Automation of interdisciplinary connections detection in higher education through information technologies

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Abstract

This study presents an automated approach to detecting interdisciplinary connections in higher education curricula. In the digital world's transformation during the 21st century, it requires specialists not only to know deeply their professional domain, but for them also to integrate knowledge across multiple disciplines. Therefore, effectively coordinating interdisciplinary links became a key factor in improving educational quality. Authors use both national studies and international studies. Also they propose a model of an automated system that has algorithms to identify disciplinary intersections. For quantitative assessment, the Dice coefficient is applied, which allows revealing intersections in the range of 0.14 to 0.77 and highlights core disciplines that shape the foundation of academic programs. The proposed system lets users remove all duplicate content, develop fully integrated courses, and design more personalized educational trajectories for all students.

The software implementation of the system provides efficient storage, processing, and analysis of large educational data sets. Automation modernizes education plan, eliminates redundancies, creates customized learning paths, and develops integrated programs for students. Such systems have a practical relevance for improving of the quality of higher education within Kazakhstan. The study does also underline their relevance for the advancing of the concept of a "smart university", where teaching aligns with demands of the digital economy as it is built upon interdisciplinary integration.

Keywords

interdisciplinary connections, curriculum analytics, higher education, automation, information technologies, intelligent systems, semantic content analysis

1. Introduction

The digital transformation of society has imposed new demands on higher education: graduates must combine deep domain expertise with the ability to integrate knowledge across disciplines. As a result, systematically managing interdisciplinary connections has become a critical lever for curriculum quality and relevance [1,2].

Nevertheless, the practical implementation of interdisciplinary approaches encounters a number of systemic challenges, including fragmented and overlapping curricula, the absence of tools for formalized analysis of overlaps, and the insufficient readiness of faculty to adopt digital technologies. These challenges emphasize the urgency of developing automated solutions for the detection of interdisciplinary connections.

The purpose of this study is to develop and empirically test an automated system for identifying interdisciplinary connections by combining a relational data model with semantic content analysis and quantitative assessment.

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2. Literature review

In pedagogy sphere, the issue of interdisciplinarity has been explored from socio-pedagogical, philosophical, psychological, and other perspectives. According to the Educational Data Mining review for the period 2013–2023, machine learning, deep learning, and hybrid approaches are increasingly adopted as tools in educational analytics, particularly for predicting academic performance, analyzing student behavior, and visualizing learning data. This confirms the feasibility of applying such methods to the task of detecting interdisciplinary connections between academic subjects [3].

The problem of interdisciplinarity in pedagogy has been discussed since the mid-20th century. After 2010, research on interdisciplinary connections has expanded, focusing on the digitalization of education, the integration of STEM disciplines, and the development of practical models of interdisciplinary learning [4,5]. Julie Thompson Klein remains one of the leading theorists in this domain [5]. Her publications of the 2010s highlight practical models of knowledge integration in university programs as well as institutional strategies for supporting interdisciplinary research. Allen Repko has presented fundamental works such as Introduction to Interdisciplinary Studies, where he outlines a methodology of interdisciplinary analysis, including the integration of concepts, theories, and methods from various fields [1]. Robert Frodeman, as editor of The Oxford Handbook of Interdisciplinarity (2010, 2017), has provided a foundation for studying interdisciplinarity in philosophical and educational contexts, offering a classification of forms and methods of integration [6].

In the European context, E. Vasconi and his colleagues have applied network analysis to curricula, demonstrating that graph-based models can identify key intersection points between disciplines and enhance curricular connectivity. In Asian studies, J. Park and S. Kim proposed a digital metric, the curriculum synergy score, for quantitatively assessing the degree of disciplinary integration, particularly in STEM education. In the context of digitalization and integrated educational programs, interdisciplinarity is becoming a key requirement: students must not only master specialized knowledge but also be able to identify and apply interdisciplinary connections [7]. Thus, current research increasingly focuses on developing practical tools for detecting and evaluating interdisciplinary connections, enabling a shift from theoretical models to their application in educational practices worldwide.

