future.

- 1 (I totally disagree) – 5 (I totally agree)

5. What level of digital competences do teachers need nowadays?

- 1 (Lowest level) – 5 (Highest level)

6. In your opinion, what level of digital competences do teachers have in public education?

- (Please draw on your experience)

- 1 (Lowest level) – 5 (Highest level)

7. The digital competences of teachers in public education are at the expected level.

- 1 (I totally disagree) – 5 (I totally agree)

8. In teacher training, more emphasis would be placed on developing digital competences.

- 1 (I totally disagree) – 5 (I totally agree)

9. I am concerned that in the future digital tools will transform the current form and methods of education (e.g. through artificial intelligence).

- 1 (I totally disagree) – 5 (I totally agree)

11. I am concerned about having to use digital tools in education in the future.

- 1 (I totally disagree) – 5 (I totally agree)

Development and Validation of the AI and Flow Learning Questionnaire (AIFLQ)

Dalma Lilla Dominek¹

¹associate professor, Ludovika University of Public Service, Ludovika square 2. Budapest 1082, Hungary, dominek.dalma.lilla@uni-nke.hu

Abstract

As artificial intelligence (AI) becomes more embedded in education, comprehending its influence on students' psychological involvement is crucial. Flow theory, created by Csikszentmihályi, provides a framework for examining optimal learning experiences characterized by intense concentration and intrinsic motivation. This study introduces the AI and Flow Learning Questionnaire (AIFLQ), an enhanced and psychometrically validated iteration of Dominek's original tool. A 24-item, 5-point Likert-scale questionnaire was administered to university students (N=44) in AI-assisted classes. Exploratory factor analysis identified three dependable dimensions: Immersion, Balance, and AI Integration (Cronbach's alpha: 0.805, 0.738, 0.825). Statistical findings revealed significant gender disparities in flow, with female participants achieving higher scores, and a marked impact of educational attainment on immersion. Despite AI being associated with increased variance and diminished scores, the instrument exhibits significant potential for assessing student engagement in digital contexts. The AIFLQ functions as a comprehensive metric for forthcoming investigations on flow experiences within AI-augmented learning environments.

Keywords: Artificial Intelligence; Flow; Education; Questionnaire

1. Introduction

Today, the exponential development of Artificial Intelligence (AI) is undeniably reshaping many aspects of our daily lives. In addition to industrial and technological sectors, AI is increasingly present in everyday life, from smartphones to online communication platforms to education. While the use of AI can bring significant benefits, it is important to consider the potential negative impacts it may have on human cognition, communication and social interactions in the long term. In parallel with the rise of AI, it is crucial to address the question of what human competencies will be essential in the 21st century. Human competences are understood as the integrated knowledge, skills, attitudes and values that enable individuals to function effectively in different social, economic and cultural contexts (Rychen – Salganik, 2003). They include not only specific professional knowledge but also a wide range of cognitive, social and emotional skills.

In the literature, competences are often grouped into three basic categories (Rychen – Salganik, 2003; European Parliament and Council, 2006; Ferrari, 2013): Cognitive competences (e.g., complex problem solving, critical thinking, creativity, analytical skills);

Social and emotional competences (essential for successful interactions and conflict management); and Technological and digital competences (including confident use of IT tools, digital literacy, and skills for interacting with AI). The OECD (OECD, 2019) and the World Economic Forum (World Economic Forum, 2020) predict that as AI and automation become more widespread, some human competencies will become more valuable. While machines can effectively automate repetitive tasks, human creativity, intuition, moral judgement, and social intelligence are difficult to adequately replicate. Particularly important skills for the future are considered to be creativity, emotional and social intelligence, ethical reasoning and responsibility, and learning capacity.

As artificial intelligence becomes more prevalent in education, it is crucial to understand its impact on students' psychological engagement. Csíkszentmihályi's flow theory provides a framework for examining optimal learning experiences characterised by intense concentration and intrinsic motivation. This study introduces the AI and Flow Learning Questionnaire (AIFLQ), an improved, psychometrically validated version of Dominek's original tool (Dominek, 2023). The AIFLQ serves as a comprehensive metric for future research on flow experiences in AI-enhanced learning environments.

This study's distinctive contribution lies in its conceptual and empirical integration of artificial intelligence as an innovative third factor in the flow experience. By explicitly incorporating AI integration into the measurement model, the AIFLQ broadens the scope of traditional flow assessment frameworks, offering new insights into how intelligent technologies influence learners' engagement and motivation. This conceptual advancement reflects the evolving nature of digital learning environments and establishes the AIFLQ as a valuable instrument for exploring modern educational experiences.

However, the generalisability of the findings is limited by the relatively small sample size used in the validation process. Future research should therefore replicate and extend these findings through large-scale, longitudinal studies, in order to better understand the stability and applicability of the instrument across diverse educational settings and populations. This would strengthen the psychometric robustness of the AIFLQ and provide deeper insights into the sustained impact of AI integration on students' flow states.

2. Literature Review

The flow theory, developed by Mihály Csíkszentmihályi (1975, 1990), describes a mental state of complete immersion, concentration and enjoyment while performing an activity. Flow

occurs when the level of challenge is just right for the person's abilities; if the challenge is too high, anxiety may develop, while if it is too low, boredom may occur (Csíkszentmihályi, 1998).

AI-based educational applications play a role in facilitating the flow experience (Hwang et al., 2012). For example, AI-based systems can identify learners' individual learning styles, pace, strengths and weaknesses. Based on this, the system can provide personalised learning paths and tasks that are optimally challenging for the learner, thus facilitating the flow experience. The immediate and adaptive feedback provided by the system can help learners monitor their progress and maintain motivation, which is also a factor related to flow. The clear goals and continuous, targeted feedback that intelligent tutoring systems provide are key elements of the flow experience (Csíkszentmihályi, 1990). AI-generated learning analytics can help learners see their own progress. Perceiving progress and experiencing growth in competence can positively influence motivation and contribute to the experience of flow (Bandura, 1977).

While AI has significant potential to facilitate the Flow experience in educational development, it is important to address the challenges and ethical issues associated with its implementation that can negatively impact the Flow experience. These include the collection and use of student data, which raises serious privacy and security concerns. Loss of trust and control can reduce student engagement and negatively impact the flow experience (Selwyn, 2021). Unfair or discriminatory assessment or learning opportunities can lead to frustration and loss of motivation due to biased algorithms, hindering the development of the flow experience. If AI takes over too much of the educator's role in personal interaction and learner support, it can reduce the sense of connectedness and richness of the learning environment, which can negatively impact the flow experience. Unequal access to AI-based tools may prevent some learners from experiencing the benefits of personalised learning and the potential flow experience, increasing frustration and feelings of exclusion. In order to measure AI and flow learning outcomes, the author created an improved version of the Dominek Learning Flow Questionnaire (Dominek, 2023), the AI and Flow Questionnaire (AIFLQ), which will be presented in detail later in this paper.

3. Research objective

The primary research objective is to explore students' flow experience within Artificial Intelligence (AI)-supported learning environments and to investigate factors influencing this experience, specifically using the AI and Flow Learning Questionnaire (AIFLQ). Particular emphasis is placed on examining gender, educational attainment, and age differences among

university students regarding the dimensions of the flow experience (Immersion, Balance, AI Factor) and the total flow score. The study aims to utilize the AIFLQ as a comprehensive metric for this investigation.

3.1. Research questions

1RQ: What are the dimensions of the flow experience in AI-supported learning environments as measured by the AIFLQ?

2RQ: Are there significant gender differences in the flow experience (Immersion, Balance, AI Factor, Total score) among students participating in AI-supported learning environments?

3RQ: Does educational attainment (secondary vs. higher education) influence the flow experience (Immersion, Balance, AI Factor, Total score) among students in AI-supported learning environments?

4RQ: Are there significant differences in the flow experience (Immersion, Balance, AI Factor, Total score) among students of different age groups (18-25 years, 26-33 years, over 34 years) in AI-supported learning environments?

5RQ: How do students perceive the role of artificial intelligence in their flow experience during learning tasks?

4. Methodology

In developing the AI and Flow Learning Questionnaire (AIFLQ), we reviewed the AI and Flow literature, examined previously used measurement instruments and their associated item banks (Webster - Trevino - Ryna 1993; Ghani - Deshpande 1994; Novak - Hoffmann 1997; Oláh 1999, 2005; Chen 2006; Magyaródi 2013, Dominek 2023). After reviewing the item banks and eliminating duplicates, the AI and Flow Learning Questionnaire was created, resulting in an improved version of Dominek's Learning Flow Questionnaire, a 24-item, five-point Likert-scale measure (1: very characteristic; 2: characteristic; 3: neutral; 4: not characteristic; 5: not at all characteristic).

In order to test the instrument, an empirical study was carried out in university classes for students of the Ludovika University of Public Service (hereafter: LUPS), in which a total of 44 students completed the questionnaire. An exploratory factor analysis was carried out for item selection, descriptive factor statistics and reliability, with the aim of checking the separation of the scales. The items were grouped into three factors to obtain a 24-item, three-factor (immersion, balance and AI factor) model.

The „immersion” factor captures the experience of the lesson, focusing on engagement, the quality of the experience and accompanying phenomena such as changes in time perception and disregard for the environment. Csíkszentmihályi (1997) described flow as deep involvement that is enjoyable in itself and involves maximum concentration on the task and its solution. Involvement and becoming one with the task depends on the individual's attitude towards the activity (Diaz, 2011) and whether he or she has the necessary developmental potential to be activated.

The „balance” factor relates to the task and activity and its content covers the areas of challenge-skill balance, control and clear goals in classroom tasks. In their early Experience Sampling Method studies, Csíkszentmihályi, Rathunde and Whalen (2010) defined flow experience as the optimal ratio of perceived challenge to perceived skill (high and balanced). Kawabata and Mallett's (2011) research also showed that individuals are more likely to enter a state of flow when there is a balance between challenge and ability.

The „AI” factor refers to the experience and balance of challenge and skill in the AI tasks given in class. This factor represents the integration of the two factors mentioned above (immersion and balance) in the context of AI tasks. Four questions explore the immersion factor and four questions explore the balance factor in relation to AI tasks. This factor therefore covers both the instructional experience provided by AI and the areas of challenge-skills required to continue the AI activity. An appropriate level of digital literacy is essential for the successful completion of classroom tasks and its development is the responsibility of the teacher. This is supported by the study by Zawacki-Richter et al. (2019), which, in analysing research on AI, highlights the importance of developing digital competence in both teachers and students.

The questionnaire was used to measure mixed-methods communicative lessons supplemented with different AI programs (N=44), and then repeated exploratory factor analysis was used to test the structure of the questionnaire. SPSS statistical software was used to analyse the data. Based on the above, exploratory factor analyses were performed on the questionnaire in order to develop a reliable measure of AI and flow in learning environments. The questionnaire is an extended version of the previous Dominek Learning Flow Questionnaire with 16 items and 2 factors, which now includes a third factor to measure AI.

5. Results

This paper presents descriptive statistics and reliability indicators for the 24-item scales of the AI and Flow Learning Questionnaire. The results indicate that the reliability indicators of the three factors were psychometrically adequate (“Balance” scale: Cronbach's Alpha = 0.738; “Immersion” scale: Cronbach's alpha = 0.805; “AI” scale: Cronbach's alpha = 0.825) (see Tables 1, 2 and 3).

Table 1. Reliability statistics for Balance factor
Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on standardized Items	N of Items
0.738	0.742	8

Table 2. Reliability statistics for Immersion factor
Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on standardized Items	N of Items
0.805	0.829	8

Table 3. Reliability statistics for AI factor
Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on standardized Items	N of Items
0.825	0.820	8

The necessary descriptive statistics have been presented for the three factors and for the overall results. These show that sample respondents scored on average higher on the deepening factor than on the balance factor, but lowest on the AI factor. However, the standard deviation scores for responses to the AI factor resulted in higher standard deviation scores than for the other two factors. In addition, respondents scored an overall average of 92.795 points (see Table 4).

Table 4. Descriptive Statistics for factors and total score

	Immersion factor	Balance factor	AI factor	Total
N Valid	44	44	44	44
Mean	32.5909	32.909	27.2955	92.7955
Std. Deviation	5.23991	4.37657	6.99362	9.57851

The reliability tests carried out showed that the questions met the validation value, so no further testing was deemed necessary. The factor analyses of the questionnaire are presented in Tables 5, 6 and 7.

Table 5. Descriptive statistics of immersion factor
Item statistics

	Mean	Std. Deviation	N
1. I regularly checked my watch to see how much time was left in the lesson.	4.27	0.785	44
2. I became aware of the non-lesson related things going on around me during the lesson.	3.59	1.300	44
3. I also remembered my personal or other problems during the lesson.	4.20	0.978	44
4. I was very interested in the lesson.	4.48	0.698	44
6. I was bored in class.	4.57	0.789	44
12. I was so absorbed in my work that I didn't notice that half the lesson was over.	3.45	1.302	44
13. I was completely relaxed during the lessons.	3.37	1.208	44
15. My attention was fully engaged in the task(s) assigned.	4.30	0.795	44

Table 6. Descriptive statistics of balance factor
Item statistics

	Mean	Std. Deviation	N
5. I was easily distracted from the lesson.	4.16	1.055	44
7. Sometimes, after completing a big task, I felt joy in the classroom.	4.23	0.743	44
8. It took effort to complete the lesson task(s).	3.27	1.149	44
9. I felt I could meet the requirements of the class.	4.20	0.823	44
10. I was motivated enough to complete the task(s) in class.	4.16	1.010	44
11. I didn't understand the exercises given in class.	4.09	0.858	44
14. The task(s) felt very difficult.	4.45	0.975	44
16. I was aware of the lesson task(s).	4.34	0.645	44

Table 7. Descriptive statistics of AI factor
Item statistics

	Mean	Std. Deviation	N
17. I did not find the AI tasks in the classroom challenging enough.	3.66	1.219	44
18. The AI made it easier for me to concentrate on getting things done.	2.84	1.238	44
19. The use of AI tools made my learning experience more enjoyable.	3.41	1.335	44
20. During the AI application, time passed more slowly and I was less able to immerse myself in the tasks.	3.66	1.430	44
21. AI applications helped me keep my attention in the classroom.	2.77	1.327	44
22. With the help of the AI, I did better on the tasks.	3.00	1.364	44
23. I found it difficult to use the AI during the lessons to complete the tasks.	3.77	1.273	44
24. I felt uncomfortable using AI applications.	4.18	1.225	44

To research potential gender-based differences in the experience of flow, a series of Mann–Whitney U tests were conducted using gender (male vs. female) as the independent variable and four flow-related factors – Immersion, Balance, AI, and Total flow score – as dependent variables (see Table 8). These factors represent core components of the flow state as measured by the flow questionnaire. Across all factors, female participants consistently demonstrated higher mean ranks compared to male participants (Figures 1–3), suggesting a more intense or positive flow experience overall.

The differences were statistically significant for Immersion, Balance, and the Total score. The significantly higher Immersion scores among women indicate that they reported a deeper involvement and absorption in the activity. In the Balance factor – which reflects the perceived equilibrium between challenges and skills – women also scored significantly higher, suggesting a greater subjective alignment between task demands and personal competence. The Total flow score, representing a comprehensive measure of the flow state, was likewise significantly elevated for female participants, pointing to a generally richer and more cohesive flow experience.

In contrast, while women again showed higher mean ranks in the AI factor, the difference did not reach statistical significance. This subscale may tap into the participant's perception of system intelligence or adaptability, and its non-significance could imply that both genders evaluated this aspect similarly, or that the AI component was less central in eliciting flow.

Overall, the results indicate a gender-related pattern in the intensity of flow experiences, with women reporting stronger engagement in key dimensions of the flow state. These findings raise important questions about how different user characteristics, including gender, shape subjective experiences during digital tasks. The non-significant difference in the AI-related subdimension further suggests that technological aspects may be perceived more uniformly, warranting additional research on how AI interfaces interact with individual differences in generating flow.

Table 8. Mann-Whitney U test results by gender
Hypothesis test summary

Null hypothesis	Test	Sig. ^{a,b}	Decision
1. The distribution of Immersion factor is the same across categories of Gender.	Independent-Samples Mann-Whitney U Test	<0.001	Reject the null hypothesis.
2. The distribution of Balance factor is the same across categories of Gender.	Independent-Samples Mann-Whitney U Test	0.019	Reject the null hypothesis.
3. The distribution of AI factor is the same across categories of Gender.	Independent-Samples Mann-Whitney U Test	0.558	Retain the null hypothesis.
4. The distribution of total points is the same across categories of Gender.	Independent-Samples Mann-Whitney U Test	<0.001	Reject the null hypothesis.

- a. The significance level is 0.050.
b. Asymptotic significance is displayed.

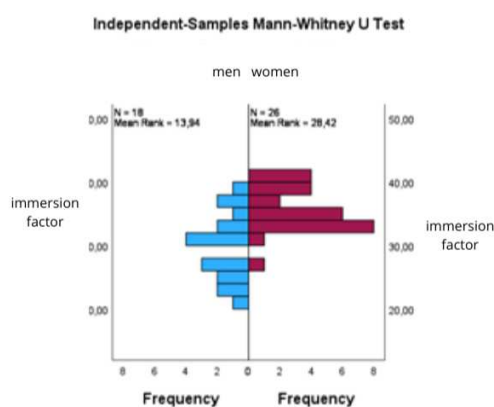


Fig. 1. Distribution of Immersion Factor Scores by Gender

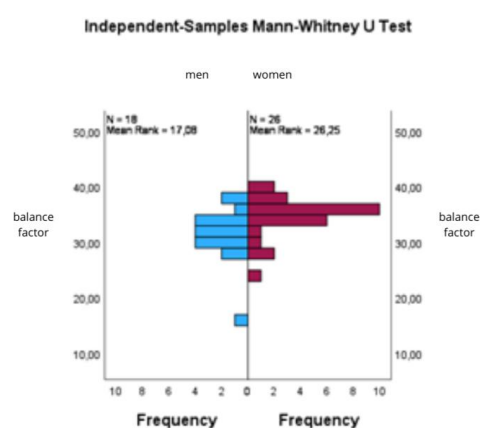


Fig. 2. Distribution of Balance Factor Scores by Gender

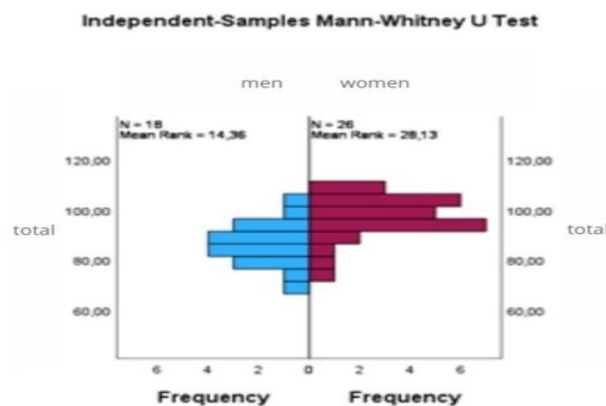


Fig. 3. Distribution of Total Flow Score by Gender

To explore the influence of educational background on the experience of flow, Mann–Whitney U tests were conducted comparing individuals with higher education to those with secondary education across the four flow-related factors: Immersion, Balance, AI, and Total flow score (see Table 9).

The results indicate a statistically significant difference only for the Immersion factor. As illustrated in Figure 4, participants with higher education achieved significantly higher mean ranks in this dimension, suggesting that they experienced deeper psychological engagement and absorption during the task. This finding implies that educational attainment may enhance one's ability to fully concentrate and lose oneself in an activity – an essential feature of the flow state.

Table 9. Mann-Whitney U test results by Educational Attainment
Hypothesis test summary

Null hypothesis	Test	Sig. ^{a,b}	Decision
1. The distribution of Immersion factor is the same across categories of Education level.	Independent-Samples Mann-Whitney U Test	0.043	Reject the null hypothesis.
2. The distribution of Balance factor is the same across categories of Education level.	Independent-Samples Mann-Whitney U Test	0.600	Retain the null hypothesis.
3. The distribution of AI factor is the same across categories of Education level.	Independent-Samples Mann-Whitney U Test	0.355	Retain the null hypothesis.
4. The distribution of Total score is the same across categories of Education level.	Independent-Samples Mann-Whitney U Test	0.083	Retain the null hypothesis.

- a. The significance level is 0.050.
- b. Asymptotic significance is displayed.

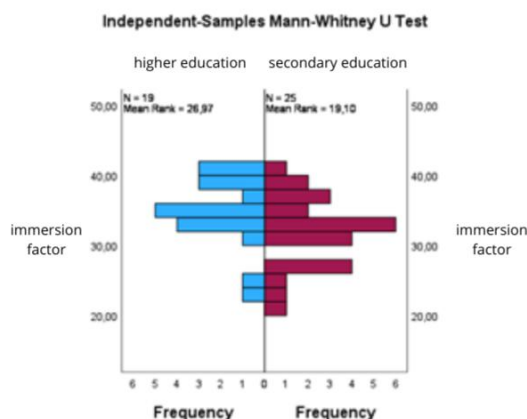


Fig. 4. Distribution of Immersion Factor Scores by Educational Attainment

To assess whether age influences the experience of flow, participants were categorized into three age groups: 18–25 years, 26–33 years, and 34 years and above. These groups were compared across the four flow-related factors (Immersion, Balance, AI, and Total flow score) using Kruskal–Wallis H tests (see Table 10).

The analysis revealed no statistically significant differences between the age groups for any of the flow dimensions. Although minor variations in mean ranks were observed across the groups, none of these differences reached the threshold for significance. This suggests that the subjective experience of flow was relatively stable across the age spectrum represented in the sample.

The lack of significant age effects may indicate that the capacity to experience flow is not strongly tied to chronological age, at least within the adult population examined. It is possible that the task and context provided a sufficiently universal structure for engagement, minimizing the influence of age-related factors such as cognitive processing speed, technological familiarity, or life experience. Alternatively, it may reflect that age-related differences are overshadowed by other variables, such as individual motivation, personality traits, or prior exposure to similar digital environments.

Overall, these results suggest that, unlike gender and educational attainment (in the case of Immersion), age does not appear to be a distinguishing factor in how users experience flow in this context.

Table 10. Kruskal-Wallis H Test Results by Age Group
Hypothesis test summary

Null hypothesis	Test	Sig. ^{a,b}	Decision
1. The distribution of Immersion factor is the same across categories of Age encoded.	Independent-Samples Kruskal-Wallis Test	,073	Retain the null hypothesis.
2. The distribution of Balance factor is the same across categories of Age encoded.	Independent-Samples Kruskal-Wallis Test	,957	Retain the null hypothesis.
3. The distribution of AI factor is the same across categories of Age encoded.	Independent-Samples Kruskal-Wallis Test	,287	Retain the null hypothesis.
4. The distribution of Total is the same across categories of Age encoded.	Independent-Samples Kruskal-Wallis Test	,828	Retain the null hypothesis.

a. The significance level is 0.050.

b. Asymptotic significance is displayed.

6. Discussion

The primary aim of this research was to explore the flow experience of students in an artificial intelligence (AI)-assisted learning environment and to investigate the factors influencing the flow experience using the Artificial Intelligence and Flow-Learning Questionnaire (AIFLQ). Particular emphasis was placed on investigating possible differences in demographic characteristics - gender, education and age - on the dimensions of flow experience and overall flow score. To this end, the AIFLQ questionnaire was developed, validated and then administered to university students. The results of the study provide rich insights into how students experience AI-enhanced learning and how this relates to achieving an optimal experience, the flow state.

RQ1: What are the dimensions of the flow experience in an AI-enhanced learning environment as measured by the AIFLQ?

One of the main outcomes of this research is the development and validation of the AIFLQ questionnaire, which identified three reliable dimensions (factors) to measure the flow experience in an AI-enhanced learning environment. These dimensions were separated based on exploratory factor analysis:

Immersion factor: This dimension measures intense concentration and total immersion in the activity. It includes items relating to the exclusion of distractions, loss of sense of time and interest in the task.

Balance factor: This factor reflects the perceived balance between challenge and ability, and the sense of competence required to complete tasks successfully. Items focus on task difficulty, sense of accomplishment and motivation.