Today, interdisciplinarity is viewed not only as a teaching methodology but also as a component of the digital transformation of education. Emerging intelligent decision-support systems make it possible to automate the course design process. The issue of automatic identification of interdisciplinary connections in educational systems is actively being considered by modern researchers. A number of works emphasize that traditional methods of curriculum analysis rely on expert assessments and manual comparison of topics, which leads to high labor costs and subjectivity [19]. In foreign practice, there is a growing interest in digital educational graphs, which make it possible to formalize the dependencies between courses and competencies [20].

One of the most common tools for link analysis is the Neo4j graph database, which makes it possible to identify hidden dependencies in complex structured data by representing objects as nodes and relationships [21]. Such works demonstrate the effectiveness of Louvain, PageRank, and Jaccard Similarity graph algorithms for clustering disciplines and detecting similar thematic domains [21].As we mentioned above, Neo4j allows to do visual analytics. In contrast to this approach, the program developed in this paper uses semantic content analysis of educational and methodological documentation, extracting thematic keywords and measuring the degree of their overlap. This approach allows us to work at the level of semantic categories and detect interdisciplinary dependencies even if terminology does not match. Automated detection of intersections makes it easier to audit training programs, recommend integrated courses, and identify duplicate material.

To evaluate the effectiveness of the methods, a comparative analysis of the functionality of Neo4j graph analytics and the developed program was carried out. Unlike the graph model, which focuses primarily on structural connections between objects, the proposed system analyzes the contents of modules and thematic blocks, forming connections at the competence level. Table 1 summarizes the functional differences between the approaches.

Table 1
Functional comparison of graph-based analytics and the proposed semantic system

Criteria	Neo4j	The developed program
Data type	Graph structure (nodes/edges)	Semantic text data
Link detection method	Graph analytics algorithms (Louvain, PageRank, Jaccard)	Thematic analysis, keywords
The accuracy of interdisciplinary connections	High for structural relations	High for meaningful intersections
Automatic audit of curricula	Limited and requires models	Implemented purposefully
Discipline clustering support	Yes, with high modularity	Through thematic groups
Required user qualifications	High (data engineer)	Low (teacher/methodologist)
Identification of duplicated material	Difficult, requires extensions	Implemented directly
Institutional integration	Difficult without dedicated DevOps support	Designed for curriculum-oriented deployment

The comparison showed that Neo4j is highly efficient when working with large, structurally formalized data, but it does not have built-in subject semantics [22]. In the context of educational programs, this leads to incomplete detection of intersections if disciplines use different terminology.

The developed system is based on meaningful features extracted from curricula, and thus provides a deeper interpretation of interdisciplinary connections.

In addition, this model provides teachers with recommendations on the redistribution of academic modules, the elimination of thematic duplicates and the formation of integrated courses, which in modern conditions is a key factor in educational reform.

The integration of graph methods and semantic analysis makes it possible to significantly improve the accuracy of detecting intersubject relationships [23]. Neo4j provides a scalable framework for structural dependencies, while the developed program demonstrates an advantage in meaningful analysis of educational materials. The combined application of these approaches can form a full-fledged digital tool for designing curricula for higher education.

3. Interdisciplinary connection

Interdisciplinary connection is a didactic condition for enhancing the level of students' scientific knowledge. It serves functions such as strengthening the role of learning, fostering students' cognitive and creative abilities, and developing their intellectual interests.

Let's consider the types of interdisciplinary connections identified by V.S. Kukushin for the formation of systemic knowledge and the design of integrated courses. Please check Table 2.

Table 2
Types of interdisciplinary connections

Connection type	Characteristic
Direct	Arise when studying the material of one discipline based on the knowledge of another
Problem based	Formed when investigating common objects or tasks by two or more disciplines
Mental	Related to the development of cognitive skills such as systems thinking and imagination.
Applied	Use of concepts from one science to explain processes in another

Among the levels mentioned above, the third one (mental connection) is considered the most optimal and effective, since it is important for students to perceive a certain system in the teacher's work and activities. At the same time, the use of interdisciplinary connections should not create an excessive burden for students, but rather contribute to the formation of a scientific worldview.

Interdisciplinarity in education is closely linked to the philosophy of science. Modern knowledge does not evolve in isolation but emerges at the intersection of different fields. For example, the emergence of disciplines such as bioinformatics, cognitive science, or fintech is directly related to the integration of various domains.