AI Integration Factor: This dimension specifically measures the role of AI in the learning process and the students' experience of it. Items relate to AI-related challenge, concentration, performance, enjoyment and ease of use.

The reliability of these dimensions is supported by corresponding Cronbach's alpha values (Immersion: 0.805; Balance: 0.738; AI Factor: 0.825), indicating that the questionnaire consistently measures these constructs. The results indicate that the flow experience in AI-supported environments is also multi-component and that it is particularly important to examine the role of AI as a separate dimension.

RQ2: Are there significant gender differences in flow experience (immersion, balance, MI factor, total score) between students in AI-supported learning environments?

Statistical analyses (Mann-Whitney U-tests) revealed significant gender differences in flow experience. Female participants scored significantly higher than male participants on the dimensions of Immersion (Figure 1), Balance (Figure 2) and Total Flow Score (Figure 3). This means that women in this sample reported greater psychological engagement and depth (higher Deepening scores). They also had a better sense of balance between the challenge of the tasks and their own abilities, reflected in a higher score on the Balance dimension. The overall results also show that women generally had a richer and more cohesive flow experience in AI-supported classes. It is important to note that there were no significant gender differences on the AI factor. Although the average score for women was higher here, this difference did not reach the level of statistical significance. This may indicate that both genders perceived or valued the AI component of the learning process similarly, or that the role of AI was less central to the flow differences between the genders. The results raise the question of how user characteristics, such as gender, influence subjective experiences in digital environments.

RQ3: Does educational level (secondary vs. higher education) influence the flow experience (Immersion, Balance, AI factor, Total score) of students in AI-enhanced learning environments?

Based on Mann-Whitney U tests examining the effect of educational attainment, a significant difference was found only in the Immersion factor between participants with higher and

secondary education (Figure 4). Participants with higher education had significantly higher mean scores on the Immersion dimension. This finding may suggest that higher levels of education may increase the ability of students to become more deeply immersed and focused during an activity, a key characteristic of the flow state. There are no significant differences in Balance, AI Factor or Total Flow scores by level of education in this sample.

RQ4: Is there a significant difference in flow experience (Immersion, Balance, AI Factor, Total score) between students of different ages (18-25 years, 26-33 years, 34 years and above) in AI-supported learning environments?

No statistically significant differences were found in any of the dimensions of flow experience (immersion, balance, AI factor) or in the total flow score, based on Kruskal-Wallis H-tests examining differences between age groups (18-25 years, 26-33 years, 34 years and over). This result suggests that the subjective experience of flow was relatively stable across the adult age groups studied in this specific context. Age-related factors such as cognitive processing speed, technological ability or life experience did not show a significant influence on flow in this study. It is possible that the nature of the task or the structure of the learning environment generally supported engagement, or that other individual-level variables (e.g. motivation, personality traits) had a stronger effect than age.

RQ5: How do students evaluate the role of AI in their experience of flow during their learning tasks? The assessment of the role of students' AI is most evident in the AI factor scores and related statistics. Overall, in terms of mean scores, students scored lowest on the AI factor (mean 27.2955) compared to Immersion (32.5909) and Balance (32.9091). In contrast, the standard deviation of scores on the AI factor was the highest (6.99362) compared to the other two factors. The abstract also mentions that AI was associated with increased variance and decreased scores.

These results suggest that although AI was present in the learning environment, students on average perceived it as less directly supportive of the flow experience than general immersion in the learning task or the balance of challenge and ease. And the higher variance suggests that students' perceptions of AI and its impact on flow were more varied than other dimensions of flow.

The mean scores of the items specific to the AI factor provide further detail. Some items dealing with negative or challenging aspects of AI (e.g. "I did not find the AI tasks challenging enough" - mean 3.66; "I found the time spent using AI..." - mean 3.66; "I found it

difficult to use the AI..." - mean 3.77; "I felt uncomfortable using the AI applications" - mean 4.18), showing relatively high mean scores on a 5-point Likert scale, where 1 means "very typical" and 5 means "not typical at all" (some items were reverse scored). In contrast, items measuring the positive contribution of AI (e.g. "AI applications helped me keep my attention" - mean 2.77; "AI helped me perform better on tasks" - mean 3.00; "Using AI made it easier to concentrate" - mean 2.84; "Using AI tools made the learning experience more enjoyable" - mean 3.41) show lower means, closer to the "neutral" (3) or "typical" (2) categories. This pattern suggests that some students experienced challenges or discomfort when using AI, which may reduce flow, while the perceived benefits of AI (help with attention, performance, concentration, enjoyment) were less likely to be considered typical or salient to the flow experience, at least on average.

The final part of the research confirms this interpretation, highlighting that while AI has the potential to support flow (personalised challenges, clear goals, immediate feedback), its practical implementation raises a number of challenges and ethical issues. Privacy, loss of trust, algorithmic bias, lack of human interaction, loss of autonomy or unequal access can all have a negative impact on flow. The results obtained (low average AI factor, high variance) are consistent with these potential negative effects and the complexity of AI integration.

7. Conclusions

The research successfully demonstrated the AIFLQ questionnaire as a tool for measuring flow experiences in an AI-supported learning environment. It was found that flow in this context can be divided into three main dimensions: immersion, balance and the AI-specific factor. The results suggest that demographic factors such as gender and educational level significantly influence flow experience, particularly in the immersion dimension. Women tended to have a deeper flow experience, while those with higher levels of education tended to be more immersed in the learning tasks. Age did not show a significant relationship with flow in this sample. The assessment of the role of AI in flow shows a more complex picture. The lower mean score and higher variance of the AI factor suggest that AI was perceived less consistently and positively as a facilitator of flow than other aspects of learning. Students' experiences were varied and the item level results suggest that difficulties, discomfort or lack of challenge associated with using AI may have a negative impact on flow.

All this supports the conclusion of the sources that AI can be a promising tool to promote flow, but only if it is integrated in a pedagogically conscious and ethical way. Addressing the human factors (e.g. teacher support, social interaction) and the challenges posed by AI

(privacy, bias, autonomy) is essential to achieve an optimal learning experience and flow in AI-enhanced environments. AIFLQ could be a useful tool to further explore these dynamics in future research.

8. Limitations and Future Work

Artificial intelligence offers great potential for enhancing learners' flow experiences in education. The ability of AI-based systems to generate personalised challenges tailored to individual abilities and developmental pace is key to achieving a state of flow (Csikszentmihalyi, 1990). It is also important to formulate clear goals and structured tasks, and AI can assist with this by clarifying learning pathways and scaffolding cognitive demands to maintain learner focus. Furthermore, the immediate and relevant feedback offered by AI-powered tutoring systems and assessment tools allows for the continuous monitoring and correction of progress, which are dynamic components of the flow process (Hwang et al., 2012).

However, the implementation of AI in education also raises critical ethical and social concerns. Poorly designed or excessive AI integration can hinder rather than enhance student immersion and motivation. For example, algorithmic biases in personalisation systems can lead to inequitable learning experiences, and overly directive AI systems can undermine learners' autonomy, which is essential for sustaining intrinsic motivation and flow (Deci & Ryan, 2000). Furthermore, AI alone cannot replace the socio-emotional support and human connection vital to student well-being (Selwyn, 2021). Excessive screen time and reduced face-to-face interaction may diminish the positive emotional states typically associated with flow. This highlights the invaluable role of educators (Dominek, 2022), who must integrate AI tools in a pedagogical and ethical manner to support learners' individual needs, stimulate critical thinking and creativity, and avoid merely automating learning tasks. Teachers must preserve human relationships, foster social-emotional development, and cultivate an environment in which flow can naturally emerge.

Beyond its theoretical significance, the AI and Flow Learning Questionnaire (AIFLQ) has notable practical applications in educational settings. As a validated tool that captures the dynamic interplay between AI integration and flow experiences, the AIFLQ can inform evidence-based instructional design. It enables educators and curriculum developers to identify conditions that foster optimal engagement, contributing to learning environments characterised by sustained attention, intrinsic motivation and deep cognitive involvement.

In teacher education, the AIFLQ can be used for diagnosis and reflection. It can help pre-service teachers to explore how technological components influence learner engagement, and guide them in developing pedagogical strategies that leverage AI tools effectively to support diverse learning needs. Professional development programmes based on AIFLQ findings can enhance teachers' ability to create balanced, learner-centred approaches in AI-enhanced environments.

Furthermore, the AIFLQ shows promise in advancing adaptive learning systems. By embedding flow-sensitive diagnostics into AI-driven platforms, these systems can respond dynamically to learners' changing needs, adjusting content difficulty, pacing or instructional modality in real time to sustain flow. Thus, the AIFLQ supports the evaluation of learning experiences and enhances the personalisation and overall effectiveness of AI-mediated education in multiple areas.

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Appendix A**AI and Flow Learning Questionnaire**

For each of the statements below, think about the tasks you will be doing in class. Using the scale, indicate how often the statement occurs to you. Please mark one appropriate response for each item listed:

1 - Not at all often - 5- Very often

1. I regularly checked the clock to see how much time was left in the lesson. * 1 2 3 4 5
2. I was aware of things going on around me during the lesson. * 1 2 3 4 5
3. I was also aware of personal or other problems during the lesson. * 1 2 3 4 5
4. I was very interested in the lesson. 1 2 3 4 5
5. I was easily distracted from the lesson. * 1 2 3 4 5
6. I was bored during the lesson. * 1 2 3 4 5
7. I sometimes felt happy in class after doing a big task. 1 2 3 4 5
8. It took effort to do the task(s) in class. * 1 2 3 4 5
9. I felt I could meet the requirements of the lesson. 1 2 3 4 5
10. I felt motivated to complete the task(s) in the lesson. 1 2 3 4 5
11. I did not understand the tasks given in class. * 1 2 3 4 5
12. I was so absorbed in my work that I didn't notice that half the lesson was over. 1 2 3 4 5
13. I was completely relaxed during the lesson. 1 2 3 4 5
14. I found the task(s) very difficult. * 1 2 3 4 5
15. My attention was fully focused on the task(s). 1 2 3 4 5
16. I was aware of the lesson task(s). 1 2 3 4 5
17. I did not find the AI tasks in class challenging enough. 1 2 3 4 5
18. The use of AI made it easier for me to concentrate on the task(s). 1 2 3 4 5
19. The use of AI tools made my learning experience more enjoyable. 1 2 3 4 5
20. Time passed more slowly and I was less able to concentrate on tasks when using AI. 1 2 3 4 5
21. AI applications helped me keep my attention in class. 1 2 3 4 5
22. AI helped me perform better on task(s). 1 2 3 4 5

23. I had difficulty using AI in class to complete class assignments* 1 2 3 4 5

24. I felt uncomfortable using AI applications* 1 2 3 4 5

* reverse position

Bridging the AI Gap: How Organizational Literacy and Individual Competencies Drive Implementation Success Across Industries

Lucie Depoo^{1*}, Lenka Hajerová-Mullerová², Zdeněk Kronberger², Gabriela Říhová², Marek Strítěský², Marie Hořáková², Kateřina Legnerová², Marcela Palíšková², Otakar Němec², David Šmíd², Tomáš Jurčík², Martin Kopecký²

1 Department of Human Resources, Faculty of Business Administration, Prague University of Economics and Business, W. Churchilla 1938/4, Prague, 12000, Czechia, lucie.depoo@vse.cz (*corresponding author)*

2 Department of Human Resources, Faculty of Business Administration, Prague University of Economics and Business, W. Churchilla 1938/4, Prague, 12000, Czechia, lenka.hajerova@vse.cz, zdenek.kronberger@vse.cz, gabriela.rihova@vse.cz, marek.stritesky@vse.cz, marie.horakova@vse.cz, katerina.legnerova@vse.cz, marcela.paliskova@vse.cz, otakar.nemec@vse.cz, david.smid@vse.cz, tomas.jurcik@vse.cz, martin.kopecky@vse.cz

Abstract

This study examines artificial intelligence adoption patterns and competency requirements across economic sectors in the Czech Republic. The research investigates sectoral differences in AI implementation, required competencies, and organizational impacts. Data were collected via computer-assisted web interviewing and analyzed using descriptive statistics, correlation analysis, and chi-square testing. Results reveal intensive AI usage (78%). Significant sectoral variations emerged: primary sectors focus on general AI tools, secondary sectors emphasize manufacturing-specific applications including quality control and predictive maintenance, while tertiary sector organizations employ the broadest range of AI solutions encompassing specialized finance, healthcare, and legal applications. All sectors invest heavily in employee training and reskilling, though tertiary sector organizations experience the most significant structural transformations including workforce redeployment and role redesign. Statistical analysis confirms significant sectoral differences in AI adoption patterns and validates that higher organizational AI literacy correlates with superior implementation outcomes. These findings contribute to understanding sector-specific AI adoption strategies and inform competency development frameworks for successful organizational AI integration.

Keywords: artificial intelligence; transformation; human resources; sector; competence

1. Introduction

AI is having an exponential impact on the global economy, organizations and society (Suciu et al., 2023). Competitiveness is being achieved through the implementation of advanced technologies such as artificial intelligence (AI), big data analytics, robotics, machine learning, Internet of Things (IoT) (Wittenberg, 2016, Monostori et al., 2016). These disruptive changes are leading experts to predict that the nature of work will change dramatically in the coming decade (Butler, 2016; Davenport & Kirby, 2016).

Based on the experience of the 1990s, when personal computers redefined work in the workplace, the emergence of artificial intelligence could be analogous (Li & Kim, 2024). Just as computer literacy has become a basic requirement for many jobs, the proliferation and

sophistication of AI across industries suggests that AI-related readiness could soon become equally essential (Uren and Edwards 2023).

The discussion about the future of work brings conflicting views (Jaiswal et al., 2022). While critics of AI firmly believe that advanced technologies will replace humans in many jobs, advocates of advanced technology envision new jobs with value creation (Ågerfalk, 2020; Sullivan et al., 2020). The International Labor Organization (2023) states that 24% of white-collar jobs will be highly likely to be exposed to technological change. For example, in the USA, approximately 47% of jobs are in the upper risk zone of potential automation (Frey and Osborne, 2017). In Germany, although AI-based robotization has not had a major impact on employment, it has reduced the employment of young people (World Bank Group, 2019). The consensus is clear, advanced technologies will disrupt the balance in employment (Bughin et al., 2017; Østerlund et al., 2021).

As artificially intelligent machines gradually take over tedious, mechanical, and mundane human tasks such as documentation, planning, equipment inspection, data collection, and preliminary analysis (Huang et al., 2019; Huang & Rust, 2018), AI systems augment human capabilities by perceiving, understanding, learning, and acting (Daugherty & Wilson, 2018).

According to Li & Kim (2024), with the increasing integration of AI technologies, employees will be expected to engage, use, and collaborate with them in their daily work routines.

This study aims to investigate the role of AI literacy as a determinant of successful AI implementation in organizations, examining both organizational-level literacy effects and competency impacts on technology acceptance and usage. Additionally, this research seeks to identify sector-specific variations in AI competency requirements to provide targeted insights for specific AI adoption.

2. Literature review

AI is expected to be the fastest growing business opportunity in today's growing economy. AI's contribution to the global economy is projected to reach \$15.7 trillion by 2030, more than the current combined output of China and India (Rao & Verweij, 2017). According to a report by McKinsey & Company, the potential impact of AI technologies on the global economy is estimated at \$17.1 to \$25.6 trillion (Chui et al. 2023). According to current literature, the main industries and sectors where there are opportunities to create added value through increased digitalization include: manufacturing (Al Suwaidan, 2021, García-Muiña et al., 2020), agri-food industry (Al Suwaidan, 2021, Oltra-Mestre et al., 2021), automotive industry, fast-moving

consumer goods, logistics, retail trade and business services (Demeter et al., 2020), financial sector (Wyrwa, 2020, Zhang et al., 2020).

AI-based technological solutions are commonly used, for example more efficient data collection, more efficient sorting of relevant data for further decision-making, improving logistics operations, reducing manual labor, increasing labor productivity (Srivastav, 2019). According to Bhalerao et al. (2022), organizations should understand the importance of AI, strive to overcome obstacles, and leverage strategic advantages. As Suciu et al. (2023) pointed out that digitalization and technological advances affect labor market stability, both directly, such as by displacing traditional jobs, resulting in layoffs, and indirectly, by increasing labor demand in industries that are being transformed by technological advances.

AI technologies introduce innovative changes that increase efficiency and productivity and revolutionize how people work (Borana, 2016; Chen & Lin, 2023; Jarrahi, 2018) and how they communicate in a digitalized work environment (Ismail & Hassan 2019; Rymarczyk 2020).

Implementation of new advanced technologies according to Becker-Ritterspach & Gröger (2018), Chen & Zhou (2020), Janssen et al. (2017) lead to the need to develop technical skills such as programming, data analysis, system integration, etc., the need for new technical skills, development of soft skills such as critical thinking, creativity, problem solving, adaptability (Krings et al., 2017, Naciri et al., 2018, Paulraj et al., 2017, Stojanovic & Sostaric, 2018), development of lifelong learning to remain competitive in the labour market (EESC, 2017), and changes in organizational structure (Suciu et al., 2023).

Understanding the competencies required for AI applications is becoming more important than ever for human resource development practitioners and scholars (Li & Kim, 2024). The multidimensional approach defining individual competencies (Le Deist & Winterton, 2005) intended to guide individuals to perform their jobs effectively and successfully. In addition, workers should also acquire new competencies that will enable them to meet the changing demands of the labor market. For example, Fareri et al. (2020) identify not only the need to integrate existing competencies into professional models, but also the creation of completely new competencies adapted to the trends of the transition from Industry 4.0. to Industry 5.0. Thus, the main competency seems to be the digital skills of individuals, which include the functional use of AI, but also the recognition of its ethical consequences (Kong, Cheung & Zhang, 2023; Williams et al., 2022; Zhang et al., 2022).

Kim (2022) proposes an approach to new competencies that focuses on the individual who uses new technologies - the strategic focus is on the competencies that employees need to adopt and

adopt AI technologies; and on the application, use of new tools - competencies for learning and development in relation to AI (e.g. the development of an AI-based educational system). In this sense, Industry 5.0 places considerable emphasis on human-machine cooperation (Suciu et al., 2023).

Issa et al. (2022) define AI competencies under the influence of (1) the approach to human-machine collaboration, (2) the ability to anticipate the strategic impact of AI, respectively the technological infrastructure, and (3) data management capabilities. In contrast, Younnis and Adel (2020) define five categories of competencies needed in connection with the adoption of AI solutions: (1) hard and soft, (2) cognitive (problem solving, creativity, judgment and critical thinking), (3) social and emotional (teamwork, leadership and communication), (4) technological and (5) research. Furthermore, the model proposed by Jaiswal et al. (2021) as a prerequisite for improving the human-AI relationship emphasizes the need to develop cognitive and technological competencies at a higher level and includes five critical competencies: data analysis, digital, complex cognitive, decision-making, continuous learning. In this regard, Qureshi et al. (2021) reveal a critical place between the available information and the competencies that are needed to meet the requirements of AI technologies.

Long & Magerko (2020) looked at a set of competencies as literacy (the authors define the set of competencies in the field of AI as AI literacy) that enable individuals to: evaluate AI technologies, communicate and collaborate effectively with AI, use AI (Magerko, 2021; Perchik et al., 2023; Pinski & Benlian, 2023; Wienrich & Carolus, 2021). According to Ng et al. (2021), Steinbauer et al. (2021) AI literacy at the individual level includes: understanding AI technologies, learning to use AI technologies.

It is expected that AI literacy will become a common part of education (Adams et al. 2023; Chai et al. 2023; Jang, Jeon & Jung 2022). This will be particularly important for organizations, as generations with the necessary AI literacy will enter the labor market over time. At the organizational level, success will currently depend on the ability to develop AI literacy among existing employees (Chowdhury et al., 2023). If employees have a certain level of knowledge about the possibilities of AI, they may perceive AI as more accessible and effective, and their readiness to use AI will also reduce pressure and stress in the workplace (Del Giudice et al. 2023).

Cetindamar et al. (2024) view AI organizational competence as a collective capability that can be disseminated as organizational literacy through the interactions of individuals within an organization. Cetindamar et al. (2024) argue that although AI literacy is often viewed as an individual-level competency, it can also be viewed as an organizational capability, where

individual competency culminates in a collective organizational strength that enables coordinated tasks and their resolution, efficient use of resources to achieve desired outcomes (Teece, 2007). Understanding the organizational competencies required for interacting with AI is therefore essential. When formulating strategies for developing AI organizational literacy, organizational culture needs to be taken into account (Robinson, 2020), as AI literacy also carries over into the work environment. The importance of ethics in the use of AI technologies needs to be emphasized (Lee et al. 2022; Robinson 2020). By incorporating values-related content, organizations can effectively increase workers' readiness to learn and adopt AI technologies.

The Technology Acceptance Model (TAM) can be used to identify organizational competencies in AI. It distinguishes:

- Skill domain – the real-world use of AI skills (knowledge and understanding of AI, use and application of AI, evaluation and creation of AI, resolution of ethical issues) (Ng et al., 2021).
- Relevance domain – the evaluation and practical use of AI skills (Ng et al., 2021, Cetindamar et al., 2024, Tenório et al., 2023, Schleiss et al., 2022, Yi, 2021). For example, Yi (2021) emphasizes the ability of metacognition, which refers to how to access the information we need to know, with whom and how to engage, what learning strategies to use, how to explore different methods and forms of learning. Relevance can be considered the most critical competency for AI literacy, as it primarily uses the ability to anticipate.
- Ethics – concerns the definition of values, the appreciation of individuals and groups (Cetindamar et al. 2024; Ng et al. 2021; Tenório et al. 2023). For example, Cetindamar et al. (2024) emphasize not only the interaction and understanding of AI systems, including the evaluation of their outputs, but also their limitations. Ethical issues in the use of AI can lead not only to low performance, but also to harm the individual, organization and society (Asaro 2019; Mittelstadt 2019). Ethics is a critical ability for decision-making in everyday routine activities, including the inclusion of privacy, accountability, transparency, etc. (Laupichler et al. 2022; Lee et al. 2022; Perchik et al. 2023; Tenório et al. 2023).
- Knowledge domain – includes not only basic technical knowledge about AI, but also knowledge of principles, decision-making, and critical thinking (Charow et al. 2021; Long and Magerko 2020; Ng et al. 2021; Tenório et al. 2023).

Zhang (2023) defines a competency model for managers involved in the integration of AI solutions. It includes: planning, control regulation, systematic decision justification, initiative behavior, and fairness and impartiality. This model can be complemented by collaborative intelligence (Chowdhury et al., 2022) and critical evaluation (Liaw et al., 2022). Chatterjee et al. (2021) add organizational agility as a crucial factor that facilitates the development of AI competencies, which are necessary for the successful implementation of these technologies. Zhang's competency model represents de facto cross-cutting competencies that are essential for

a sustainable, resilient and inclusive transition to a digital workplace that will deliver long-term positive effects. It is considered essential for both leaders and employees to possess them.

According to Suciu et al. (2023), the most important transversal competencies include the ability to use, monitor and control technological devices; analytical and innovative thinking; lifelong learning; development of technological and programmatic solutions; creativity, originality and initiative; emotional intelligence; leadership; ability to solve complex problems. By developing transversal competencies, individuals will be better prepared for jobs (e.g. software developer, robotics engineer, Internet of Things specialist, digital marketing specialist, database and network specialist, artificial intelligence specialist, materials engineer, information security analyst, renewable energy engineer, process automation specialist, etc.).

Currently, the competencies needed to hold these positions are not widely shared among individuals. This is a significant problem. According to Suciu et al. (2023), managers need to focus more on aspects such as employee safety, working conditions, physical and mental well-being or satisfaction of employees integrated into a digitalized work environment.

Relatively few studies have examined competencies related to positive attitudes and intrinsic motivation (self-motivation). Such workers are strongly focused on achieving their goals and proactively adapt to new AI technologies. They recognize that competencies related to AI education are crucial. Martinez-Plumed et al. (2021) defined them at the level of seven classes: knowledge representation, learning, communication, perception, planning, robotics, and collective intelligence.