The automation of detecting interdisciplinary connections can be applied in different directions, such as:

- Curriculum modernization – eliminating duplicate disciplines and developing integrated courses;
- Personalized learning trajectories – the system can recommend additional courses from related fields, thereby strengthening students' competencies;
- Scientific research – automatic identification of interdisciplinary topics for master's and doctoral dissertations;
- Quality assurance in education – objective evaluation of course content and their integration.

Modern information technologies provide a wide range of tools for implementing automated systems for detecting interdisciplinary connections. Among them are:

1. Database Management Systems (DBMS) – such as MySQL, PostgreSQL, and Oracle, which allow storing and processing large datasets of academic curricula.
2. Artificial Intelligence (AI) technologies – including machine learning, natural language processing (NLP), and neural networks, which enable curriculum text analysis, automatic extraction of key concepts, and the construction of associative links.
3. Big Data – processing massive volumes of educational information (curricula, student performance, learning trajectories) to discover hidden patterns.
4. Web technologies – development of user-friendly web interfaces providing access to the system for both instructors and students.

In the process of developing our automated system for identifying interdisciplinary connections between various subjects, it is necessary to create a database that will store information about the selected academic major, disciplines, topics, and their associated concepts.

4. Methodology

This study employed a comprehensive approach that combined the analysis of philosophical, pedagogical, and information technology sources related to the problem of interdisciplinary connections [8,9].

Modern approaches to the automation of educational processes actively utilize machine learning methods and big data analytics. Our colleagues, for instance, applied machine learning to analyze borrowings from the Russian language in Kazakhstani social media, identifying hidden patterns in textual data. Similar methods can be effectively applied to the analysis of curricula and interdisciplinary connections, enabling the formalization of intersection points between disciplines and the prediction of potential areas of integration in higher education [16].

The empirical basis of this research included two curricula in pedagogical and engineering specialties and more than 100 disciplines across these fields. The work was carried out in four stages:

1. Curriculum analysis – examining academic plans for pedagogical and engineering specialties.
2. Identification of intersections – detecting points of overlap between disciplines (e.g., Information Systems – Computer Science).
3. Database construction – developing a structured repository of interdisciplinary connections.
4. Algorithm development – designing a procedure for detecting and quantitatively assessing interdisciplinary overlaps.

The proposed model for automating the detection of interdisciplinary connections is grounded in two fundamental principles:

- Knowledge base formation. All detected links are stored in a unified database that can be accessed by both instructors and students;
- Processing algorithm. An optimized algorithm was developed to manage the detection and classification of interdisciplinary connections.

The use of dedicated software tools facilitates the identification of latent patterns and trends that are not easily discoverable by conventional methods.

To operationalize the system, a relational database was designed, incorporating five primary tables:

- Specialties – containing identifiers, codes, and titles of academic specialties;
- Disciplines – linked to specialties and listing courses with their corresponding codes and names;
- Topics – associated with individual disciplines and representing the thematic structure of courses;
- Concepts – defining key terms and notions related to specific topics.

Each table within the database was designed with predefined fields (columns). For example, the spec (specialty) table includes:

- ID — the numerical identifier of the specialty;
- CODE — the specialty code;
- NAME — the title of the specialty.

When creating the database schema, data types, element sizes, and other parameters specified for each column in advance.

The system also supports a range of operations, including data modification, selection, deletion, duplication, and export. This structure ensures flexibility and efficiency in managing educational data and provides a robust foundation for automated interdisciplinary analysis.

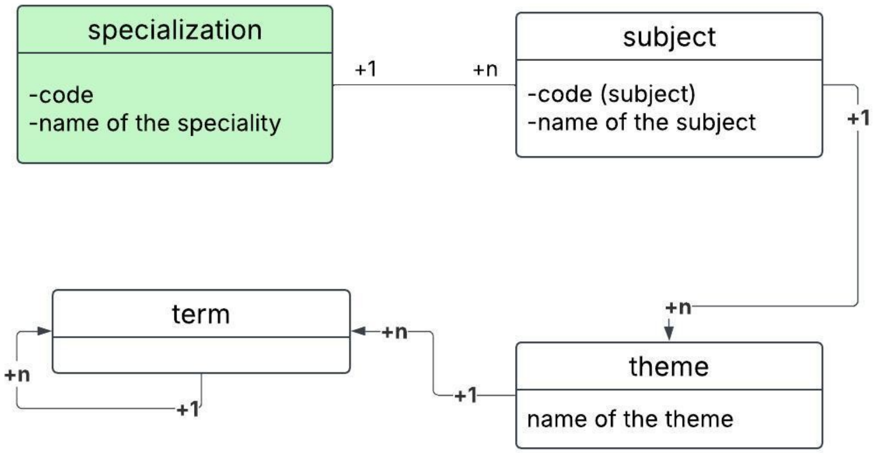

Figure 1: Entity-Relationship (ER) diagram of the automated system for detecting interdisciplinary connections