Success in the AI era depends on acquiring the competencies needed to effectively collaborate with and use AI (Borana et al. 2016; Chen and Lin 2023; Jarrahi 2018), which go beyond simply understanding AI, but also include other areas such as application, evaluation, creation, and even the ethical dimension of AI (Ng et al. 2021).

3. Research goal and hypotheses

This study aims to investigate the role of AI literacy as a determinant of successful AI implementation in organizations, examining both organizational-level literacy effects and competency impacts on technology acceptance and usage. Additionally, this research seeks to identify sector-specific variations in AI competency requirements to provide targeted insights for specific AI adoption.

Based on the literature review, we can identify several promising research hypotheses that emerge from the gaps and relationships discussed.

H1: The use of AI competencies varies significantly across industry sectors.

H2: Organizations with higher levels of AI literacy demonstrate significantly better AI implementation compared to organizations with lower AI literacy levels.

H3: Higher AI competency levels positively correlate with effective use of AI technologies in the workplace.

These hypotheses address the key gaps in the literature review, particularly around empirical testing of the relationships between competencies, barriers, and implementation success. They allow formulation of practical implications for organizations seeking to improve their AI adoption outcomes.

4. Materials and methods

This study employed a quantitative research approach utilizing empirical data collected from 40 organizations selected from the top one hundred companies operating in the Czech Republic. Only organizations listed in the Czech Top 100 were included in the survey. The response rate was 40%. The primary data were obtained through a structured questionnaire administered via computer-assisted web interviewing (CAWI) methodology. The research instrument was designed to examine multiple dimensions of organizational AI adoption, including current AI utilization patterns, specific AI tools and application areas, competencies required for effective AI implementation, and organizational changes related to AI integration such as employee reskilling, training initiatives, recruitment strategies, workforce transitions, job transformations, and skill requirements in the AI era. The questionnaire development was grounded in established theoretical frameworks and validated by previous empirical studies, particularly those conducted by Long et al. (2021) and Perchik et al. (2023). Competency assessment items were systematically reviewed and refined based on relevant literature and theoretical foundations established in this research.

The sampling frame comprised organizations specifically engaged in AI utilization, ensuring relevance to the research objectives. Organizations were strategically selected across diverse industries and geographic regions within the Czech Republic's top one hundred companies to achieve sample representativeness. The selection criteria included organizational location, size, business sector classification, and ownership structure. Each participating organization was represented by a single respondent holding senior-level positions, specifically general managers, human resources managers, or specialized professionals working full-time in AI-related capacities.

The final sample distribution reflected the actual economic structure, with primary sector organizations comprising 7%, secondary sector organizations representing 17%, and tertiary sector organizations constituting 76% of the total sample. This distribution closely mirrors the real-world economic sector composition in the Czech Republic, enhancing the external validity of the findings.

Data collection procedures involved initial email contact with target organizations, followed by distribution of the online questionnaire. Respondents were specifically instructed to identify competencies deemed necessary for successful AI implementation within their work environments. The resulting dataset underwent systematic cleaning and processing to ensure data quality and analytical reliability.

Statistical analysis was conducted using IBM SPSS Statistics 22 software. The analytical approach incorporated descriptive statistics to characterize sample demographics and response patterns, correlation analysis to examine relationships between variables, and association tests to identify significant connections between organizational factors and AI adoption patterns. Additionally, multivariate factor analysis was employed to identify underlying competency dimensions and reduce data complexity. Chi-square and Spearman's correlation tests were utilized to examine sectoral differences and relations in AI adoption patterns and competency requirements, with statistical significance set at $p < 0.05$. The chi-square assumptions (e.g., minimum expected counts) were reached in the case of secondary and tertiary sector organizations. Therefore, the chi-square test was used to test the differences between those sectors. The consistency was tested by Cronbach Alpha and the result reached over 0.8, which is satisfactory for further analyses. Factor analysis was not used to test sectors, as there were not enough responses to provide relevant base for such an analysis.

5. Results

The results show that surveyed organizations are using AI on daily basis for in many areas. Intensively use AI 77.8% of respondent organizations. The general AI tools are used by most organizations, such as customer support (68.8%) and data analysis (also 68.8%), content generation (60%), language translations (56.3%) and surprisingly, large use of AI is among human resources (53.9%).

5.1. AI Tool Usage

According to the data, the use of AI is sector specific. The AI tools used by the primary sector cover the most commonly used AI such as customer support and service: e.g., chatbots or virtual assistants, human resources: e.g., recruitment automation, data analysis: e.g. processing of

larger amounts of data and predictive analysis, content generation: e.g. automated compilation of data summaries or writing articles, product descriptions, etc. and language translations and localization: e.g. content localization or AI-powered language translations. The secondary sector is specific by using AI for manufacturing and operation management: e.g., quality control or predictive maintenance and supply chain management: e.g., demand forecasts or optimization of distribution routes, which is almost exclusively used by the secondary sector organizations. The tertiary sector organizations in addition use AI for finance and risk management: e.g., automated invoice extraction, fraud detection or algorithmic trading, healthcare management: e.g., assistance in determining a patient's diagnosis and treatment process, and legal services: e.g., contract analysis or legal research in the area of searching for relevant cases and laws. The AI tools used by all three sectors are the general AI tools used by the primary sector. The differences between sectors are statistically significant. The Chi-square test indicated the difference with $p=0.000$. The use of AI tools is displayed in the Fig. 1.

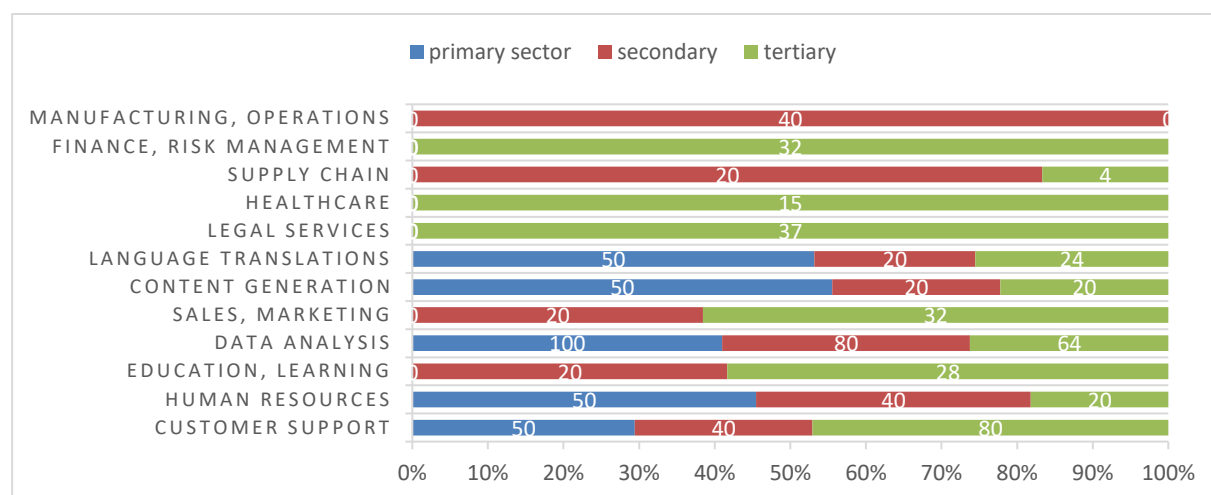


Fig. 1. AI tools among sectors

According to the survey result, the most commonly used AI competencies are analytical competencies (84.38%), followed by digital competencies (78.13%), and critical thinking (65.63%). Strategic competencies are important in relation to AI use in 50% of respondent organizations. The least importance was shown within soft skills.

5.2. Competency Patterns

The respondent organizations indicated that the most important AI-related skills are analytical (84.4%), digital (78.8%) and critical thinking (65.6%). However, significant differences among sectors were recorded also in the area of use of competences necessary for AI use in business. All three sectors reported the use of competencies related to digital, critical thinking, and analytical skills. Problem solving skills are used by primary and tertiary sector organizations.

Communication by secondary and tertiary sector organizations and team competencies only by tertiary sector organizations. Again, Chi-square test confirmed significant differences in AI-related competency use among sectors ($p=0.000$). Details are in Fig. 2.

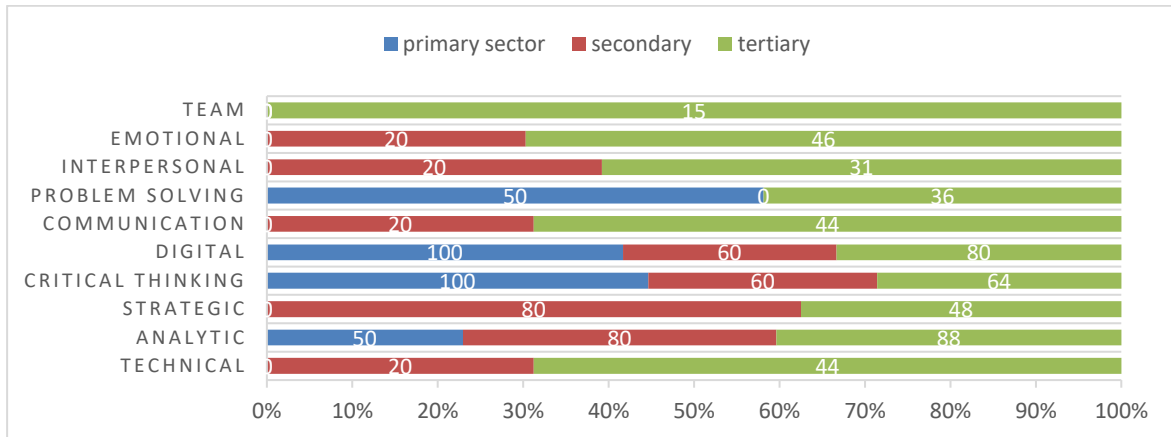


Fig. 2. AI-related competencies among sectors

5.3. Organizational Impact

Finally, the impact of AI incorporation into daily procedures has a significantly different impact on organizations based on their sector ($p=0.000$). As indicated in Fig. 3, all three sectors are focusing on employee training and reskilling. Organizations from secondary and tertiary sector organizations also reported no change in their job structure and no transformation. The tertiary sector organizations are, according to expectations, experiencing the most of the changes in relation to job structure and transformation based on AI use among all sectors, including the need of hiring new employees, outplacement of some employees that are no longer needed and transfer to different tasks.

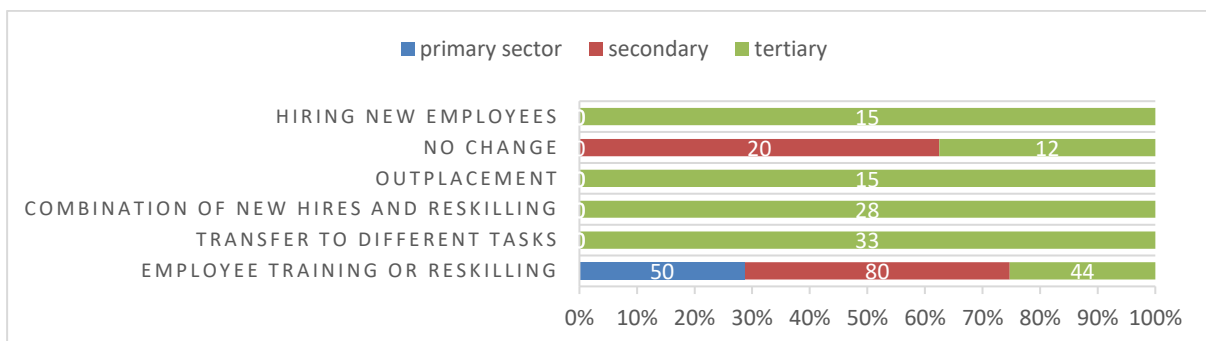


Fig. 3. Impact of AI on jobs among sectors

Based on the results above, the Chi-square test confirmed the H1, as there are statistically significant differences in AI use among sectors ($p=0.000$). The test also confirmed, that organizations which actively use AI demonstrate significantly better AI implementation compared to organizations with lower AI literacy levels. This concludes that H2 was valid

($p=0.000$). On the other hand, the H3 was not confirmed. The use of AI indicated a very weak correlation with focus on use of technologies ($r=0.129$). AI is used by all organizations without their primary focus or the level of use of technologies.

6. Discussion

The research findings align closely with the theoretical framework suggesting that AI represents the fastest growing business opportunity in today's economy, with projections indicating its contribution to the global economy (Rao & Verweij, 2017; Chui et al. 2023). The intensive daily use of AI by 77.8% of surveyed organizations demonstrates that this theoretical potential is being actively realized across various sectors, confirming that AI-based technological solutions are becoming integral to organizational operations for more efficient data collection, improved decision-making processes, enhanced logistics operations, and increased labor productivity (Srivastav, 2019).

The sectoral differences observed in AI implementation patterns reflect the literature's identification of key industries where digitalization creates added value, including manufacturing, agri-food industry, automotive, logistics, retail trade, and financial services (Al Suwaidan, 2021; García-Muiña et al., 2020; Demeter et al., 2020; Wyrwa, 2020; Zhang et al., 2020). The secondary sector's focus on manufacturing-specific AI applications such as quality control and predictive maintenance directly corresponds to the theoretical expectation that manufacturing would be among the primary beneficiaries of AI integration. Similarly, the tertiary sector organizations adoption of specialized AI tools for finance, healthcare, and legal services validates the theoretical framework's emphasis on these sectors as key areas for AI value creation.

The competency requirements identified in the study strongly support the theoretical model proposed by various scholars regarding the multidimensional nature of AI-related skills. The prominence of analytical competencies (84.4%) and digital competencies (78.1%) among surveyed organizations aligns with Jaiswal et al.'s (2021) model emphasizing data analysis and digital skills as critical competencies for improving human-AI relationships. The importance of critical thinking (65.6%) mirrors the theoretical emphasis on cognitive competencies including problem solving, creativity, judgment and critical thinking as defined by Younnis and Adel (2020). The relatively lower priority given to soft skills in the survey results contrasts somewhat with theoretical frameworks that emphasize social and emotional competencies such as teamwork, leadership, and communication as essential for AI adoption.

The sectoral variations in required competencies reflect the theoretical understanding that AI implementation necessitates different skill sets depending on the organizational context. The Technology Acceptance Model's distinction between skill domain, relevance domain, ethics, and knowledge domain (Ng et al., 2021; Cetindamar et al., 2024) provides a framework for understanding why different sectors prioritize different competencies. The tertiary sector organizations emphasis on team competencies and communication skills aligns with the theoretical expectation that service-oriented industries would require stronger collaborative intelligence (Chowdhury et al., 2022) and human-machine cooperation capabilities as emphasized in Industry 5.0 transitions (Suciu et al., 2023). Therefore, the tertiary sector could consider incorporating employee trainings specifically focusing on these areas.

The organizational impacts observed, particularly the focus on employee training and reskilling across all sectors, directly support theoretical predictions that AI implementation leads to fundamental changes in workforce requirements and organizational structures (Becker-Ritterspach & Gröger, 2018; Chen & Zhou, 2020; Janssen et al., 2017). The tertiary sector organizations experience of more significant transformations, including workforce redeployment and role reassignment, validates theoretical frameworks suggesting that AI technologies introduce innovative changes that revolutionize how people work and communicate in digitalized environments (Borana, 2016; Chen & Lin, 2023; Jarrahi, 2018; Ismail & Hassan, 2019; Rymarczyk, 2020).

The confirmation of Hypothesis 2, demonstrating that organizations with active AI use show superior implementation compared to those with lower AI literacy levels, strongly supports the theoretical framework of AI literacy as both an individual and organizational capability (Long & Magerko, 2020; Cetindamar et al., 2024). This finding validates the theoretical proposition that AI literacy enables individuals to evaluate AI technologies, communicate effectively with AI systems, and use AI tools efficiently (Magerko, 2021; Perchik et al., 2023; Pinski & Benlian, 2023; Wienrich & Carolus, 2021). The organizational perspective of AI literacy as a collective capability that emerges through individual interactions within organizations (Cetindamar et al., 2024) is supported by the research findings showing that higher organizational AI literacy correlates with better implementation outcomes.

Interestingly, the rejection of Hypothesis 3, showing only weak correlation between AI usage and organizational technology focus, challenges some theoretical assumptions about technology adoption patterns. This finding suggests that AI has transcended traditional technology-focused organizations and has become a universal business tool, supporting the theoretical framework that emphasizes AI's transformative potential across all industries

regardless of their primary technological orientation. This universal adoption pattern aligns with theoretical predictions about the pervasive nature of AI technologies and their potential to revolutionize diverse organizational contexts (Bhalerao et al., 2022; Suciú et al., 2023).

7. Conclusions

This study examines artificial intelligence adoption patterns across different economic sectors, revealing significant variations in implementation, required competencies, and organizational impacts. The research demonstrates widespread AI adoption, with 77.8% of surveyed organizations using AI tools intensively on a daily basis. The study reveals distinct sectoral patterns in AI implementation: Primary Sector organizations utilize general AI applications including customer support chatbots, HR recruitment automation, data processing for predictive analysis, automated content generation, and language translation services. Secondary Sector organizations demonstrate unique specialization in manufacturing-focused AI applications, incorporating quality control systems, predictive maintenance tools, and supply chain optimization including demand forecasting and distribution route optimization. Tertiary sector organizations employ the broadest range of AI applications, encompassing all general tools while also implementing specialized solutions for finance and risk management (automated invoice processing, fraud detection, algorithmic trading), healthcare management (diagnostic assistance, treatment planning), and legal services (contract analysis, legal research).

Organizations identified critical AI-related competencies in order of importance: analytical skills (84.4%), digital competencies (78.1%), and critical thinking abilities (65.6%). Strategic competencies were deemed important by 50% of respondents, while soft skills received the lowest priority ratings. Competency requirements also varied by sector, with all sectors emphasizing digital, critical thinking, and analytical skills. Primary and tertiary sector organizations additionally prioritized problem-solving capabilities, while secondary and tertiary sector organizations valued communication skills.

AI implementation has generated varying organizational responses across sectors. All sectors have prioritized employee training and reskilling initiatives. Secondary and tertiary sector organizations reported minimal changes to job structures, while the tertiary sector organizations experienced the most significant transformations, including new employee recruitment, workforce redeployment, and role reassignment.

The research employed tested three hypotheses to provide important insights into AI adoption patterns. The first hypothesis was confirmed, demonstrating that statistically significant differences exist in AI use among economic sectors ($p=0.000$), which validates the sectoral

variations observed in implementation strategies and application focus areas. The second hypothesis was also confirmed, showing that organizations with active AI use demonstrate superior implementation compared to those with lower AI literacy levels ($p=0.000$). However, the third hypothesis was rejected, as AI usage showed only weak correlation with organizational technology focus ($r=0.129$), indicating that AI adoption occurs regardless of an organization's primary technological orientation and suggesting that AI has transcended traditional technology-focused sectors to become a universal business tool across diverse organizational contexts. The findings suggest that while AI adoption is widespread across all economic sectors, implementation strategies and impacts are highly sector-dependent. Czech organizations in similar economic contexts may consider developing tailored approaches that align with their sector's specific needs while building appropriate competency frameworks to support successful AI integration.

This research acknowledges several methodological and contextual limitations that may influence the generalizability and interpretation of findings. The relatively small sample size of 40 organizations, while representative of the Czech economic structure, limits the statistical power for detecting nuanced differences between sectors and may restrict the applicability of findings to larger organizational populations. The cross-sectional design captures AI adoption patterns at a single point in time, potentially missing the dynamic nature of technological implementation and organizational adaptation processes that evolve continuously.

Several promising research directions emerge from this study's findings and limitations. Longitudinal research designs would provide valuable insights into the temporal dynamics of AI adoption, tracking how organizational competency requirements, implementation strategies, and sectoral differences evolve over time. Expanding the geographic scope through comparative international studies would enhance understanding of how cultural, regulatory, and economic factors influence AI adoption patterns across different national contexts.

Future research should incorporate larger, more diverse samples including organizations at various stages of AI adoption, from non-adopters to advanced implementers. Mixed-methods approaches combining quantitative surveys with qualitative case studies would provide richer understanding of organizational experiences, implementation challenges, and success factors.

Ethics statement

This article does not involve any original experimental studies with human or animal subjects. Therefore, no ethical approval was required for this work.

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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.

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Digital well-being as an educational challenge: a mapping review study

Michal Černý 1*

1* Masaryk University, Czech Republic, email mcerny@phil.muni.cz

Abstract

Digital well-being in educational contexts is becoming increasingly important in educational policies, teaching processes and research. However, due to the dynamic nature of the topic, a deeper conceptualisation of the whole phenomenon is lacking. This review study analyses 15 Web of Science studies related to this area and identifies the key themes and components of the phenomenon in relation to educational practice. Explicitly: the inappropriateness of using simple metrics such as screen time, the importance of the way digital wellbeing is talked about, the emphasis on the relationship between family and school, the limited possibilities of applications, the need to regulate selected services, and the importance of participatory methods in teaching and developing digital wellbeing, which appears to be changeable through education. The study offers insights into practical educational practice.

Keywords: digital wellbeing; review study; competence; psychology; TikTok; restriction; screen time; scrolling.

1 Introduction

Technology is fundamentally transforming the world we find ourselves in. We live in an information society that has long been viewed with strong optimism (Breivik, 1985; Webster, 1999, 2014; Zlatuška, 1998). This optimistic discourse gradually began to change, with critical theory entering the debate about the nature of society, drawing attention to the discourse of government and corporate power (Elmborg, 2006; Freire, 2014; Irving, 2020), which gradually evolved into a critique of large corporations diminishing human freedom (Bridle, 2018; Dijck et al., 2018). The education space is simultaneously linked to a process of accumulation of crises or polycrises (Beck, 2009; Matějčková, 2023), to which it must respond.

Within this framework, a debate is gradually taking shape about the impact of digital technology on human psychological well-being. Starting from the notion associated with Heidegger, who spoke of living in the drag of technology (Heidegger, 1967) and tried to accentuate the importance of the ontological distinction between humans and technology, we gradually move into the discussion of digital wellbeing (Cecchinato et al., 2019; Giraldo-Luque et al., 2020), its position in the set of digital competencies (Carretero et al., 2017), and its possible relationship with artificial intelligence (Kaya et al., 2025)

This is an area where it is possible to encounter many different approaches that try to move between them. One can see a tradition emphasising the connection between ethics and digital well-being (Burr & Floridi, 2020), which relates to the need to create space for free thinking

and humanity as such. According to Floridi, digital wellbeing is linked to the impact of technology on living a good life. The good life - this category of Greek philosophy - is one of the most commonly used concepts in the ethics of digital wellbeing.

There are discourses associated with a strongly restrictive conception, which seek - ideally - to ban digital devices or to regulate them heavily at least among adolescents or in school settings (Gerosa et al., 2024; Islambouli et al., 2025). At the same time, UNESCO documents show that a techno-pessimistic approach is not inconsiderable (West, 2023). However, we can also see studies that highlight the importance of a balanced approach and the role of education in achieving digital wellbeing (McCoy & Marcus-Quinn, 2025)

From the above, we can say that there are widely varying views on approaching digital wellbeing. Similarly, we can see different approaches associated with achieving it. Some authors lean towards concepts emphasising participation (Lister et al., 2022; Peters & Ahmadpour, 2021) as a prerequisite for actively shaping digital wellbeing at the individual level. It is possible to encounter a group of authors who lean more towards digital minimalism (Newport, 2019) and find the boundaries of where we want to work with technology and where we do not. Floridi highlights the blurring of the boundaries between technology and humans (Floridi, 2015), leading to the belief that the way forward cannot be to exclude technology from life, but rather to seek some dynamic approach (Vanden Abeele, 2021), which in some ways harks back to participatory methods and the need to rethink the world in new and different ways radically (Helgason et al., 2020; Latour, 2021)

This review study will describe what approaches are emerging in digital wellbeing education and how they can be considered and developed. We believe that the ability to work with technology, digital competence, must be linked to a progressively learned ability to critically find ways to use it to one's advantage, to work with it with feelings that are not negative. We believe in digital wellbeing as a digital competence, as the European Framework of Digital Competences for Citizens (Carretero et al., 2017) works with it.

1.1 Research objectives and questions

This research will analyse the current literary field related to digital wellbeing in educational contexts and establish a thematic analysis of the topic, findings, and associated contexts. Motivation is to identify educational approaches or practical impacts that can be realistically implemented as starting points for educational practice. At the same time, we will focus on academically relevant research, which is included in the Web of Science database and sufficiently cited.

Research question: What key conclusions or themes can be identified in current research on digital well-being in relation to educational policy and practice?

2 Methodology

To develop the mapping review study, we adopted a qualitative approach to look for ways and methods to implement digital well-being education. We aim to create an overview of the knowledge structure in this area that can serve, for example, educational policy makers. Therefore, we chose a qualitative research design. For this, we decided on a survey study as a form.

2.1 Data collection

We search all studies in the Web of Science (WoS) database with the highest academic relevance. Studies listed there can be expected to have both intrinsic quality and integrity, as well as an impact on knowledge, further research, and the use of theoretical knowledge in practice.

- Search query: "digital wellbeing" OR "digital well-being". The term digital well-being is used in both forms in the literature. The usage ratios are relatively balanced. A search of WoS reveals 342 documents containing the term "digital well-being" and 259 documents containing "digital well-being".
- Language limitation: we only searched for studies in English. This is attributable to two factors. Firstly, the linguistic limitations of the author of the study. Secondly, the emphasis on the broader implications of the study. To a certain extent, the selection may be considered arbitrary.
- Geographical limitation: by being a psychological topic, digital wellbeing can be expected to be sensitive to the location of the study, both in terms of data collection and researchers' approach. Therefore, we focused our research on European countries only. A Dutch research team conducted one study, but the data were collected in the USA. Nevertheless, we decided to include it in the research.
- Document limitation: We only included studies in journals. The objective of the present study was to concentrate on studies which had undergone a rigorous review process, which is not necessarily as strict in cases of anthologies or books.
- Time limitation: We only look at studies published after 2022 for timeliness. The rapid development of technology, societal transformation, and other factors significantly

impact the durability of individual findings. It is imperative to emphasise the significance of timeliness to formulate a contemporary perspective on digital wellbeing. Conversely, implementing more stringent time limits was deemed impractical, given the filter's limited applicability.

- Thematic reduction: studies from psychology, education, social sciences and related fields were included in the research. The overarching focus of this study pertained to the domain of education, necessitating the exclusion of the results relating to medical or technical domains.

In this way, we obtained 69 studies (Figure 1), from which we selected the 15 most cited ones, which we carefully reviewed and present in the results section. The notion of citation is regarded as a factor open to scrutiny and should not be considered the sole barometer of a study's quality. Nonetheless, it offers some insight into the influential nature of research and its impact. The review study does not identify the most significant studies, but rather those that have a relevant influence on current professional discourse through citations. These are studies with five or more citations in WoS, demonstrating their (at least partial) influence on academic discourse. Due to carefully chosen filtering criteria, we did not have to exclude any outputs from the search results.

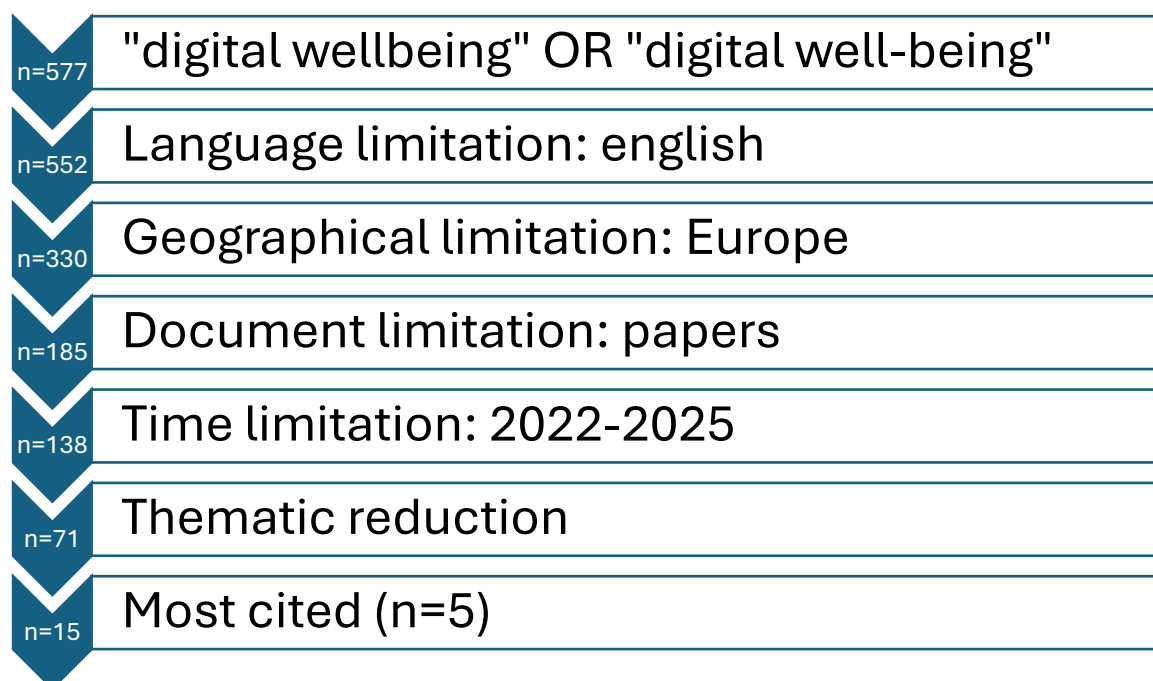


Figure 1. Prisma paper selection diagram

3 Results

A description of the research sample is recorded in Table 1. The table shows that quantitative research methods (12) dominate our research sample, while qualitative (3) and mixed research designs (1) are the minority. There were no theoretical or review studies in the sample. Regarding states, some are mentioned explicitly, where it is not clear where the data was collected, we take the state where the author's institution is located. This is the dominant part of the target research sample for the target group. The table aims to offer a fundamental insight into the sample, but is somewhat indicative of the critical findings that can be worked with in the quantitative section.

Author	Quality/ Quantity	State	Topic	Research sample
Fauville	Quant	Sweden, USA	Zoom	Adults
Gui	Quant	Italy	Media education	High school students
Gennari	Qual	Italy	Social context	High school students
Lyngs	Quant	Irrelevant	App reviews	Whole population
Widdicks	Qual	Sweden, USA	Environmental aspects	College students
Dekker	Quant	The Netherlands	Notification	Undergraduates
Lazou & Tsinakos	Quant	Greece, Bulgaria, Romania	Augmented Reality	High school students
Nguyen & Hargittai	Quant	Netherlands	FOMO	Adults
Rosic	Quant	Slovenia	Testing scale	Adolescents
Wolfers	Quant	Germany (?)	Mothers and stressful situations	Adults
Virós-Martín	Quant	Spain	TikTok	Adolescents

Wolfers	Quant	Netherlands, USA	Parents' feelings	Parents
Lister	Mix	UK	How to teach digital wellbeing	College students
Gerosa	Quant	Italy	The impact of the phone on learning outcomes	Adolescents
Lafton	Qual	Norway	How to talk about digital wellbeing?	Families

Table 1. Overview of further qualitatively analysed studies. In research design, we differentiate between quantity (Quan), quality (Qual), and mixed design (Mix).

3.1 Summary of studies

The study (Fauville et al., 2023) addresses the phenomenon of Zoom fatigue. The Swedish-American research team shows that the feeling of fatigue depends on psychological subjective factors (unpleasant feelings associated with looking in the mirror), but also on experience (more frequent use of video conferencing leads to more fatigue), as well as on social-psychological factors related to the difficulty of working with non-verbal communication with a large number of people to focus on. The research is based on a large-scale (n=9787) quantitative study.

A quantitative research (Gui et al., 2023) from Northern Italy (42 secondary schools, n=789) focused on media education opportunities and their impact on reducing screen time. The data show a small but existing effect of education that works better for girls than boys. The study is optimistic in highlighting the positive impact of media education on pupils' wellbeing while finding no effect of digital competence on screen time.

A design-oriented study (Gennari et al., 2023) from Italy shows the importance of a design approach to understanding digital well-being in students. It sets it as one way to think about the whole issue in more depth and detail. The study's authors offer a comprehensive set of activities for secondary school students, aiming to ensure that well-being is perceived not only as a private phenomenon but also as a social phenomenon with a broader societal impact. This is qualitative research (n=24). The study also highlights the potential of new technologies in the speed and concreteness of prototype development, which is crucial to a design approach to learning.

Many tools promise users gains in digital self-control by reminding them of goals, blocking pages, and many other ways. The study (Lyngs et al., 2022) analysed user reviews (1,529 in total) and tried to look for patterns and concepts that may be functional from the design perspective of such tools. One of the conclusions of this analysis is that users demand and better

evaluate more comprehensive tools than a set of single-purpose tools. The study also shows a relationship between general self-regulation ability and digital well-being. It seems that users who struggle with it often label themselves as ADHD persons or procrastinators, leading to a cycle of learned helplessness. This self-labelling can substantially negatively impact digital well-being, *per se*.

The study (Widdicks et al., 2022) focuses on a different approach to the limitations of digital technologies in the environmental context. It draws on reflection from a workshop (n=13) for high achievers to think critically about when students need technology and when they do not. The aim was to limit environmental burdens, but as the authors say, to reflect on how working with digital tools is essential to digital wellbeing, including limiting it in a meaningful way.

Turning off notifications is a commonly recommended measure linked to mobile phone use, concentration or digital wellbeing. However, a study by a Dutch team (Dekker et al., 2025) showed that none of this is measurable - that notifications do not distract or reduce a person's attention. But they carry with them two other phenomena. The first is that while the time and manner of phone use have not changed, the sense of control over it has increased. On the other hand, the respondents both felt that they were missing out on something important. The study used quantitative research with university students (n=205).

What feelings do learners have when working in augmented reality? The study's authors (Lazou & Tsinakos, 2023) work with augmented reality learning and suggest learners develop Critical Immersive Activated Literacy, which aims to create a set of skills for learning in digital augmented or virtual reality environments. This new literacy should contribute not only to the ability to learn in such environments, but also to digital wellbeing, the specificities experienced in augmented reality or digital immersive environments. The quantitative study (n=77) focused on students aged between 13 and 17 in Greece, Bulgaria and Romania.

In the context of digital well-being, the relationship between device use and negative or positive feelings is intensely debated. The study (Nguyen & Hargittai, 2024) focused on 105 users who were asked to fill in a questionnaire six times a day; the average age of the respondents was about 40 years old. It turns out that feelings are more complicated than commonly thought. Difficult to measure the individual current psychological influences on users that will have a significant impact. The second (and key) finding is that good feelings with disconnection are associated with being in physical social contact with others and, conversely, if one is disconnected and alone, such a combination creates negative feelings. Thus, the theme of digital wellbeing needs to be much more about social factors and contexts than we have seen.

An important question is how teachers can identify which children are experiencing negative impacts of technology on their well-being. These are the ones that can be targeted for intervention. The study (Rosič et al., 2024) works with the setting of Slovenia, where they conducted interviews (n=5) and subsequently validated the instrument with adolescents (n=161 and n=1040). The output is a measurement tool that combines social, cognitive and emotional aspects. Students in Slovenia show a significant decrease in their perceived cognitive performance due to increasing time spent on digital devices. At the same time, research shows that girls perceive their ability to regulate emotions in digital technologies as lower than that of boys. Students with higher academic profiles are more likely to perceive the negative impacts of technology. The ability to work with digital well-being increases with age.

Phones can be a stress management tool, consistent with how they are commonly used. German researchers (Wolfers et al., 2023) focused on mothers (n=209) and investigated how they deal with stress. It turns out that mothers do not have sophisticated self-regulation strategies for coping with stressful situations with a digital device. However, if it serves any purpose, it is as a distraction or to "forget" or gain distance. The challenge for education may thus be both to reflect on these approaches and to develop specific forms of working with crises and stress using them.

Research (Virós-Martín et al., 2024) on Spanish adolescents (n=737) focuses on TikTok and highlights three important aspects related to its use. Firstly, there are strong gender stereotypes in what content is consumed (fashion, beauty x sports, games). The second important finding is that time does not cause bad feelings in adolescents, but it reduces the ability to self-control. TikTok has similar effects on self-regulation as drugs, so it is essential, say the study authors, to regulate time spent on the devices on the part of parents. The way to go is not an individual ban, but some form of time restriction on TikTok availability.

The study (Wolfers et al., 2025) by Dutch authors (but with a US sample) focused on parents (n=141) and examined their guilt about giving mobile devices to their children. The study notes that many negative phenomena may not be negative in themselves. However, experiencing them in a social context (demonising screen time in children) can lead to negative feelings and adverse effects, including damage to the child-parent relationship. This paper is an essential input into how to talk about digital wellbeing in a way that avoids unnecessary, unintended negative consequences through guilt or stress.

A study with a mixed research design from the UK (Lister et al., 2022) sought to find educational principles for teaching digital wellbeing. It sees participatory methods that allow each participant to be active as essential. At the same time, they emphasise a holistic and

inclusive approach in course design or building a partnership approach to develop the topic. The study shows quite clearly that both the topic of digital wellbeing itself and its combination with non-frontline methods are essential. The research was conducted among academics and university students.

An extensive study from Italy (Gerosa et al., 2024) says that gaining a mobile phone before age 11 significantly reduces digital competence, language skills, math skills, etc. Girls and people from lower socio-demographic backgrounds acquire phones earlier. According to the authors, this creates a new digital divide that is no longer linked to the inability to access the internet or devices, but to the failure to control them.

The family environment plays a key role in developing digital wellbeing, or rather, the values realised and experienced in the family. Families that can talk and discuss values and actions create a better environment for digital well-being than restrictive families (Lafton et al., 2024). Family climate and culture seem to be the ones that have a significant influence on children's complex development, including in the area of digital wellbeing. The study was conducted with interviews with 10 members of different families and focus groups (n=10) with children between 5 and 10 years old.

4 Discussion

The research question of this study was: What key conclusions or themes can be identified in current research on digital wellbeing in relation to educational policy and practice? The following seven themes can be identified based on an analysis of 15 documents. In discussing each theme, summarise the results of this research, supplement them with a discussion in the context of broader studies and the current state of knowledge, and draw educational implications from them.

The first general finding of this review study is that much attention is still being paid to **screen time** or other simple metrics. As much as studies (Vanden Abeele, 2021) show that simple time is not an appropriate metric, but that quality of time, social context and many other variables are involved, it seems that, especially for quantitative studies, this is still the dominant approach (Dekker et al., 2025; Gui et al., 2023; Nguyen & Hargittai, 2024). For educational practice, it can be inferred that focusing on minimising students' time spent on the device is not an effective strategy for working with digital well-being.

How **digital wellbeing is discussed** is crucial - social perceptions and narratives are fundamental to experiencing what interactions are perceived as good and what are not. We suggest that there may also be a factor for differences in perceptions of digital well-being across

generations. A study (Roffarello & De Russis, 2023) demonstrates that narrative is crucial for conceptualising how we relate to technology. This dimension is also noted in the studies in our sample (Lafton et al., 2024; Wolfers et al., 2025). At the same time, it is essential to highlight how users talk about themselves and how they frame themselves (Lyngs et al., 2022), which has implications for their digital well-being. The educational recommendation is a critical but open and balanced collaborative reflective journey of seeking digital wellbeing. Focusing on predominantly harmful or risky factors can lead to a deterioration in the overall well-being of learners. The premises of positive psychology (Seligman, 2011) agree with this statement.

Participatory methods are a fundamental approach to take the topic of digital wellbeing forward and across all age groups (Craven et al., 2019; Martzoukou et al., 2020; Vanden Abeele, 2021). The collaborative sharing of experiences, often associated with prototyping, testing or design thinking, constitutes a critical discourse, as seen in the studies we have analysed (Gennari et al., 2023; Lister et al., 2022). These approaches associated with design thinking (Avsec & Savec, 2019; Pearlman, 2010) are associated with creativity as a tool for achieving meaningful learning, entering the context of everyday life, in the process of attaining a good life with technology that cannot be brought from outside (Burr & Floridi, 2020). Educational recommendations include the use of workshops and the development of prototypes that allow students to formulate their own optimistic scenarios and insights.

Family background and school influence are essential to digital wellbeing (Almourad et al., 2021; Dennis & Ziliotti, 2023). Finding common family values and sharing goals is an important relational parameter in digital well-being. In this respect, it can be considered part of a broader wellbeing, i.e. in a particular broader perspective (Filep et al., 2024; Themelis & Sime, 2019). This fact is also illustrated by the research in our study (Gerosa et al., 2024; Lafton et al., 2024; Wolfers et al., 2025). The educational recommendation is therefore to focus not only on the level of schooling but also to work systematically on the development of the family background in this area.

TikTok and **social media** represent a significant and specific topic related to digital well-being, which has been the focus of a large number of studies (Crepax, 2020; Diefenbach & Anders, 2022; Hellemans et al., 2021) and in a largely negative way (West, 2023). As much as one can find studies accentuating the positive aspects of their use (Collie & Wilson-Barnao, 2020; Khlaif & Salha, 2021), it can be argued that the discourse is shifting towards a strongly negative perception in our study as well (Virós-Martín et al., 2024). What positive aspects social media should bring to adolescents in the long run is questionable. From an educational perspective, collaboration with parents is key, as well as considering other forms of distribution of

interactions and content than those offered by social media, such as through school information systems or special communication platforms.

Apps for gaining self-control and digital well-being are among the traditional themes of research in this area, including emphasising that digital well-being cannot be reduced to a problem of users, but also of corporations and designers (Al-Mansoori et al., 2023; Roffarello & De Russis, 2023). Their potential has not yet been fully exploited and should be given new attention. With excellent possibilities, this topic is linked to participatory tools and methods—studies in our review (Lyngs et al., 2022). In terms of education, they can serve well as elements of reflection or thinking. Still, there seem to be more effective ways to work with digital self-management as it is closely related to self-management per se (Dekker et al., 2025).

At the same time, studies agree that the whole **phenomenon of digital wellbeing is complex** and many factors enter into it (Fauville et al., 2023; Gennari et al., 2023; Gui et al., 2023), which was already pointed out by Vanden Abeele (2021), whose work is still underappreciated in the context of this review study. It seems impossible to formulate some simple advice, procedures and principles. Nevertheless, it is possible to talk about the positive aspects of education in this topic (Gui et al., 2023) or its understanding and development as a specific competence (Lazou & Tsinakos, 2023). At the same time, education can help with more meaningful crisis management, but again, this requires education and not just an intuitive approach (Wolfers et al., 2023). The educational conclusion is therefore that education in this area is not perfect or a complete solution to all problems, as it runs into the determinants of many individual psychologies (Fauville et al., 2023; Rosič et al., 2024), but it still makes sense.

5 Conclusion

This review study shows that digital well-being is a timely and powerful topic that makes sense to research. However, its reading in educational practice is ambivalent. While some studies take the side of restrictions and limitations and consider technology as a form of evil and danger, we believe a more nuanced approach is in order, based on the literature analysed. If we combine the claims of two highly influential studies in this area (Burr & Floridi, 2020; Vanden Abeele, 2021), we can say that the goal of education should be to create the conditions for each individual to lead a good life on their own using technology. The parameter of the "good life" is primarily individual in nature. However, this does not diminish the importance of education and the cultivation of these personal beliefs, nor the importance of a restrictive approach where technology destroys human freedom (Virós-Martín et al., 2024).

Regarding education, the importance of family and school collaboration, participatory methods and approaches, or the overall use of creativity, reflectivity and cooperation in working with this topic can be emphasised. It turns out to be extremely sensitive to personal psychological settings and the sense of social proximity and language-value discourse, in which educational institutions are fundamentally involved. At the same time, it can be said that there does not seem to be much difference between the different groups in the need for participatory methods in the development of digital wellbeing. These works, from the studies we have analysed, are very universal.

At the same time, research has shown that it is essential not to limit oneself to simple metrics such as screen time or the number of notifications in digital wellbeing. It is necessary to consider the quality and social context of digital technology use. School education can make a fundamental contribution through this form of cultivation, quality, and depth.

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Understanding the Hidden Crisis: A Multi-Dimensional Analysis of Student Dropout Factors in Higher Education

Tommy Turner ¹, Lucie Depoo ^{2*}

1 University of Economics and Management, Narozni 2600/9a, Prague, 15800, Czechia*

*2 University of Economics and Management, Narozni 2600/9a, Prague, 15800, Czechia, lucie.depoo@vsem.cz
(*corresponding author)*

Abstract

Student dropout affects 40-80% of higher education students globally, yet limited research examines institutional practices in private business education. Building on Tinto's and Bean's theoretical frameworks, this study analyses multidimensional dropout factors through content analysis of 287 student responses from a private business university (2017-2025). Using validated coding methodology ($\kappa = 0.87$), nine categories emerged: financial issues (75 occurrences), communication problems (65), academic misalignment (55), assessment issues (45), administrative burden (40), format inflexibility (35), cultural concerns (30), technical problems (25), and personal circumstances (150). Key institutional barriers included high costs (28), poor information quality (18), curriculum mismatch (20), and electronic testing criticism (18). While personal circumstances dominated, substantial institutional factors represent addressable barriers. The research contributes theoretically by empirically validating dropout categorizations and practically by providing a transformation framework successfully implemented by the case institution through student-centred reforms.

Keywords: student dropout; higher education; attrition factors; institutional challenges; student retention

1. Introduction

Student dropout in higher education has emerged as a persistent global challenge, with implications extending beyond individual academic failure to encompass broader socioeconomic consequences (Ghignoni, 2017; Prenkaj et al., 2020). The phenomenon has been particularly acute during periods of crisis, as evidenced by increased attention to dropout rates during the COVID-19 pandemic (Macana et al., 2023; Fernandez & Rios, 2024). Despite extensive research on the topic, the complex interplay of factors contributing to student attrition remains insufficiently understood, particularly within the context of private higher education institutions.

Recent literature has highlighted multiple dimensions of the dropout crisis. Teuber et al. (2021) emphasized the importance of satisfying students' psychological needs during institutional crises, while González-Ortiz-de-Zárate et al. (2024) demonstrated the effectiveness of peer mentoring programs in reducing dropout rates. Additionally, studies have shown that financial factors, technological challenges, and institutional responses significantly impact student retention (Branson & Whitelaw, 2024; López & Chiyong, 2021).

The theoretical framework for understanding student dropout has evolved to recognize the multifactorial nature of the phenomenon. Schnettler et al. (2020) applied expectancy-value theory to investigate the motivational processes underlying dropout intentions, while Sureda-Garcia et al. (2025) identified vulnerability typologies in second-chance education programs. These perspectives emphasize that dropout decisions result from complex interactions between individual characteristics, institutional factors, and external circumstances.

This study addresses a critical gap in the literature by providing a comprehensive empirical analysis of institutional factors contributing to student dropout in a private business education context. Through systematic content analysis of actual student dropout reasons, this research offers unique insights into the specific challenges that institutions can address to improve retention rates.

2. Literature Review

Student dropout has been conceptualized through various theoretical lenses, each contributing to our understanding of this complex phenomenon. The expectancy-value theory, as applied by Schnettler et al. (2020), suggests that students' decisions to continue or discontinue their studies are influenced by their expectations of success and the value they place on their education. Their longitudinal study of 326 undergraduate students revealed that intraindividual changes in intrinsic value, attainment value, and perceived costs significantly related to dropout intentions.

The ecological model of higher education, utilized by Cavagnoud and Ames (2024) in their study of Peruvian scholarship students, emphasizes the multiple environmental factors that influence student persistence. This framework recognizes that student success depends on the interaction between individual characteristics and various environmental contexts, including institutional, social, and economic factors.

2.1. Financial Factors and Economic Pressures

Financial considerations represent one of the most consistently identified factors in dropout literature. Ghignoni (2017) demonstrated that family background and socioeconomic status significantly influence dropout rates, particularly during economic crises. The study revealed that changes in student demographics and family circumstances play a major role in aggregate dropout rate fluctuations.

The COVID-19 pandemic has further highlighted the role of financial pressures in student attrition. Branson and Whitelaw (2024) found that South African students from lower socioeconomic backgrounds were disproportionately affected by pandemic-related disruptions, though financial aid programs provided some protection against dropout.

Lopes and Rebelo (2025) explored the relationship between unemployment rates and academic dropout, distinguishing between opportunity costs and expected benefits of higher education. Their findings suggest that employment prospects in specific academic fields significantly influence dropout rates, with practical implications for course evaluation and enrollment management.

2.2. Communication and Institutional Support

The quality of institutional communication and support systems has emerged as a critical factor in student retention. Wollast et al. (2023) examined the role of supervisor support in doctoral student persistence, finding that perceived structure and autonomy significantly influenced emotional well-being and continuation intentions among both male and female students.

The importance of institutional responsiveness during crises has been demonstrated across multiple contexts. Teuber et al. (2021) found that students' satisfaction with institutional strategies during COVID-19 was positively related to basic psychological need satisfaction and academic engagement, while negatively associated with dropout intentions.

2.3. Academic Content and Program Quality

Academic satisfaction and program alignment with student expectations significantly influence retention decisions. Nurmalitasari et al. (2023) identified academic satisfaction and performance as among the most influential factors in dropout decisions at Indonesian private universities. Their mixed-methods study revealed that misalignment between student expectations and actual program content contributes significantly to attrition.

The quality of educational materials and delivery methods also impacts student engagement and retention. Zhao et al. (2022) demonstrated that game-based learning approaches could enhance student experience and knowledge gain in programming courses, though they noted differential impacts based on student demographics and educational backgrounds.

2.4. Technology and Distance Learning Challenges

The rapid expansion of online and distance learning has introduced new factors influencing student dropout. Fernandez and Rios (2024) found that inadequate digital skills among teaching staff significantly impacted student dropout rates during the COVID-19 crisis, contributing to low motivation and negative attitudes toward learning.

López and Chiyong (2021) compared dropout rates between online and face-to-face course modalities, finding that while academic performance showed no significant differences, the explanations for dropout phenomena were diverse and context-dependent.

2.5. *Crisis Periods and Institutional Adaptation*

Research has consistently shown that crisis periods exacerbate existing vulnerabilities in higher education systems. Macana et al. (2023) identified distinct student profiles during the COVID-19 pandemic, finding that adapted students were more likely to be female and have guardians with higher income and education levels. Access to technology and broadband connections significantly reduced dropout risk.

The literature suggests that institutional responses during crises can either mitigate or amplify dropout risks. Studies have shown that proactive institutional support, clear communication, and flexible policies can help maintain student engagement during challenging periods (Takács et al., 2023; Esposito et al., 2023).

Despite the growing body of research on student dropout, significant gaps remain in understanding how specific institutional practices contribute to attrition decisions, particularly in private business education contexts. While theoretical models provide frameworks for understanding dropout processes, limited empirical research has systematically examined the relative importance of different institutional factors as perceived by students who have actually discontinued their studies.

3. Research Question

Given the complexity of factors influencing student dropout decisions and the limited empirical analysis of specific institutional practices in private higher education settings, this study addresses the following research question:

What are the primary institutional and personal factors contributing to student dropout decisions in private business higher education, and how do these factors manifest in students' actual departure experiences?

This research question encompasses several subsidiary inquiries: (1) Which institutional practices most frequently contribute to student dropout decisions? (2) How do students perceive and articulate the relative importance of different dropout factors? (3) What patterns emerge in the interaction between institutional and personal factors in dropout decisions? (4) Which institutional factors represent the most actionable opportunities for improving student retention?

4. Methods

This study employed a comprehensive content analysis methodology to examine student attrition patterns at a private business-focused higher education institution. The research

utilized a systematic survey approach targeting all students who discontinued their studies over an eight-year period spanning 2017 to 2025, ensuring a representative dataset for analysis.

Data collection was conducted through structured exit surveys administered to all students formally terminating their enrollment. The survey included both closed-ended questions addressing predetermined categories and open-ended responses allowing students to elaborate on their specific circumstances and concerns. This mixed approach ensured comprehensive capture of both anticipated and emergent dropout factors.

The investigated institution is an established private business university with over 25 years of operational experience, specializing exclusively in business education programs. The institution delivers undergraduate and graduate degree programs across four primary domains: management, economics, marketing, and human resources development. This focused academic scope provides a controlled environment for examining discipline-specific attrition factors.

4.1. Sample

The final analytical sample comprised 287 students who formally terminated their enrollment during the study period. The demographic composition included: 57% female and 43% male participants; 82% undergraduate students and 18% graduate students; 25.6% enrolled in full-time programs and 74.4% in part-time or distance learning formats. This distribution reflects the institution's student body composition and provides insights across different enrollment modalities.

4.2. Content Analysis Framework Development

The content analysis framework was systematically developed through multiple phases. The analytical categories were constructed based on established higher education retention literature and empirical findings from comparable institutional studies. Initial theoretical domains were identified from Tinto's model of student departure, Bean's student attrition model, and contemporary research on higher education challenges during crisis periods.

The categorization framework evolved through iterative analysis:

Deductive Phase: Initial categories were derived from theoretical literature, including: (1) Employment and career factors; (2) Institutional culture and environment; (3) Personal and family circumstances; (4) Academic expectations and reality alignment; (5) Institutional communication effectiveness; (6) Academic program quality and design; (7) Financial considerations and constraints; and (8) Administrative processes and bureaucratic complexity.

Inductive Refinement: Through preliminary analysis of 50 responses, additional categories emerged, leading to expansion and refinement of the framework. This process identified technology-related issues and specific subcategories within major domains.

Final Framework Validation: The refined framework was tested against the full dataset, with inter-rater reliability assessment conducted on 10% of responses ($\kappa = 0.87$, indicating strong agreement).

Within each major category, subcategories were identified through thematic analysis of response content. Subcategories were created when specific themes appeared in multiple responses and represented distinct concerns within broader categories. The development process prioritized specificity while maintaining analytical coherence.

Survey questions and response categories were formulated using established theoretical frameworks while incorporating adaptations specific to business education contexts. Open-ended response opportunities were included to capture concerns not addressed in structured categories.

The analytical instrument underwent preliminary testing with a small cohort of former students to ensure comprehensibility and construct validity. Based on feedback from this pilot phase, modifications were implemented to improve clarity and ensure accurate measurement of intended constructs.

4.3. Analytical Methodology and Coding

Each student response underwent systematic content analysis using both deductive (theory-driven) and inductive (data-driven) coding approaches. Two independent researchers initially coded responses, with discrepancies resolved through discussion and consensus. Responses were examined for explicit mentions of specific concerns, with many containing multiple thematic elements requiring comprehensive categorization.

The analytical approach employed frequency counting to identify the most prevalent concerns across the sample. Each thematic occurrence was documented regardless of whether individual responses contained single or multiple concerns, providing insight into the relative prominence of different institutional challenges. Multiple coding was permitted when responses contained distinct themes across different categories.

To ensure analytical rigor, coding consistency was maintained through systematic review of categorization decisions and regular calibration of coding criteria throughout the analysis process. A random sample of 20% of responses was dual-coded to verify reliability.

4.4. Categorization Framework Summary

The final analytical framework comprised nine major categories with 23 subcategories, as detailed in Table 1:

Table 1. Content Analysis Category Framework

Major Category	Subcategories	Description
Financial Issues (75 occurrences)	High costs/Unaffordable fees (28); Administrative fees criticism (15); Automatic enrollment charges (12); Payment for unused services (8); Financial hardship (12)	Economic barriers to continued enrollment, including institutional financial practices and external economic pressures
Communication Problems (65 occurrences)	Poor information quality (18); Inadequate notification (15); Staff inconsistency (12); Accessibility issues (10); Unprofessional behavior (10)	Institutional communication system failures affecting student-institution relationships
Academic Content Issues (55 occurrences)	Curriculum mismatch (20); Poor study materials (15); Limited practical connection (12); Delayed specialization (8)	Discrepancies between advertised and delivered academic content, quality concerns
Assessment & Examination Issues (45 occurrences)	Electronic testing criticism (18); Unfair evaluation (12); Thesis supervision problems (15)	Problems with evaluation methods and academic support systems
Administrative Processes (40 occurrences)	Bureaucratic burden (15); Changing conditions (12); Inflexible policies (13)	Institutional administrative challenges affecting student experience
Study Format & Flexibility (35 occurrences)	Distance learning limitations (12); Schedule conflicts (10); Interruption restrictions (13)	Institutional inflexibility in accommodating diverse student needs
Institutional Culture (30 occurrences)	Profit-focused perception (15); Student support lack (15)	Student perceptions of institutional values and support systems
Technical & System Issues (25 occurrences)	Website problems (12); Communication platform issues (8); Technical support (5)	Technology-related barriers to student success
Personal Circumstances (150 occurrences)	Health issues (45); Work-life balance (50); Family obligations (35); Financial hardship (20)	Individual circumstances affecting ability to continue studies

The data analysis proceeded through systematic stages:

1. Initial Coding: All responses were coded according to the established framework
2. Frequency Calculation: Occurrence counts were compiled for each category and subcategory
3. Pattern Identification: Relationships between categories were examined to identify common co-occurrence patterns
4. Thematic Integration: Findings were synthesized to identify overarching themes and implications

This analysis represents feedback exclusively from students who completed the voluntary termination process, potentially underrepresenting perspectives of students who discontinued enrollment without formal notification. Additionally, the temporal span of data collection may reflect evolving institutional practices and external factors affecting student experiences over the eight-year period. The focus on a single institution limits generalizability, though the systematic methodology provides a replicable framework for similar studies.

5. Results

The comprehensive content analysis of 287 student dropout responses revealed a complex landscape of institutional and personal factors contributing to student attrition. The findings demonstrate that while personal circumstances represent the largest single category of dropout reasons, institutional factors collectively account for a substantial proportion of student departures, suggesting significant opportunities for institutional intervention and improvement.

5.1. *Financial Barriers as Primary Institutional Challenge*

Financial issues emerged as the most significant institutional challenge, affecting over 75 students across multiple dimensions. High costs and unaffordable fees represented the most frequent concern (28 occurrences), with students consistently expressing inability to meet financial obligations. Administrative fees criticism appeared in 15 responses, with students characterizing additional charges as "nonsensical" or disconnected from educational value.

A particularly concerning pattern emerged around automatic enrollment charges, mentioned in 12 responses. Students reported being enrolled in subsequent academic years without explicit consent, often discovering this through billing notifications. This practice generated significant negative reactions and contributed to perceptions of institutional unfairness.

The theme of paying for unused services appeared in 8 responses, with students expressing frustration about continued charges for services they could not access or utilize. An additional 12 responses specifically mentioned financial hardship due to external circumstances such as job loss or family economic pressures.

5.2. *Communication System Failures*

Communication problems represented the second most frequent institutional challenge, appearing in over 65 responses. Poor information quality was the most common issue (18 occurrences), with students receiving unclear, conflicting, or incorrect information from institutional representatives.

Inadequate notification practices affected 15 students, who reported receiving important communications exclusively through email systems they did not regularly monitor, often with insufficient advance notice for critical decisions. Staff inconsistency emerged as a significant problem (12 occurrences), with students receiving contradictory information from different institutional representatives.

Accessibility issues prevented effective communication for 10 students who found institutional policies limiting contact to application-based systems rather than allowing direct phone

communication. Unprofessional behavior from staff was reported in 10 responses, describing interactions characterized as arrogant, impersonal, or unhelpful.

5.3. Academic Content and Program Misalignment

Academic content issues affected over 55 students, with curriculum mismatch representing the primary concern (20 occurrences). Students reported significant discrepancies between advertised program specializations and actual course content, with many programs dominated by generic economics content regardless of the stated field of study.

Poor study materials quality was criticized in 15 responses, with students describing textbooks as poorly written and video learning content as boring or ineffective. Limited practical connection appeared in 12 responses, with students expressing frustration about theoretical content that seemed disconnected from real-world applications.

The delayed availability of specialization courses until the third year was mentioned in 8 responses, meaning students invested significant time and financial resources before accessing their chosen field of study.

5.4. Assessment and Evaluation Concerns

Assessment methods generated significant dissatisfaction among 45+ students. Electronic testing criticism was the most frequent issue (18 occurrences), with students viewing computerized exams as inadequate for evaluating true understanding and reporting deliberately misleading question formats.

Unfair evaluation practices were reported by 12 students, including exam content that extended beyond taught material and inconsistent grading standards. Thesis supervision problems affected 15 students through supervisor changes mid-process, difficulty securing appropriate guidance, and inadequate support for final project completion.

5.5. Administrative Burden and Inflexibility

Administrative processes created significant barriers for over 40 students. Bureaucratic burden was reported in 15 responses, with students describing overwhelming paperwork requirements that consumed time without adding educational value.

Changing conditions during studies affected 12 students through mid-program requirement modifications that created uncertainty and additional costs. Policy inflexibility was mentioned in 13 responses, with students reporting inability to secure reasonable accommodations for individual circumstances.

5.6. Study Format and Flexibility Limitations

Study format inflexibility affected 35+ students who required accommodation for work and family obligations. Distance learning limitations appeared in 12 responses, with students reporting either unavailable or poorly implemented remote learning options.

Schedule conflicts affected 10 students through weekend-heavy class schedules that conflicted with family responsibilities and other commitments. Interruption restrictions were mentioned in 13 responses, with students unable to temporarily pause studies without financial penalties.

5.7. Institutional Culture and Student Support

Institutional culture concerns appeared in over 30 responses, revealing student perceptions that financial considerations outweighed educational mission. Profit-focused perception was mentioned in 15 responses, with students feeling that revenue generation took precedence over student success.

Student support deficiency was reported in 15 responses, describing absence of meaningful assistance systems that left individuals to navigate challenges alone when appropriate intervention might have prevented withdrawal.

5.8. Technical Infrastructure Problems

Technical and system issues affected 25+ students through inadequate digital infrastructure. Website problems were reported in 12 responses, with students describing unclear navigation and chaotic information architecture that made it difficult to find necessary resources.

Communication platform issues affected 8 students through system limitations that prevented ongoing dialogue when clarification was needed. Technical support inadequacy was mentioned in 5 responses.

5.9. Personal Circumstances and Institutional Support Opportunities

While personal circumstances represented 150+ departure reasons, these often revealed opportunities for enhanced institutional support. Health issues affected 45 students, work-life balance challenges impacted 50 students, family obligations influenced 35 departures, and financial hardship contributed to 20 withdrawals.

These personal circumstances frequently interacted with institutional factors, suggesting that improved support services and more flexible policies might enable students to continue despite personal challenges.

Table 2 presents the frequency distribution of dropout factors across all nine categories. While personal circumstances represented the largest single category (150 occurrences, 28.8%), institutional factors collectively accounted for 370 occurrences (71.2% of total), with financial issues (75), communication problems (65), and academic content misalignment (55) emerging as the most prevalent institutional challenges.

Table 2: Frequency Distribution of Dropout Factors

Category	Occurrences	% of Total	Top Subcategories
Personal Circumstances	150	28.8%	Work-life balance (50), Health issues (45), Family obligations (35), Financial hardship (20)
Financial Issues	75	14.4%	High costs (28), Administrative fees (15), Automatic enrollment (12), Unused services (8), Hardship (12)
Communication Problems	65	12.5%	Poor information quality (18), Inadequate notification (15), Staff inconsistency (12), Accessibility (10), Unprofessional behavior (10)
Academic Content Issues	55	10.6%	Curriculum mismatch (20), Poor materials (15), Limited practical connection (12), Delayed specialization (8)
Assessment Issues	45	8.7%	Electronic testing criticism (18), Thesis supervision (15), Unfair evaluation (12)
Administrative Burden	40	7.7%	Bureaucratic burden (15), Inflexible policies (13), Changing conditions (12)
Format Inflexibility	35	6.7%	Interruption restrictions (13), Distance learning limitations (12), Schedule conflicts (10)
Institutional Culture	30	5.8%	Profit-focused perception (15), Student support lack (15)
Technical Problems	25	4.8%	Website problems (12), Communication platform issues (8), Technical support (5)
Total	520	100%	<i>Note: Total exceeds N=287 as students often reported multiple factors</i>

6. Discussion

The findings of this study provide compelling evidence of the multifaceted nature of student dropout decisions in higher education, revealing critical insights for institutional improvement across the sector. The comprehensive analysis demonstrates that while personal circumstances remain significant contributors to attrition, institutional factors collectively represent systematic challenges that require attention throughout higher education. Notably, following this research, the case institution has implemented substantial reforms addressing many of the identified concerns, transforming its approach to become more student-centered and responsive to student needs.

Financial issues (75 occurrences) align with existing literature (Ghignoni, 2017; Branson & Whitelaw, 2024) but reveal how barriers extend beyond affordability. Automatic enrollment (12), excessive fees (15), and charges for unused services (8) eroded trust and suggested

revenue prioritization over educational value—patterns common across private institutions globally.

These findings highlight how financial barriers operate beyond simple affordability. Students reported frustration with practices that appeared to prioritize revenue generation over educational value, suggesting that financial policies can significantly impact student trust and institutional relationships. The case institution has since restructured its financial policies to eliminate automatic enrollment without consent, implement transparent fee structures, and align charges with actual service utilization.

For other institutions, these findings underscore the importance of financial policy transparency and student autonomy in enrollment decisions. The data suggest that students value clear, predictable financial obligations that correspond directly to educational services received.

The extensive communication problems identified (65 occurrences) illuminate how information systems fundamentally shape student experience. Staff inconsistency (12 occurrences), inadequate notification practices (15 occurrences), and accessibility barriers (10 occurrences) created cascading effects that amplified other institutional challenges.

The finding that contradictory information from different staff members eroded student trust aligns with research emphasizing coherent institutional support (Wollast et al., 2023). Following this study, the case institution implemented comprehensive staff training programs, established unified information systems, and expanded communication channels beyond email-only platforms.

These findings have broader implications for higher education institutions, suggesting that communication effectiveness represents a foundational element of student retention. Institutions should recognize that communication failures can transform manageable challenges into dropout-inducing crises, while effective communication systems can help students navigate temporary difficulties.

The substantial academic content misalignment (55 occurrences) reveals how curriculum-marketing disconnects undermine student satisfaction and institutional credibility. Students reported programs dominated by generic content regardless of advertised specializations (20 occurrences), delayed access to field-specific courses, and limited practical application (12 occurrences).

This misalignment issue resonates with research identifying academic satisfaction as a primary retention factor (Nurmalitasari et al., 2023). The case institution has since restructured its

curriculum to ensure early access to specialization content, improved alignment between marketing and actual program delivery, and enhanced practical application components.

For the broader higher education sector, these findings suggest that authentic program differentiation and early specialization access represent critical retention factors, particularly for working adult learners seeking efficient, targeted educational experiences.

The criticism of assessment approaches (45 occurrences) reflects broader tensions in higher education between efficiency and educational effectiveness. Electronic testing concerns (18 occurrences) and thesis supervision problems (15 occurrences) indicate that assessment methods significantly influence student perception of educational quality.

Students reported assessment practices that seemed designed to create obstacles rather than evaluate learning, suggesting misaligned institutional incentives. The case institution has since reformed its assessment approaches to emphasize learning evaluation over administrative convenience and improved faculty support systems for thesis supervision.

These findings suggest that assessment methods communicate institutional values to students and can either support or undermine educational relationships. Institutions should ensure that evaluation approaches align with educational rather than purely administrative objectives.

The administrative burden reported by students (40 occurrences) demonstrates how bureaucratic complexity can create barriers to educational access. Students described overwhelming paperwork requirements (15 occurrences) and policy inflexibility (13 occurrences) that seemed disconnected from educational outcomes.

The pattern of mid-program requirement changes (12 occurrences) suggests that institutional adaptability, while necessary, requires careful management to maintain student trust. The case institution has since simplified administrative processes, stabilized policy frameworks, and increased flexibility for individual circumstances.

For other institutions, these findings highlight the importance of student-centered administrative design that minimizes bureaucratic barriers while maintaining necessary quality standards.

While personal circumstances represented the largest single category (150 occurrences), the interaction between personal challenges and institutional responses suggests significant opportunities for enhanced support. Health issues (45 occurrences), work-life balance challenges (50 occurrences), and family obligations (35 occurrences) often interacted with institutional factors to influence dropout decisions.

Research demonstrates that appropriate institutional interventions can help students persist despite personal challenges (Branson & Whitelaw, 2024). The case institution has implemented enhanced counseling services, flexible accommodation policies, and crisis intervention programs to better support students facing temporary difficulties.

These findings suggest that institutional support systems can significantly influence whether personal challenges result in temporary interruption or permanent departure from higher education.

6.1. Theoretical Implications: Organizational Learning and Governance

The case institution's transformation following this research exemplifies key principles of organizational learning theory and higher education governance reform. The findings and subsequent institutional changes can be understood through Argyris and Schön's (1978) framework of double-loop learning, wherein the institution moved beyond addressing surface-level problems (single-loop) to questioning and reforming fundamental assumptions about student-institution relationships.

The shift from profit-focused to student-centered operations represents what Senge (1990) terms a "learning organization" - one capable of systematic reflection and adaptive change based on stakeholder feedback. The implementation of comprehensive reforms across financial policies, communication systems, and academic structures demonstrates organizational capacity for what Kezar (2014) identifies as "transformational change" in higher education, characterized by deep cultural shifts rather than incremental adjustments.

From a governance perspective, the institutional response aligns with contemporary models emphasizing stakeholder engagement and distributed decision-making (Shattock, 2013). The research-driven approach to reform exemplifies evidence-based governance, wherein systematic data collection and analysis inform policy development rather than traditional top-down administrative mandates.

The findings also contribute to understanding institutional resilience during crisis periods. The identification of specific vulnerabilities enabled targeted interventions that strengthened institutional capacity for responsive adaptation - a critical capability highlighted in recent literature on higher education crisis management (Fernández-Terol & Domingo-Segovia, 2025). This suggests that systematic attention to student departure reasons can function as an early warning system for broader institutional challenges.

Furthermore, the successful transformation demonstrates that private higher education institutions can reconcile financial sustainability with educational mission through student-

centered approaches - challenging assumptions that commercial viability requires compromising educational values. This finding contributes to ongoing debates about the role and governance of private institutions within broader higher education ecosystems.

6.2. *Practical Implications*

The research identifies several priority areas that have proven effective in the case institution's transformation:

5. **Financial Policy Transparency:** Clear, predictable fee structures that align with educational service delivery and eliminate exploitative practices.
6. **Communication System Integration:** Unified information systems, comprehensive staff training, and multiple communication channels that ensure consistent, accessible student support.
7. **Academic Program Authenticity:** Curriculum alignment with marketing materials, early specialization access, and enhanced practical application opportunities.
8. **Student Support System Development:** Comprehensive counseling services, flexible accommodation policies, and proactive intervention programs for students facing challenges.
9. **Administrative Simplification:** Streamlined processes that minimize bureaucratic barriers while maintaining educational quality standards.

The findings suggest systemic challenges across private higher education that require sector-wide attention. The patterns identified in this study likely reflect common issues in institutions balancing financial sustainability with educational mission, particularly those serving working adult populations. The case institution's successful transformation demonstrates that comprehensive reform is achievable and can enhance both student satisfaction and institutional sustainability. The implementation of student-centered policies has resulted in improved retention rates and stronger institutional reputation.

The research reveals that student dropout decisions typically result from accumulation of multiple institutional and personal factors rather than single critical incidents. Students appear to tolerate individual challenges but reach breaking points when multiple issues converge without adequate institutional support.

Understanding this cumulative pattern suggests that early intervention and responsive institutional support can prevent manageable challenges from escalating to dropout decisions. Institutions should develop early warning systems that identify students facing multiple stressors and provide targeted support before challenges become overwhelming.

7. **Conclusion**

This comprehensive analysis provides empirical evidence of the complex factors influencing student dropout decisions while demonstrating that institutional reform can effectively address

these challenges. The case institution's transformation following this research illustrates that student-centred approaches can simultaneously improve retention and institutional sustainability.

The findings contribute to growing literature on student dropout by providing specific, actionable insights that have proven effective in practice. The research emphasizes that student dropout should be understood as a systemic challenge requiring comprehensive institutional response rather than individual failure.

The successful implementation of reforms at the case institution demonstrates that higher education institutions can create supportive, effective environments that promote student success while maintaining financial viability. The transformation from a profit-focused to student-centred approach has resulted in improved outcomes for both students and the institution.

For the broader higher education sector, these findings suggest that sustainable institutional success depends on authentic commitment to student-centred values, transparent policies, and responsive support systems. The research provides a roadmap for institutional transformation that balances educational mission with operational requirements.

7.1. Future Research Avenues

Future research should examine the long-term outcomes of institutional reforms and explore how student-centred approaches impact institutional sustainability across diverse higher education contexts. The findings suggest that investing in student success represents both an ethical imperative and a sound institutional strategy for long-term viability in competitive higher education markets.

7.2. Limitations

While this study provides valuable insights into dropout factors and institutional responses, several limitations merit consideration. The single-institution focus, though enabling deep contextual analysis, constrains generalizability across diverse higher education contexts. The case institution's characteristics - private ownership, business-focused curriculum, and substantial part-time/distance learning enrolment (74.4%) - represent specific organizational and educational configurations that may not fully represent public institutions, comprehensive universities, or traditional residential programs.

The geographic and cultural context of the institution further limits transferability of findings. Dropout factors and their relative importance may vary significantly across national higher

education systems with different funding models, regulatory frameworks, and cultural expectations regarding student-institution relationships. The eight-year study period (2017-2025), while providing temporal depth, encompasses significant external disruptions including the COVID-19 pandemic, potentially influencing the types and frequency of reported dropout factors.

The methodology developed here - combining systematic categorization with inductive analysis of open-ended responses - provides a replicable framework for such comparative and longitudinal studies, potentially enabling accumulation of comparable evidence across institutions and contexts.

7.3. *Ethical Considerations*

The voluntary nature of dropout reporting introduces several methodological and ethical considerations that warrant explicit acknowledgment. Students who formally completed withdrawal processes and responded to exit surveys may differ systematically from those who discontinued enrolment informally, creating potential selection bias in the analyzed sample.

The research involved students at a vulnerable transition point, having made difficult decisions to discontinue studies. Ethical considerations included: informed consent, anonymity, and non-coercion.

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Declaration of competing interest

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Impact of Educational Escape Games on Students' Semantic Lexicon in Environmental Science: A Word Association and AI-Based Analysis

Mihály Kovács^{1*}

^{1*} Observatory and Science Experience Center, Eszterházy Károly Catholic University, Eszterházy sq. 1., Eger 3300, Hungary, kovacs2.mihaly@uni-eszterhazy.hu

Abstract: Gamification, including escape games, has proven to be an effective tool for changing environmental behaviour. However, little research has been done on the impact of this game type on students' conceptual networks, particularly in relation to environmental science and chemistry. Therefore, this study examines the semantic lexicon of primary and secondary school students using word association tests with selected call words from these subjects. Students were asked to provide answers immediately before the game and exactly one week later. The pre- and post-tests were analysed using the rather robust but complicated Garskof-Houston formula and the results were compared to the analysis of a smaller generative AI running on a laptop to find a more user-friendly way to evaluate this type of survey. The Garskof-Houston formula showed that the relations of the words "mixture", "precipitation" and "rain" changed the most, but the smaller, and therefore presumably weaker, LLM found the most changes for the relations of the words "compound", "precipitation" and "rolling". Since the meaning of a concept can be defined as a list of words with which it is associated, these results suggest that learners' concepts have changed, which is quite important from the perspective of constructivist learning theory. However, further research is needed on the use of LLMs for this type of evaluation.

Keywords: Gamification; Escape Game; Conceptual Change; AI Analysis; Chemistry

1. Introduction and literature review

Gamification “is a careful and considered application of game thinking to solving problems and encouraging learning using all the elements of games that are appropriate.” (Kapp, 2012) This definition also includes serious games like educational escape games. These are “live-action team-based games where players discover clues, solve puzzles, and accomplish tasks in one or more rooms in order to accomplish a specific goal (usually escaping from the room) in a limited amount of time.” (Nicholson, 2015)

Different game types were tried in the field of environmental education (Hallinger et al., 2020) and e.g. gamification in general (Charkova, 2024) and also escape games (Chang, 2019) proved to be effective tools to form participants' environmental behaviour. However, this study examined the effects of this game type to the players' knowledge, namely their semantical lexicon.

Semantical lexicon is part of the mental lexicon, which is a storage system in the long-term memory. It contains the elements (word or concepts) and rules of the language which are related to each other. This can be modelled as a network which nodes are the concepts (Carey, 2000; Gósy, 2005). The mental lexicon may contain different strengths and types of relatedness, e.g. rhymes. The semantical lexicon is its subnetwork narrowed down to the connections based on the interpretation of the elements. Therefore, Shavelson defined the meaning of the concepts as the list of those elements, with which it is connected. (Shavelson, 1972)

Piaget (Piaget, 1964) named the process which is taking place in the learner's mind construction, because they build actively they own knowledge, which is the basic statement of constructivist learning theory. Due to individual processing, every human being has its own cognitive structure, therefore a unique meaning of the same concept (Nahalka, 2002), and Shavelson's definition makes it possible to examine this personal construction. One possible way to identify a part of the semantical lexicon is the word association test evaluated with Garskof and Houston's relatedness coefficient (RC) (Garskof & Houston, 1963; Shavelson, 1972; Tóth, 2024) and if a concept changes, its connections will change, too. Moreover, the average of RCs can describe a class's cognitive structure (Tóth, 2024) and based on this examination of conceptual change with statistical analysis is possible.

This is crucial, since conceptual change is the key moment of learning in constructivist theory. This is a conflict caused by new experiences. During this process the students question their current theories and develop new, more adaptive concepts, which they are going to use at least in certain circumstances. (Nahalka, 2002) However, it is fairly common in environmental education, that students have no naive theories and the real question is if they can use their knowledge in a new situation. (Robertson, 1994; Robottom, 2004)

In preparing this study, I used a widely applicable method that helps to recognize and visualize conceptual changes during short educational interventions. This method uses word association tests to analyse changes in students' semantic lexicon, i.e., how individual concepts are related to each other in their long-term memory. This provides a deeper understanding of the learning process, especially in the context of constructivist learning theory.

2. Research aims and questions

The research question of this paper is whether it is possible to achieve changes in the students' semantic structures with the help of escape games, if the examined concepts are selected from the field of chemistry and environmental sciences. For the purposes of the study, the following

words were selected for 7th grade: mixture, compound, and wastewater, while for 9th grade: precipitation, rain, fluid, rolling, and water cycle. Based on this, the research question can be formulated more specifically:

RQ1: How much does the 7th graders' semantic network change in relation to the concepts of "mixture," "compound," and "wastewater" as a result of the escape game?

RQ2: How much does the 9th graders' semantic network change in relation to the concepts of "precipitation," "rain," "fluid," "rolling," and "water cycle" as a result of the escape game?

Since, from a theoretical point of view, educational escape games can be linked to constructivist learning theories (Nicholson, 2018; Zhang et al., 2018), the meaning of concepts related to the game is likely to change during this activity. Hence, the research hypothesis is the following: as a result of playing escape games, changes can be observed in the strength of the connections among the selected concepts in the players' semantic lexicon.

This hypothesis was tested using statistical methods by calculating the t-test for each pair of call words. Thus, the hypotheses related to questions RQ1 and RQ2 can be reformulated as follows:

H1: For at least one pair of the call words "mixture", "compound", and "wastewater" the Garskof-Houston coefficient changes significantly between the pre-test and post-test.

H2: For at least one pair of the call words "precipitation", "rain", "fluid", "rolling", and "water cycle" the Garskof-Houston coefficient changes significantly between the pre-test and post-test.

However, calculating the Garskof-Houston coefficient is a time-consuming process, so the question came up whether word association tests could be analysed more simply but still reliably to make them easier to use in teachers' everyday work. Since the information is text-based, the use of a large language model (LLM) in the analysis seemed an interesting possibility. Since I did not ask for permission to provide the students' answers to an AI that might learn from them, for ethical reasons I could only use a weaker model run on my own computer, which is not expected to give very accurate answers. Therefore, hypothesis testing was not performed; only the theoretical possibility of this method was analysed by comparing the LLM's analyses with the calculations. This can be formulated as a research question in the following form:

RQ3: How reliable is the generative AI (LLM) analysis compared to Garskof-Houston RC?

3. Methodology

A quasi-experimental research design was used with pre- and post-testing to decide whether the students' semantic lexicon changed significantly during an escape game. According to theory, this type of game can be linked to constructivist learning theory (Nicholson, 2018; Zhang et al., 2018), meaning that when used for educational purposes, changes should occur in the students' conceptual system, which fits well to their semantic lexicon.

The students completed the pre-test immediately before the game, the post-test was written one week after the game, as long-term memory changes were relevant regarding the research question. No homework was given to the students for this week in order to measure only the impact of the game. Hopefully, this one-week break also minimized the so-called priming effect, which means that the answers given in the pre-tests should not have a major impact on the responses given in the post-tests, as the students were studying every other subjects during this time.

3.1. Participants

The examinations took place in 7th and 9th grades, with participants selected by convenience sampling from rural and urban primary schools and urban high schools. Players who completed only either the pre-test or the post-test were omitted from the statistical analysis because both results are needed to calculate the paired sample t-test. In the end, the sample included $N_7=68$ students in grade 7 and $N_9=98$ students in grade 9.

This study received Eszterházy Károly Catholic University ethics approval (reference number: RK/144/2025). All methods were carried out in accordance with relevant guidelines and regulations

3.2. Educational games

The 7th graders played an escape card game about categorizing matter and its connection with wastewater. The puzzles were in sequential order, see Fig. 1. Every card had a title created from the number of the exercise and a key word from the story. There were cards with elements of the story, with lecture materials and with exercises. The players could draw the cards of the next puzzle from their own pile only if they solved the current exercise correctly. They could check their results on answer cards set on the teacher's desk.

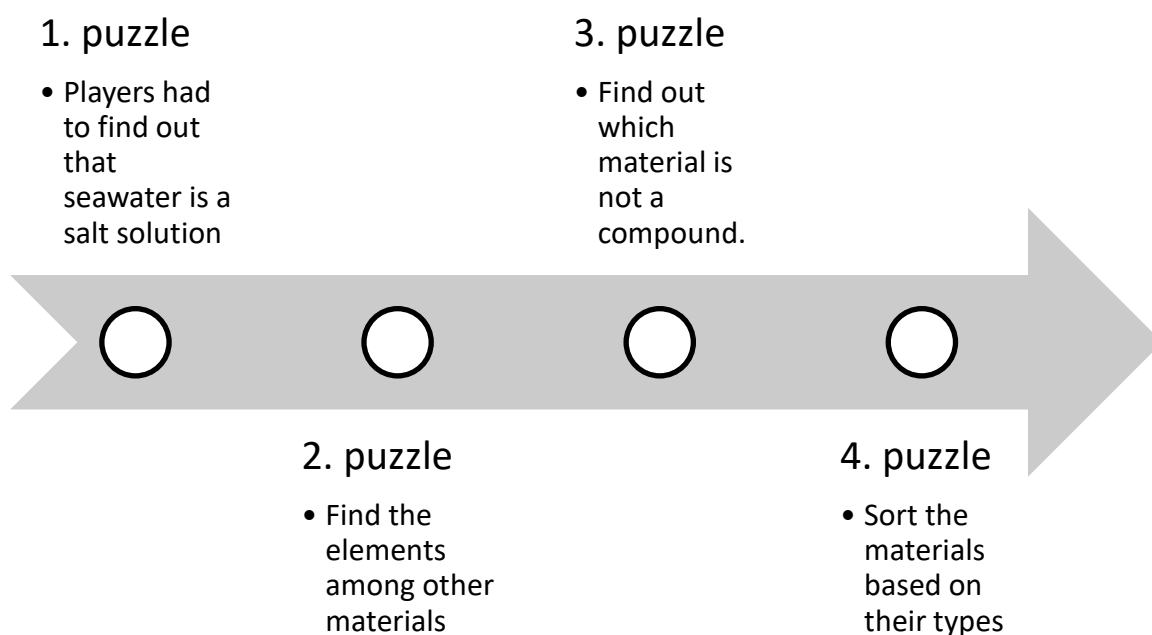


Fig. 1. Structure of the 7th graders' game

The 9th graders played a game like an escape book. Every riddle was on a separate page with some lecture materials and with the next part of the story. The exercises were also in sequential order, see Fig. 2, in this case, there were also answer cards on the teacher's desk to check their solutions. If their answer was correct, they could read the next page. The topic of this game was the water cycle and the state of matter.

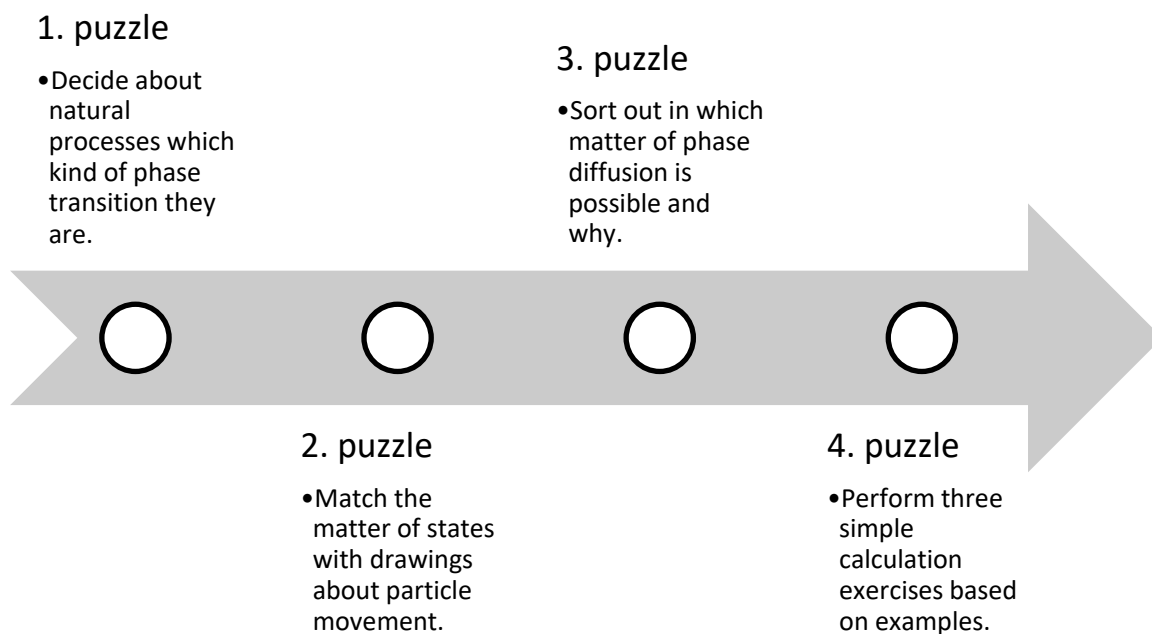


Fig. 2 Structure of the 9th graders' game

These sorting and selecting type of exercises hopefully triggered interaction, sometimes debate, among the players which could lead to cognitive conflict. (Bélanger, 2011) There were also short debriefs after both games, so the students had the opportunity to ask the teacher, who could also emphasize some points from the material, if they wanted to. However, they could not help during the game except for technical issues.

3.3. *Word association tests*

Word association tests contained call words, and the participants had to provide those words that come to their mind. A list of a call word and its corresponding associations in the order given by the respondent is called an associative meaning (i.e.: pink, magenta, colour, flower, flamingo is the associative meaning of pink).

During the test, they could work on only one word at a time, for 1 minute in this study, and after that, they had to proceed to the next buzzword and could no longer return to the previous ones. It was completed either on Microsoft Forms or on paper in this research, and the teacher measured the time. The data were anonymized right after pairing the responses to the pre- and post-test. The names were replaced with random numbers during anonymization, then the spreadsheet was sorted in ascending order based on these numbers.

Before the test, the teacher emphasized that the students should answer like an ecology specialist and they should not use complete sentences, only words or phrases. However, many students gave sentences at the end, so the answer needed to be coded, which was executed like in Daru and Tóth (2014). They cut the sentences into words and phrases but deleted the meaningless and irrelevant words like articles.

After that, negative words were also deleted, because they suggested the direction of the association and not the associated word. All the typos were corrected, too. When a student listed a set of adjectives in relation to a noun, those phrases were exceptionally split into parts. Since Hungarian is an agglutinating language and students used different kind of suffixes without meaning another word, in most cases, they were deleted, except when their changed the grammatical category of the word. Finally, the respondents gave the same associations twice in some cases, thus the second one was deleted.

The 7th graders' game was about wastewater and categorizing matter, so the selected concepts were wastewater, compounds and mixtures. The 9th graders' game was about phase change and

water cycle, so the selected concepts were water cycle, precipitation, rolling, fluid, rain. Rolling referred to the movement of particles in fluids.

3.4. Garskof-Houston relatedness coefficient

The Garskof-Houston formula (Garskof & Houston, 1963; Tóth, 2024) assigns a number called relatedness coefficient (RC) from the interval 0 to 1 to each associative meaning pair. The RC is 1 only in that case if the two buzzwords are synonyms, which means the first association is the other buzzword in both cases, and all other associations are the same in the exact same order. For example, $RC_{magenta, pink}=1$, if the associative meaning of magenta is pink, colour, flower, flamingo and the associative meaning of pink is magenta, colour, flower, flamingo. The result is 0 if there are no common words in the associative meaning of the two buzzwords. Since most papers contain some ambiguity or simplification it is useful to explain the equation in detail.

To calculate the RC, we needed to assign a rank number to all words in associative meanings of the two examined call words. The rank number of the buzzwords is equal to the number of elements of the associative report with the higher number of items. Then we had to go through the words of each associative meanings one by one, the current word was always assigned a rank number one lower than the previous one, as can be seen in Table 1.

Table 1. How to assign rank numbers to associative meanings

1st call word	rank number	2nd call word	rank number
<i>pink</i>	5	<i>blue</i>	5
magenta	4	colour	4
colour	3	sky	3
flower	2	pink	2
flamingo	1		

After this, we can understand these formulas which are:

$$RC = \frac{\bar{A} \cdot \bar{B}}{n^p(n-1)^p + (n-1)^p n^p + (n-2)^p(n-2)^p + \dots + 1} \quad (1)$$

$$RC = \frac{\bar{A} \cdot \bar{B}}{A \cdot B - [n^p - (n-1)^p]^2} \quad (2)$$

where:

- n is the biggest rank number
- p is a power weight which had to be a natural number. In education, $p=1$ is the most frequent choice (Cardellini, 2008), however if the number of associations are maximized and/or the participants had to ranking their associations, $p>1$ can be a better

choice. This can be an interesting option, especially in the case of online data collection as maximum word number is easier to implement on most online form software than time limits for every question.

- $\bar{\mathbf{A}}$ vector contains the rank number of those words in the first associative meanings which are also listed in the second associative meaning. In the meantime, $\bar{\mathbf{B}}$ vector contains the rank number in the second associative meaning of the same words in the same order than $\bar{\mathbf{A}}$.
- \mathbf{A} and \mathbf{B} vectors are identical: $[n^p \quad n - 1^p \quad \dots \quad 1^p]$. It is easy to prove with algebraic identities that the two denominators are the same.

Equation (2) is most frequently used in literature however version (1) makes it easier to understand thus it is used in this paper. Its denominator contains a scalar product of an ideal situation. In this case, the respondent uses the two words as total synonyms like in previously mentioned examples about pink and magenta. Hence, the buzzwords rank number is n in one case, when we create the $\bar{\mathbf{A}}$ vector and $n-1$ in the other case ($\bar{\mathbf{B}}$ vector), and the ranks of all other words are the exact same. This makes RC smaller than 1, with other words normalizing it. For example, based on Table 1 with the choice of $p=2$, we got the equation (3):

$$RC = \frac{[5^2 \quad 3^2] \cdot \begin{bmatrix} 2^2 \\ 4^2 \end{bmatrix}}{5^2 \cdot 4^2 + 4^2 \cdot 5^2 + 3^2 \cdot 3^2 \dots + 1 \cdot 1} = \frac{5^2 \cdot 3^2 + 2^2 \cdot 4^2}{2 \cdot 5^2 \cdot 4^2 + 3^2 \cdot 3^2 \dots + 1 \cdot 1} \approx 0.32 \quad (3)$$

Calculating RC for all student's all buzzword pair is quiet time consuming; therefore, this study used a previously validated LibreOffice macro (Kovács, 2024) for this purpose.

3.5. Statistical methods

Since the possible values of RC come from the interval 0-1, it can be analysed with a t-test if the data are normally distributed. The normality of the variables was checked with the Anderson-Darling test. The alpha level was chosen to be 0.05 for all statistical analyses. BlueSky Statistics 10.3.2 software was used to perform statistical analysis in this study. (Muenchen, 2023) The calculations were also checked using Benjamini–Hochberg procedure (Benjamini & Hochberg, 1995) The results of these calculations are presented in the conclusion, along with the limitations.

3.6. Generative AI Analysis

There may be other ways to make the evaluation of word association test simpler, for example, generative AIs. These can be used for different purposes in education, not only to help the

learners (e.g. personalized learning) but also to make the teachers' work easier since they can reduce their workload. (Iyamuremye et al., 2024; Mohebi, 2024) Thus, an LLM (Llama 3 8B in GPT4All software) was used in this research for this purpose, and its results were compared to the Garskof-Houston method. The advantage of this software is that it is running on the researcher's computer, so it is safer in the field of data protection than its alternatives, however it is much slower and weaker than the more well-known ones. Since the goal was to make teachers' work easier, I used LLM with default settings in this research, which means that temperature was rather high, equal to 0.7.

The following prompt was used on the raw data, without any coding or correcting the typos: "Answer my questions as an education specialist. You should evaluate a word association test completed by a group of students. The first call word was mixture. The following words came to the mind of the class members. The answers of each student are separated by semicolons: ... What concepts would you connect the word "mixtures" with if you should create a mind map of the students' answers?" After this, the same question was repeated for all buzzwords, separately for the pre- and the post-test. Since this LLM was a smaller one run on my computer and the temperature was set quite high, the level of its answer was varied. To make the answers comparable, I regenerated them if they did not contain categories and some words from the students' associations as an example of the categories.

This process led to a very complex network, where the nodes are the buzzwords, the categories and the examples. There were different types of connections, i.e. the strongest is when the category is also a call word, and the weakest is when the example is shared. Moreover, there were parallel connections, too. They have been simplified for greater clarity, bold lines in the graphs indicate that there was minimum a common category between the two call words and thin lines mean any other type of detectable relationship.

4. Results

Before the calculation of the RCs, I coded the answers of the tests twice with two weeks difference. After comparing the two results and making some corrections in case of 9 graders, 81.25% of the codes were identical, while in case of 7 graders, 88,7%. I accepted them, and used the improved first version, because coding of sentences was more consequent. The means of the RC values in pre- and post-tests are in Table 2 and 3.

Table 2. Means and standard deviations (SD) of 7th graders' relatedness coefficient values

	mean ± SD pre-test	mean ± SD post-test
mixture-compound	0.1±0.17	0.22±0.23
mixture-wastewater	0.01±0.03	0.06±0.17
compound-wastewater	0.01±0.04	0.05±0.05

Table 3. Means and standard deviations (SD) of 9th graders' relatedness coefficient values

	mean ± SD pre-test	mean ± SD post-test
precipitation-rolling	0±0.03	0±0.02
precipitation-fluid	0.11±0.13	0.15±0.14
precipitation-rain	0.09±0.14	0.1±0.15
precipitation-water cycle	0.07±0.13	0.1±0.16
rolling-fluid	0±0.02	0±0.02
rolling-rain	0±0	0.01±0.05
rolling-water cycle	0±0	0±0.03
fluid-rain	0.15±0.17	0.22±0.21
fluid-water cycle	0.06±0.09	0.07±0.12
rain-water cycle	0.13±0.17	0.19±0.2

Before the calculation of the t-test, normality of RC values was also checked for every buzzword pair with the Anderson-Darling test. Based on these calculations, they can be handled as normal variables, the exact results are in Table 4 and 5.

Table 4. Results of normality tests for 7th graders relatedness coefficients
(* $p<0.05$ ** $p<0.01$ *** $p<0.001$)

	A – pre-test	A – post-test
mixture-compound	11.4466***	3.7987***
mixture-waste water	24.6989***	19.5812***
compound-waste water	24.2646***	23.0988***

Table 5. Results of normality tests for 9th graders relatedness coefficients
(* $p<0.05$ ** $p<0.01$ *** $p<0.001$)

	A – pre-test	A – post-test
precipitation-rolling	34.9539***	35.1575***
precipitation-fluid	8.7939***	5.2396***
precipitation-rain	12.4284***	9.2954***
precipitation-water cycle	14.0088***	12.6949***
rolling-fluid	36.6896***	36.0987***
rolling-rain	36.6896***	33.7954***
rolling-water cycle	4.0841***	33.8596***
fluid-rain	6.1437***	3.9610***
fluid-water cycle	15.5334***	15.6805***
rain-water cycle	9.1762***	4.0841***

Table 6 presents the results of the t-tests, which showed significant changes in the case of mixture-compound ($t=-4.2403$, $p<0.001$, $d=-0.5142$) and mixture-wastewater ($t=-2.3395$, $p=0.0223$, $d=-0.2837$) call word pairs in case of 7th graders. While in case of 9th graders, t-tests showed significant changes for the precipitation-fluid ($t=-2.0586$, $p=0.042$, $d=-0.2101$), fluid-

rain ($t=-3.3560$, $p=0.001$, $d=-0.3425$) and rain-water cycle ($t=-2.6636$, $p=0.009$, $d=-0.2719$) buzzword pairs, as you can see in Table 7.

Table 6. Results of paired sample t-tests for 7th graders relatedness coefficients
(* $p<0.05$ ** $p<0.01$ *** $p<0.001$)

	t	Cohen's d	confidence interval (95%)	
			low	high
mixture-compound	-4.2403***	-0.5142	-0.7713	-0.2614
mixture-waste water	-2.3395*	-0.2837	-0.5291	-0.0405
compound-waste water	-0.3916	-0.0475	-0.2873	0.1919

Table 7. Results of paired sample t-tests for 9th graders relatedness coefficients
(* $p<0.05$ ** $p<0.01$ *** $p<0.001$)

	t	Cohen's d	confidence interval (95%)	
			low	high
precipitation-rolling	0.2387	0.0244	-0.1767	0.2255
precipitation-fluid	-2.0586*	-0.2101	-0.4140	-0.0073
precipitation-rain	-1.5430	-0.1575	-0.3602	0.0444
precipitation-water cycle	-1.6357	-0.1669	-0.3699	0.0351
rolling-fluid	-0.5985	-0.0611	-0.2625	0.1400
rolling-rain	-1.7806	-0.1817	-0.3850	0.0205
rolling-water cycle	-1.7867	-0.1824	-0.3856	0.0199
fluid-rain	-3.3560**	-0.3425	-0.5504	-0.1365
fluid-water cycle	-0.9645	-0.0984	-0.3003	0.1029
rain-water cycle	-2.6636**	-0.2719	-0.4774	-0.0678

The following section presents the mind maps generated with the help of AI. Graphs of Fig. 2 constructed based on the LLM's analysis of 7th graders' answers show that the relationship between the mixture-compound and mixture-waste water call word pairs changed from the pre-test to the post-test.

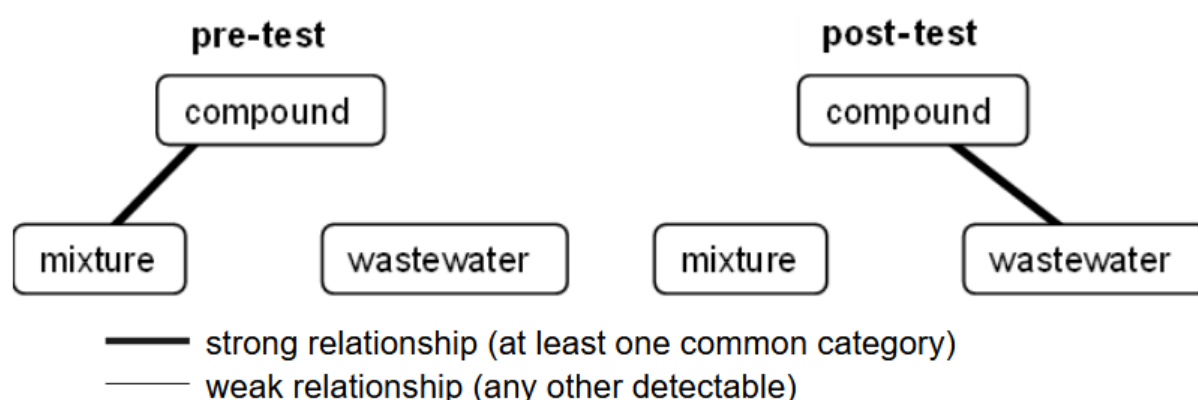


Fig. 2. Graphs constructed based on the LLM's analysis of 7th graders associations.

The 9th graders graph presented on Fig. 3 shows that precipitation-rolling connections disappeared, but rolling-rain and rolling-fluid turned up. Connections with precipitation also became weaker.

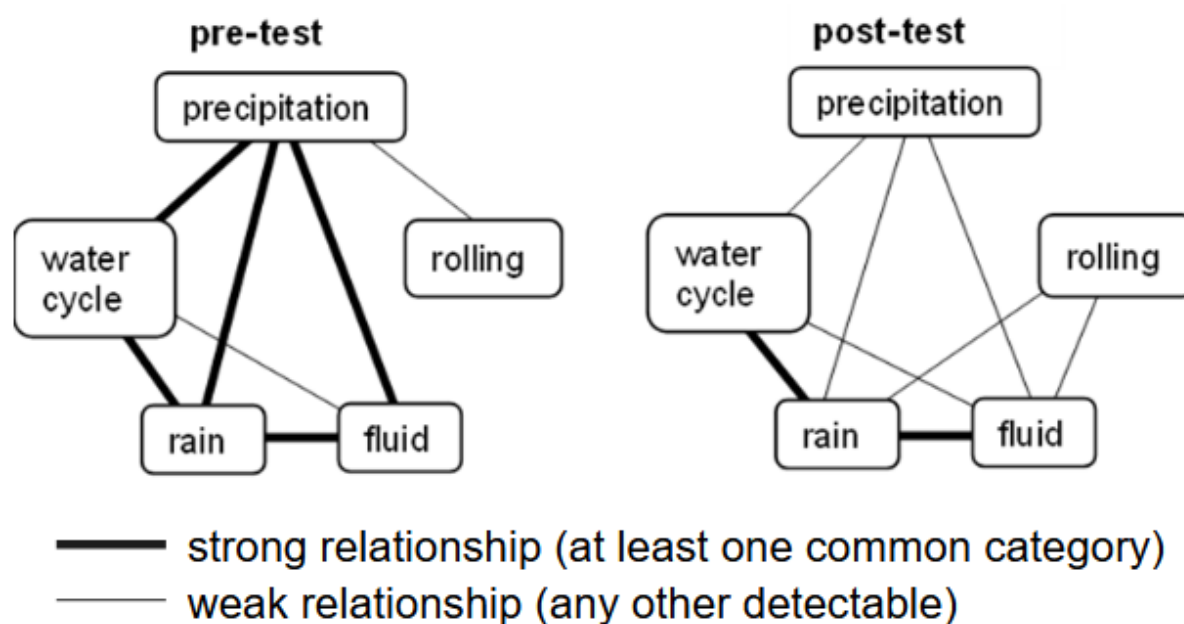


Fig. 3. Graphs constructed based on the LLM's analysis of 9th graders associations.

5. Discussion

The statistical analysis indicates that both the 7th graders' and the 9th graders' semantical lexicon has changed significantly, which means based on Shavelson's definition (Shavelson, 1972) that their understanding of the examined concepts changes. For 7th graders, the meaning of the word "mixture" changed the most, since both RC values changed significantly (mixture-compound: $t=-4.2403$, $p<0.001$, $d=-0.5142$; mixture-wastewater: $t=-2.3395$, $p=0.0223$, $d=-0.2837$). Based on this, we can accept H1, meaning that there was a significant change in the students' semantic lexicon in the case of "mixture," "compound," and "wastewater".

For 9th graders the buzzwords "rain" has changed the most, two RC values changed significantly (fluid-rain: $t=-3.3560$, $p=0.0011$, $d=-0.3425$; rain-water cycle: $t=-2.6636$, $p=0.0091$, $d=-0.2719$). Besides that, the RC changed significantly in the case of another pair of call words, namely precipitation-fluid ($t=-2.0586$, $p=0.0423$, $d=-0.2101$). This means that we can accept H2, too, meaning that there was a significant change in the students' semantic lexicon in the case of "precipitation," "rain," "fluid," "rolling," and "water cycle".

In case of 7th graders, the effect size ($d=-0.5142$) of the mixture-compound call word pair was greater than 0.39, which was the average obtained by Tamim et al. (2011) in their meta-analysis in the field of education, but the mixture-waste water pair ($d=-0.2837$) fell below average. In the case of the 9th graders, the effect size of fluid-rain pair ($d=-0.3425$) was close to average, but the other pairs fell below average ($d=-0.2719$ and $d=-0.2101$).

Turning to RQ3, LLM's analysis also points in this direction, but with some serious errors. It found the connection between the mixture and the compound in the case of 7th graders, and it realizes its change but missed the direction. It found that the meanings of precipitation and rain changed a lot, but missed the direction in this case, too. Besides, it highly overestimated the change in the meaning of rolling.

However, due to ethical reasons, a small model was used in this study, therefore its results cannot be so accurate as it would be with the most popular ones. Hence, more research is needed about the question of using LLM to analyse word association tests, and to examine someone's semantical lexicon, even on the basis of other data types (e.g. texts).

Beyond empirical results, the findings described above were discussed in a framework that can be applied in classroom work or in another research. The use of word association tests as pre- and post-tests, followed by their evaluation, can provide educators with a practical tool for understanding changes in students' conceptual networks. We discussed two methods of evaluation: statistical analysis of the Garskof–Houston coefficients obtained in this context, and evaluation using LLM. This allows for a more complex understanding of the changes taking place in students during the learning process.

6. Conclusion

Based on these considerations, educational escape games can significantly transform how students understand scientific concepts. The results, especially the more robust statistical analysis of Garskof-Houston RCs, suggest that some of the students either started to construct new concepts or at least to refine some existed ones, which is a main goal in Robertson's and in Robottom's theory (Robertson, 1994; Robottom, 2004), or some of them started the process of so called conceptual change, which is a main goal of constructivism in general (Nahalka, 2002). This means, that educational escape games can be effective tools for the purpose of constructivist-based teaching in a school environment not only on theoretical grounds (Nicholson, 2018; Zhang et al., 2018), but also on an experimental basis.

In this study, we presented a tool suitable for measuring changes in semantic lexicon, the word association test, which can even be used in a classroom environment. For 7th graders, only three call words were selected for this purpose, since we observed a high dropout rate in this age group after the third keyword in our previous research. (Kovács & Murányi, 2024) For 9th graders, the number of word pairs was increased to 5, trusting that they would be able to complete the task. There are several options for the evaluation process, including calculating

the Garskof-Houston coefficient after manually processing the responses. The calculations can be performed with a validated LibreOffice macro, and the statistical analysis with free software. Another option is to use a LLM to evaluate responses by asking it to generate a mind map based on the call words. However, the reliability of this method could not be proven in this study, although it appears to be a very promising technique.

However, there are some limitations of this study. Based on the Benjamini–Hochberg procedure (Benjamini & Hochberg, 1995), t-tests may lead to false positive results in case of mixed wastewater and precipitation-liquid call word pairs (adjusted p values were 0.0725 and 0.11 respectively). However, the other results remained significant even after correction. Besides, The LLM used in this study was a smaller, weaker model with higher temperature; further research is planned with a stronger model and stricter settings after the ethical issues have been clarified.

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Ethics statement

This study received Eszterházy Károly Catholic University ethics approval (reference number: RK/144/2025). All methods were carried out in accordance with relevant guidelines and regulations.

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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.

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Cybersecurity Awareness and Ransomware-Related Practices among University Students

Laszlo Bottyan^{1*}, Balint Nagy²

1 Self-employed, Budapest, Hungary, laszlo@bottyan.com*

2 University of Dunaujvaros, Dunaujvaros, Hungary, Óbuda University, Kandó Kálmán Faculty of Electrical Engineering, Budapest, Hungary, nagyb@uniduna.hu

Abstract

The education sector is now one of the most targeted domains of cyberattacks, with ransomware being the most prevalent threat. The present study focuses on university students' security behaviours related to ransomware, especially email and phishing vulnerability, user access and credential practices, system and software hygiene, data protection habit, and threat perception. The sample was taken in a Hungarian university with a sample size of 85 respondents. The measuring instrument was an online questionnaire consisting of 11 questions answered on a 3-point Likert scale. The results present a mixed picture: respondents appear more security-aware in relation to e-mail phishing risks and system and software security hygiene, while showing lower levels of security in user access, credential practices, data backup, and threat perception. The analysis is descriptive and exploratory, relying on item-level proportions. The study provides exploratory insights into student cybersecurity awareness, grounded in data from a single higher education institution, and highlights directions for future, broader investigations. Targeted awareness campaigns with the mentioned focus points are required to support a more comprehensive defence against ransomware.

Keywords: higher education, cyber hygiene, information security behaviour, ransomware awareness

1. Introduction

Today's education sector heavily uses information and communication technologies during teaching and learning. Learning management systems, virtual classes, and e-learning applications make it more accessible and engaging. However, the significant use of digital technology also involves the challenge of maintaining cybersecurity in this modern learning environment. As digitalization is becoming more prevalent in educational institutions, their cybersecurity threats are expected to increase. Institutions handle sensitive personal data, from logins and passwords used on various portals to financial data and even research-related data. Given that educational institutions are likely not spending as much on cybersecurity as industrial players, the data they handle is also at greater risk. However, research and daily news often point out that the human factor is the weakest link. The above shows why cybersecurity awareness among various educational stakeholders is such an important issue.

The U.S. Cybersecurity and Infrastructure Security Agency (CISA) define cybersecurity as "protecting networks, devices, and data from unauthorized access or criminal use and the practice of ensuring confidentiality, integrity, and availability of information" (Cybersecurity

and Infrastructure Security Agency, 2021). In the literature, it is often visualized as the C-I-A triad. According to the European Union Agency for Cybersecurity (ENISA) Threat Landscape 2024 report, ransomware is one of the prime threats in today's cyber environment. Ransomware is a type of cyberattack in which malicious actors take control of a target's assets and demand a ransom to restore their availability or prevent the public exposure of the target's data (ENISA, 2024). Ransomware mainly jeopardizes confidentiality and availability, two parts of the C-I-A triad. Once triggered, users experience availability loss because they can no longer access their data.

Recent trends indicate that the education sector is becoming more vulnerable to cyber threats. In the first quarter of 2023, the Education and Research sector experienced the most significant impact, suffering the highest number of cyberattacks with an average of 2,507 per organization weekly. This marked a 15% increase compared to the first quarter of 2022. Many institutions in this sector faced challenges securing their extended networks and access points as they adapted to remote learning. In the meantime, this sector was the third most affected by ransomware (CheckPoint, 2023). According to the Phishing Activity Trends Report 3rd Quarter 2022 by the Anti-Phishing Working Group, 5% of all ransomware attacks are directed at the education sector (APWG 2022). A Comparitech article details the rising number of ransomware attacks on educational institutions from 2018 to 2023, highlighting significant downtime costs—estimated at \$53 billion globally—and disruptions to student learning. Schools and colleges, particularly in 2023, have seen a surge in attacks, with ransom demands averaging \$1.5 million. The analysis shows that colleges suffer higher record breaches and downtime than schools despite schools facing higher ransom demands (Moody, 2023). Verizon's 2022 Data Breach Report (DBIR) highlights an increase in ransomware attacks, accounting for over 30% of education sector breaches driven by limited resources and large volumes of sensitive student data. Attackers often use "double" and "triple extortion" methods, targeting school systems and parents (Verizon, 2022). The DBIR report also points out that most security breaches in the education sector, around 90%, are caused by system intrusions, social engineering, and human error. Higher education institutions often face data breaches due to their valuable research and personal data, and they have unique vulnerabilities due to their open, collaborative culture (Ulven and Wangen, 2021). Further education or higher education institutions are more likely to experience various attack types, such as viruses, malware, and unauthorized access to data or networks (UK Department for Science, Innovation & Technology, 2024).

2. Literature review

Ulven and Wangen explore cybersecurity threats within universities in their research, which often face data breaches due to the valuable research and personal data they hold. The study categorizes the risks into assets, threat events, threat actors, and vulnerabilities, highlighting frequent threats like hacking, malware, and social engineering (Ulven and Wangen, 2021). Khalid et al. examined the level of cybersecurity awareness among university students in Malaysia. The study used a questionnaire to measure the respondents' awareness across areas like cyberbullying, personal information protection, cybersex, internet banking, internet addiction, and self-protection. The sample consisted of 142 second-year education students. The results showed that while the respondents displayed a high level of awareness regarding certain aspects of cyber security, such as cyberbullying, personal information, and internet banking, they had less knowledge about cybersex and self-protection (Khalid et al., 2018). Alqahtani examined cybersecurity knowledge among university students in Saudi Arabia based on 450 responses. Findings reveal that social media behaviours most significantly impact awareness, followed by browser and password security knowledge. Although students recognize the importance of cybersecurity, they need to improve their practical application of secure behaviours (Alqahtani, 2022). Gabra et al. researched Nigerian Universities to assess students' cybersecurity awareness levels. Among the questions about using hard-to-guess passwords, 204 answered no from 367; regarding opening an email from an unfamiliar person, 219 said yes out of 367. This result indicates the respondents' lack of knowledge about phishing and password management (Gabra et al., 2020). Moallem's study aimed to assess students' cybersecurity awareness and attitudes in a very technocratic area of Silicon Valley in California, USA. With respect to the question measuring participants' cybersecurity knowledge, only 26% of the 247 surveyed agreed they were knowledgeable. Trust in the security of the university system varies; 57% consider it relatively secure, but 21% believe it is not safe. Regarding password management, 52% of respondents use two-factor authentication for some accounts, 24% use it for all accounts, 3% don't, and 8% do not know what it is (Moallem, 2019). Another study among Hungarian university students found that most respondents still do not implement secure password management in practice (Kollár & Katona, 2024). Further, diverse research is underway on the topic and examines numerous factors (Tick & Mai, 2024; Avci & Koca 2023). Chasanah and Candiwan examined Indonesian college students' cybersecurity awareness across attitudes, knowledge, and behaviour. They found that while overall awareness was rated "good" (around 80%), gaps remained in specific areas such as password management (Chasanah and Candiwan, 2025). Verma and Pawar investigated college students'

cybersecurity awareness as active internet users, focusing on phishing, malware, and ransomware. Their findings show that while students demonstrate awareness of these threats, such awareness does not consistently translate into effective protective practices (Verma and Pawar, 2025). Wash, Rader, Mandia, and Fossen examined how users select passwords and found that password reuse remains widespread even when individuals are aware of the risks (Wash et al., 2017). Mathews and Haque investigated the risks of password reuse across websites of varying importance. They found that users often apply the same or similar passwords to multiple accounts, which creates cascading vulnerabilities—for example, a breach of a low-value account can endanger higher-value ones (Mathews and Haque, 2024). Marcatto, Mistichelli, and Ferrante explored how people perceive digital threats, showing that optimism bias is common and that AI is viewed as particularly unfamiliar and uncertain. This highlights how perceptions of severity and novelty shape cybersecurity awareness (Marcatto et al., 2025).

There are several ways to defend against ransomware attacks. Mohurle and Patil highlight that timely patch management and strong, unique passwords are critical first-line defences. They also stress the importance of offline backups to restore encrypted data without paying ransom (Mohurle & Patil, 2017). ENISA focuses on simple, cost-effective measures: isolate critical assets, restrict user rights, and perform routine backup and restore drills to ensure data availability (ENISA, 2020). The confident and secure use of our networked digital tools (Molnár, 2012), which are based on large databases (Benedek et al, 2015), can essentially be achieved through highly reliable digital technologies, for which appropriate technical and methodological strategies must be developed (Molnár, 2013).

Overall, effective ransomware defence relies on a combination of regularly tested backups, consistent patching and software updates, robust endpoint protection, and the careful management of access rights through the enforcement of least-privilege controls.

3. Research questions and hypotheses

The purpose of this research is to conduct an exploratory analysis regarding the awareness levels of university students regarding cyber security by looking at self-reported behaviour, primarily seeking to uncover risk factors and misconceptions that are most prevalent. This research should help to establish some guidelines on how one could improve awareness regarding cyber security while providing a foundation for future, more in-depth research.

The study is guided by three central research questions:

- RQ1: To what extent are students aware of the most common cyber threats, such as phishing, ransomware, and other online attacks?

- RQ2: To what degree do students apply secure IT practices, including password management, account usage, system and antivirus updates, as well as backup and encryption routines?

- RQ3: How do students perceive the risks posed by cyber threats, and to what extent do they recognize that such threats affect individual users as well as large institutions or data-holding organizations?

Correspondingly, we formulated three hypotheses:

- H1: Most students are able to recognize the most common cyber threats, including phishing and ransomware attacks.

- H2: Students' security practices do not consistently reflect their awareness; password reuse, shared account usage, and insufficient application of backup or encryption remain widespread.

- H3: A proportion of students underestimate the risks of cyber threats at the individual level, if attacks primarily target large institutions or organizations.

4. Methods

To address these questions, undergraduate students were surveyed from four faculties (Engineering, Economics, Pedagogy, and Other) at the University of Dunaújváros using an 11-item cybersecurity behaviour questionnaire. Data were collected online during the autumn semester of 2024/2025. Demographic variables included gender, year of study, and field of study. Responses were measured on a three-point Likert scale, assessing students' perceived knowledge of phishing and email security risks, risky internet use, attention to system settings, commitment to data protection, and password/account management practices.

Initial reliability analysis of the full 11-item scale yielded Cronbach's $\alpha = 0.699$. According to Nunnally (1978), "in early stages of research, reliabilities of 0.60 or higher are acceptable" (p. 226). Since our scale approaches the conventional 0.70 threshold, we consider its internal consistency adequate for this exploratory study. Ethical considerations were carefully observed: participation was voluntary, no personal data were collected, and respondents were informed of the study's purpose and their right to withdraw at any time.

The exploratory design was not intended to establish causal relationships but rather to provide a descriptive snapshot of students' cybersecurity awareness. Descriptive statistics were applied to identify patterns and highlight areas of vulnerability. The findings reveal gaps between awareness and practice, as well as misconceptions regarding the scope of cyber threats. These insights are valuable for universities seeking to design targeted training programs or regulatory improvements.

Beyond practical implications, the study contributes theoretically by structuring dimensions of cybersecurity awareness—online behaviour and risk perception, technical protection and system practices, and password management and threat awareness. This framework supports the identification of constructs for future research and enables comparative analyses across institutions.

In conclusion, this research offers a timely perspective on the cybersecurity culture of higher education. By mapping students' awareness, practices, and perceptions, the study provides baseline data for the development of institutional IT strategies and contributes to strengthening the cybersecurity culture of universities in an increasingly dynamic digital environment.

5. Results

5.1. Results of the individual risk behaviours

The sample comprised 85 respondents. Responses to eleven security-related items are reported as counts and percentages for three categories: Yes, I agree, I can't decide, and No, I don't agree. Table 1 presents the distribution of survey responses for each questionnaire item (Q1–Q11), showing counts and row percentages for each response category. It summarizes how respondents agreed, disagreed, or were undecided on each security- behaviour related statement.

5.2. Highlights of the item-level results towards positive security behaviour

In this section, we highlight some results that show highly positive cybersecurity behaviours from the respondents.

The responses to Question 6 clearly reveal the students' security-aware attitude. The trend suggests that a significant proportion of students recognize the crucial role of regular updates in defending against cyberattacks, see Fig. 1.

The data presented in Fig. 2 are concerning from a cybersecurity perspective, as phishing attacks aimed at obtaining user credentials remain among the most common forms of cyberattacks.

Table 1. Summary of responses per question

		Yes, I agree	I can't decide	No, I don't agree	TOTAL	
Question - survey item	Q1: Attachments or links received in an e-mail from an unknown sender can be safely opened unless they are in the spam folder.	Count	23	6	56	85
		% within Question - survey item	27.1%	7.1%	65.9%	100.0%
	Q2: Emails asking for my username and password are not suspicious to me	Count	14	4	67	85
		% within Question - survey item	16.5%	4.7%	78.8%	100.0%
	Q3: I will download any file from the internet if I have an urgent need.	Count	20	10	55	85
		% within Question - survey item	23.5%	11.8%	64.7%	100.0%
	Q4: I'd rather download cracked software than buy it at full price because it's free.	Count	20	17	48	85
		% within Question - survey item	23.5%	20.0%	56.5%	100.0%
	Q5: Pop-ups are enabled in my browser because that's the only way most websites provide the full user experience.	Count	22	8	55	85
		% within Question - survey item	25.9%	9.4%	64.7%	100.0%
	Q6: I prefer to turn off automatic system and antivirus updates because they slow down my computer.	Count	12	5	68	85
		% within Question - survey item	14.1%	5.9%	80.0%	100.0%
	Q7: By encrypting the entire hard drive, I don't need to back up my files and data regularly.	Count	14	26	45	85
		% within Question - survey item	16.5%	30.6%	52.9%	100.0%
	Q8: I use the same account on my computer for daily activities like installing new software.	Count	53	15	17	85
		% within Question - survey item	62.4%	17.6%	20.0%	100.0%
	Q9: I use the same password for several Internet accounts, so I'm sure I will remember it.	Count	38	5	42	85
		% within Question - survey item	44.7%	5.9%	49.4%	100.0%
	Q10: Shorter passwords with capital letters and special characters are more secure than long passwords without a mix of these characters.	Count	39	10	36	85
		% within Question - survey item	45.9%	11.8%	42.4%	100.0%
	Q11: Ransomware attacks mainly target those who handle and store large amounts of personal or confidential data.	Count	40	22	23	85
		% within Question - survey item	47.1%	25.9%	27.1%	100.0%

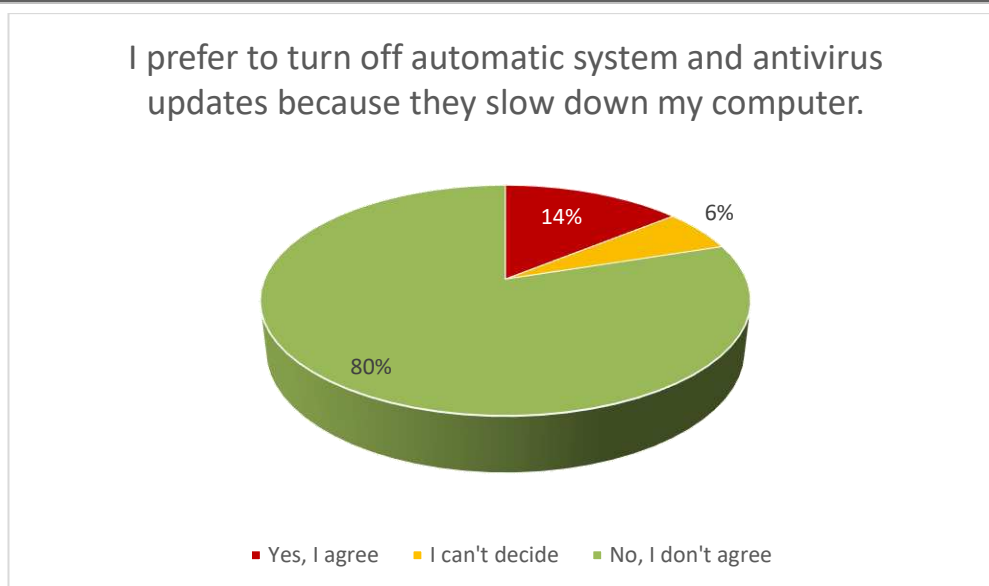


Fig. 1. Distribution of the answers in % on the statement " I prefer to turn off automatic system and antivirus updates because they slow down my computer" (Q6)".

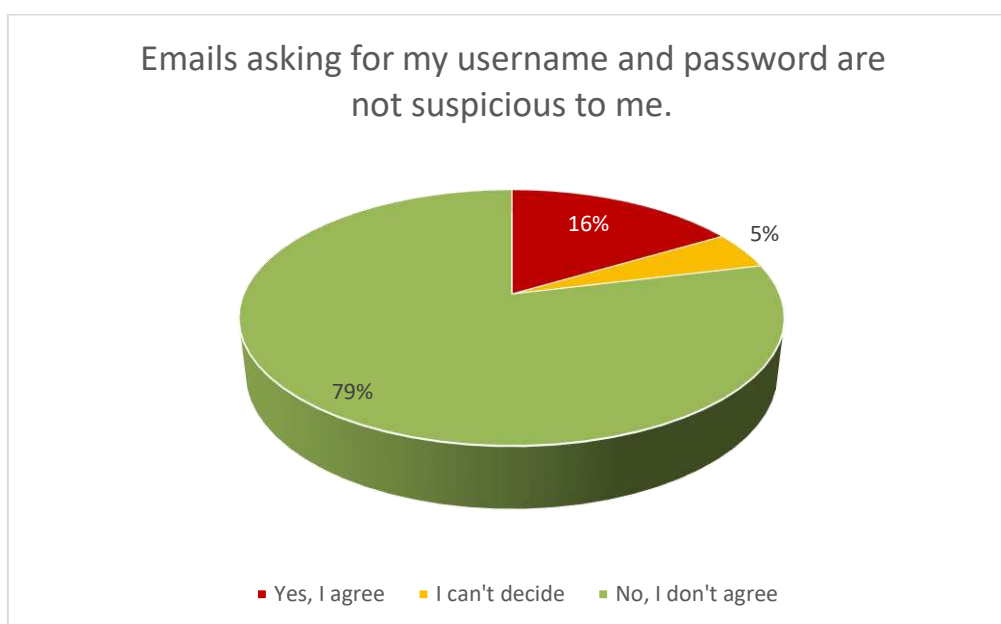


Fig. 2. Distribution of the answers in % on the statement "E-mails asking for my username and password are not suspicious to me." (Q2)

5.3. Highlights of the item-level results towards less cautious security behaviour

In this section, we present results indicating that respondents exhibit less cautious cybersecurity behaviours. The results suggest that most respondents are not fully aware of the importance of the principle of least privilege, a fundamental security concept in preventing cyberattacks. or Question 8, nearly two-thirds of the students—53 respondents—answered “yes” to using the same account for everyday activities and system-level tasks, while 15 were undecided, and 17 rejected this practice, see Fig. 3.

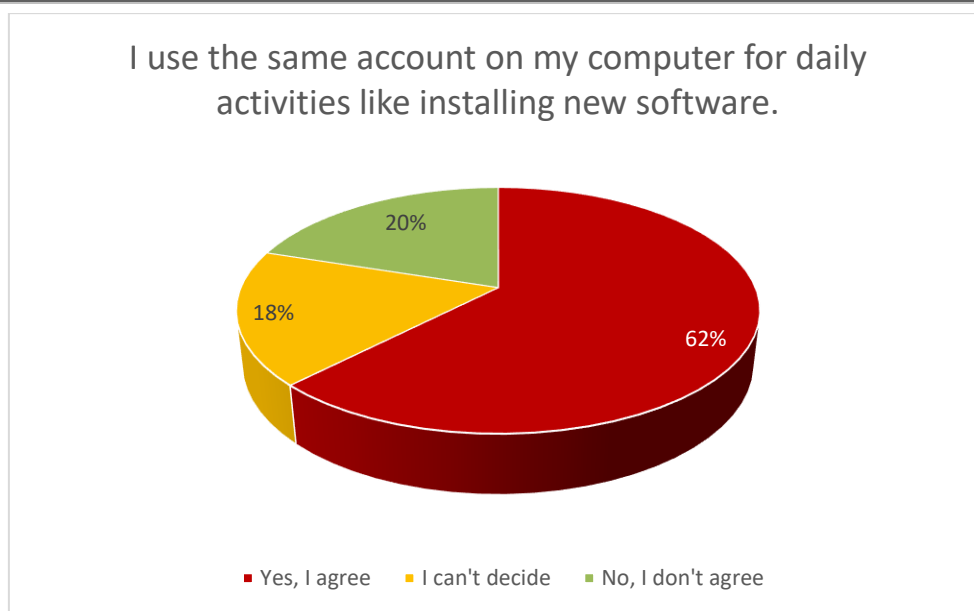


Fig. 3. Distribution of the answers in % on the statement " I use the same account on my computer for daily activities like installing new software." (Q8)

Nearly half of the respondents (44.7%) reported using the same password across multiple platforms, 5.9% were uncertain, while 49.4% indicated that they avoid this practice, see Fig. 4.

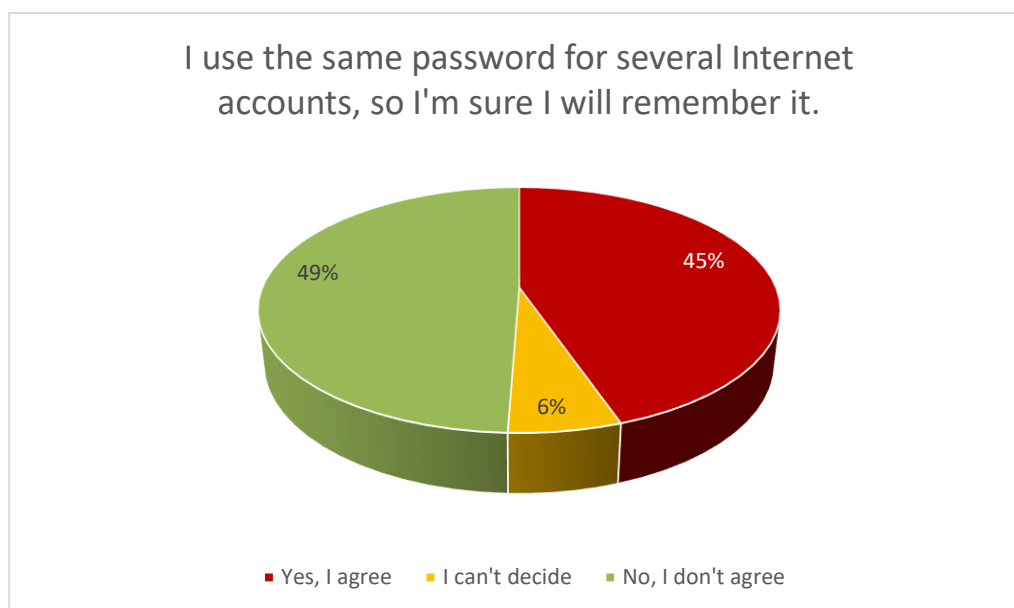


Fig. 4. Distribution of the answers in % on the statement " I use the same password for several Internet accounts, so I'm sure I will remember it." (Q9)

For Question 7, 16.5% of students agreed that encryption alone makes backups unnecessary, 30.6% were undecided, while 52.9% rejected this claim, see Fig. 5. These results reveal that

nearly one-third of respondents are not fully aware of the distinct roles of encryption and backup in data protection.

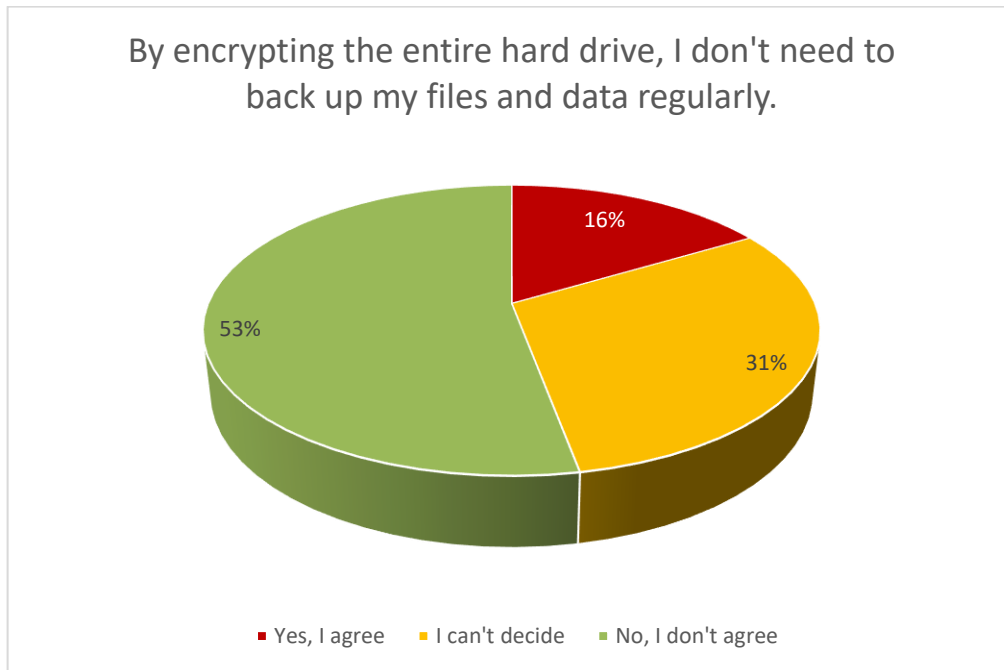


Fig. 5. Distribution of the answers in % on the statement "By encrypting the entire hard drive, I don't need to back up my files and data regularly." (Q7)

For Question 11, nearly half of the students (47.1%) agreed that ransomware mainly targets institutions handling large amounts of data, 25.9% were uncertain, and 27.1% disagreed, see Fig. 6.

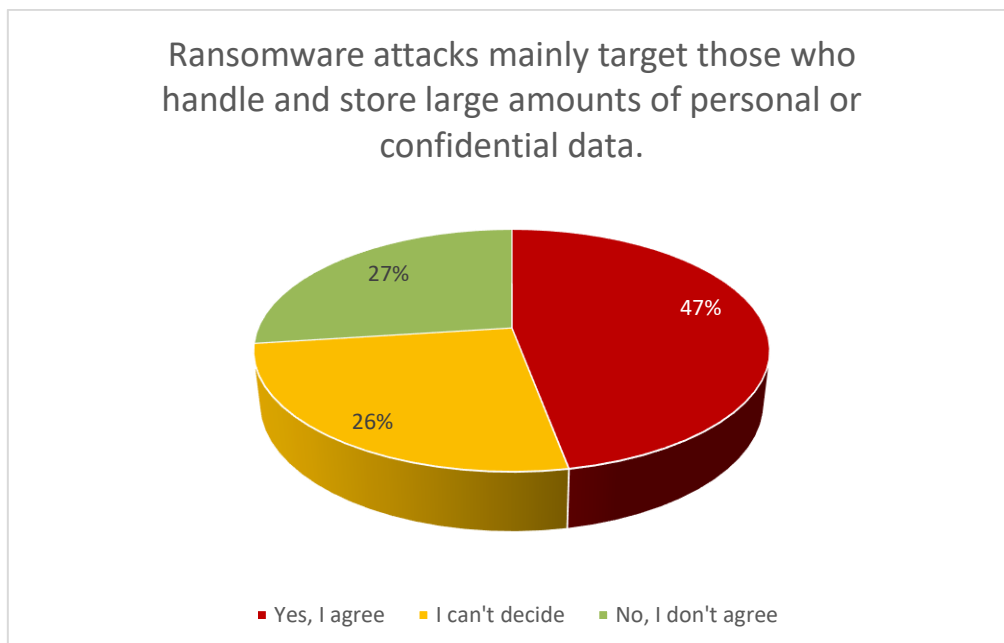


Fig. 6. Distribution of the answers in % on the statement "Ransomware attacks mainly target those who handle and store large amounts of personal or confidential data." (Q11)

The results indicate that most students are aware of the most common cyber threats, such as phishing and the importance of regular system updates. At the same time, several areas of uncertainty and misconception can be observed, including password reuse, the role of encryption, and the identification of ransomware targets. This suggests that while students are generally security-conscious, the depth of their awareness varies, and there remains a need for practice-oriented development of cybersecurity knowledge. Overall, the data clearly highlight the domains in which education should be strengthened to enhance both personal and institutional security.

5.4. Inferential Analyses of Less Cautious Security Behaviour

In this section, we selected Q7, Q8, Q9, and Q11 because they represented the weakest items in the survey. The chi-square analyses revealed no statistically significant differences across faculties (all p-values > 0.05), indicating that these problems are general among students regardless of their field of study.

Table 2. Chi-Square Test Results for Less Cautious Security Behaviors

Question (item)	Pearson χ^2	df	p-value
Q7 - By encrypting the entire hard drive, I don't need to back up my files and data regularly.	7.6	6	0.27
Q8 - I use the same account on my computer for daily activities like installing new software.	9.95	6	0.127
Q9 - I use the same password for several Internet accounts, so I'm sure I will remember it.	6.2	6	0.4
Q11 - Ransomware attacks mainly target those who handle and store large amounts of personal or confidential data.	9.33	6	0.156

6. Discussion

Both Chasanah and Candiwan (2025) and Verma and Pawar (2025) highlight that college students generally demonstrate a relatively high level of cybersecurity awareness, particularly in recognizing threats such as phishing, yet notable gaps remain in specific practices, such as password management or translating awareness into effective protective behaviour. These results reinforce Hypothesis H1, confirming that recognition of threats is common but not uniformly extended to all types of risks, nor consistently reflected in secure practices. The results of this research, such as the 78.8% phishing recognition rate, fit within this broader

pattern, underscoring that awareness is necessary but insufficient without corresponding behavioural safeguards. This result underscores the continued importance of strengthening digital self-defence and cybersecurity education within higher education environments.

System update practices also reflect positive awareness: most students did not disable automatic updates, which is a fundamental element of cyber hygiene in higher education environments. Such an attitude not only enhances individual device security but also contributes to safeguarding the institution's IT infrastructure. Conscious update management is a fundamental element of cybersecurity culture, and its presence is a prerequisite for a secure digital learning environment.

Password practices have been widely studied, and the evidence consistently highlights a gap between users' awareness of risks and their actual behaviour. Wash et al. (2017) showed that password reuse remains prevalent even when individuals acknowledge its dangers, reflecting the tension between usability and security. Building on this, Mathews and Haque (2024) demonstrated that users often apply the same password across websites of differing importance, thereby creating cascading vulnerabilities in which a breach of a low-value account can compromise more critical ones. Together, these studies reinforce Hypothesis H2, which posits that awareness of security risks does not necessarily translate into secure practices. The results, such as the 44.7% of students who reuse passwords across accounts, align closely with this body of research, situating the results within a broader pattern of risky password habits. This can lead not only to unauthorized access to personal data but also to identity theft and broader security incidents. This question therefore serves as an important indicator of the extent to which students consciously manage their digital identities.

Account handling practices also reveal gaps: nearly two-thirds of students reported using the same account for everyday activities and system-level tasks, indicating limited awareness of the principle of least privilege. This behaviour increases potential damage in case of compromise and highlights the need for targeted awareness campaigns. This question is particularly important because it does not merely address a technical habit but serves as a key indicator of user awareness and system-level security mindset. The findings highlight that strengthening cybersecurity knowledge remains a priority for both IT and non-IT students alike.

Data protection misconceptions were also evident. About one-third of students believed or were uncertain that encryption alone substitutes for backups. This reflects a misunderstanding of layered security, where encryption protects confidentiality but does not ensure availability against ransomware or hardware failure. Clarifying this distinction is essential in training

programs.

Data security is a multi-layered system in which encryption represents only one level of defence. The fact that about one-third of students remain uncertain on this issue indicates that the importance and function of backups must be further emphasized in training programs aimed at improving IT awareness.

Marcatto, Mistichelli, and Ferrante (2025) provide strong support for Hypothesis H3, which argues that individual users do not always perceive their own cyber risk. Their psychometric study shows that optimism bias leads many people to assume they are less vulnerable than others, while the “unknown risk” dimension makes emerging threats - such as AI - feel distant or unfamiliar. This combination results in underestimating personal exposure and framing cyberattacks as problems for institutions or “others.” The finding of this study that 27–30% of respondents in Q11 were uncertain or failed to recognize personal risk reflects the same mechanisms identified in their research, situating these results within a broader pattern of distorted risk perception. This question uncovers a specific misconception and underscores the importance of emphasizing in cybersecurity education that digital threats do not affect only ‘big players,’ but everyone who uses devices, data, or online services.

The analysis of the survey data reveals a nuanced picture of university students’ cybersecurity awareness and behaviour. Most participants demonstrated competence in identifying phishing emails, providing partial support for Hypothesis H1, yet considerable uncertainty emerged in recognizing ransomware attacks and the risks faced by individual users. Hypothesis H2, which addressed the gap between security practices and awareness, was also substantiated: while students generally maintain appropriate practices regarding system and antivirus updates, many reported reusing the same password across multiple accounts and relying on a single user account for everyday activities. Finally, Hypothesis H3—that a proportion of students underestimate the personal risks associated with cyber threats—was confirmed, as nearly one-third did not acknowledge that attacks may target individuals as well as large institutions.

Taken together, these findings indicate that students possess a baseline level of cybersecurity awareness, yet certain aspects of practice and risk perception remain underdeveloped and warrant further attention. The survey highlights the complexity of students’ cybersecurity behaviour, with notable vulnerabilities emerging in their responses to ransomware. Accordingly, the study addresses three principal dimensions: awareness of prevalent cyber threats; the security practices embedded in everyday computer use, including password management, account handling, and system updating; and the perception of risks posed by

cyber threats, particularly the recognition that such risks extend to individual users as well as institutions.

The results underscore critical areas where further education and awareness campaigns are indispensable—for example, reducing administrative-account reuse through least-privilege guidance, promoting unique long passwords and password managers to curb reuse, and clarifying that encryption is not a substitute for backups and that ransomware can be opportunistic. Beyond these practical implications, the study contributes theoretically by structuring dimensions of cybersecurity awareness, thereby supporting the identification of constructs for future research and enabling comparative analyses across institutions.

At the same time, several limitations must be acknowledged: the study is based on a small, voluntary sample from a single institution, relies on self-reported data, and adopts a cross-sectional design, which precludes generalization, causal inference, or the assessment of temporal change. Nevertheless, the exploratory nature of the research provides a solid foundation for larger, multi-institutional studies. Future work will aim to collect behaviour-based, objective data through system-usage logs and phishing simulations, to design targeted training interventions addressing identified knowledge gaps and risky practices, and to evaluate their impact using controlled group methods. Given the rapidly evolving nature of cyber threats, periodic reassessments are planned to monitor the progression of students' awareness and their adaptation to emerging risks.

7. Conclusion

The findings of this study yield several practically relevant insights. While most students are able to recognize fundamental forms of cyber threats, such as phishing and malicious emails, this awareness does not consistently translate into adequate protection or sustainable security practices. This underscores that cybersecurity education must extend beyond the transmission of knowledge to include the shaping of behavioural habits.

For practice, this highlights the need for further awareness-raising and skill-development programs that simulate real decision-making contexts, such as password management, system updating, and responses to data security incidents. The results confirm that cognitive knowledge alone is insufficient; fostering sustainable cybersecurity behaviour requires targeted educational interventions. At the institutional level, strengthening regulatory and technical support may also be warranted, including automatic security updates, encouragement of password manager use, and mandatory two-factor authentication. Within educational environments, regular interactive training and simulations—such as phishing exercises—can further enhance students' security

maturity. Overall, the study emphasizes that preparing students for cybersecurity cannot end with information transfer but must involve continuous, practice-oriented development that addresses attitudes, motivations, and behaviours.

Future research should extend these findings into experimental settings, for example by employing realistic but safe phishing simulations to examine actual behaviour. Additional studies could evaluate the effectiveness of educational interventions designed to enhance cybersecurity awareness, comparing different methodological approaches. Expanding the sample to include students from multiple institutions would improve generalizability, while exploring demographic and psychological factors—such as risk aversion or digital self-efficacy—could shed light on the drivers of security aware behaviour. Ultimately, future work should aim to integrate cognitive and behavioural dimensions of cybersecurity awareness to establish a stronger foundation for effective educational strategies.

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