All of the aforementioned tables are interconnected through one-to-many relationships, which ensures the logical integrity of the database and the correct functioning of the system. The conceptual model of the automated system for detecting interdisciplinary connections is illustrated in Figure 1.

In higher education, the identification of interdisciplinary connections plays a significant role in addressing challenges that arise during the learning process. Such connections are established at the level of two or more academic disciplines, making it possible to assess the degree of their complementarity and integration.

To quantify the strength of interdisciplinary links, the Dice Similarity Coefficient (DSC) was employed [12]. This statistical measure allows for the evaluation of the overlap between two sets of elements (e.g., concepts, topics, or modules of different courses). The coefficient was originally proposed by Lee R. Dice in 1945 [13] as a means of assessing the degree of similarity among biological species based on shared characteristics. Over time, it has been successfully adapted and widely applied in information technology, linguistics, medicine, education, and other domains.

In the field of pedagogy, the Dice coefficient can be applied for:

- identifying common competencies across different courses;
- analyzing topic repetition in curricula;
- designing integrated educational programs (e.g., Computer Science + Mathematics).

In automated systems, particularly those relying on relational databases of academic disciplines, the Dice coefficient is used to:

- formalize the degree of similarity between courses;
- visualize overlaps in the form of graphs;
- identify “core disciplines” with high levels of connectivity.

The advantages of the Dice coefficient include:

1. High sensitivity to matches – even with a relatively small number of common elements, the measure remains significant;
2. Symmetry – the value does not depend on which set is considered first;

3. Interpretability – results can be easily translated into a practical understanding of the degree of interdisciplinarity;
4. Universality – the coefficient is applicable across diverse fields, from text analysis to medical diagnostics and educational analytics.

Thus, the Dice coefficient represents an effective methodological tool for detecting interdisciplinary relationships in automated systems for curriculum analysis. Its implementation makes it possible to objectively measure the degree of content overlap and, on this basis, construct models of course integration in higher education.

In the developed automation system, a set of disciplines is represented as $P_1, P_2, \ldots P_n$. For each discipline, the total number of elements is determined: the number of elements in discipline P_1 is denoted as N_a, while the number of elements in discipline P_2 — is denoted as N_b. The number of overlapping elements between disciplines P_1 and P_2 is expressed as $N(a) \cap N(b)$ [13].

To provide a quantitative assessment of the interrelationship between disciplines, the Dice similarity coefficient, denoted as $\mathrm{sim}_{Dice}(a,b)$, was introduced. This coefficient characterizes the strength of the connection between disciplines P_1, P_2. Its computation is based on the following formula:

$$\mathrm{sim}_{Dice}(a,b) = \frac{2|N(a) \cap N(b)|}{|N(a)| + |N(b)|}. \quad (1)$$

The value of the coefficient j ranges from 0 to 1. A value of $j = 0$ indicates the absence of intersections between disciplines, whereas $\mathrm{sim}_{Dice}(a,b) = 1$, reflects complete equivalence of the sets. Consequently, higher Dice coefficient values correspond to stronger interdisciplinary relationships.

This metric demonstrates several important advantages. First, it remains sensitive even when the number of shared elements is relatively small, allowing it to capture meaningful connections that might otherwise be overlooked. Due to these properties, the Dice coefficient has found extensive application in information systems and data analysis, and it can be effectively employed for identifying interdisciplinary links within educational programs.

5. Results

The developed automated system for identifying interdisciplinary connections has enabled the following outcomes:

- the formalization of the process of analyzing curricula and academic disciplines;
- the identification of shared competencies across courses;
- the elimination of duplicated learning materials;
- the detection of "key disciplines" with a high degree of connectivity;
- the proposal of integrated educational programs.

Thus, the system not only facilitates the identification of existing interdisciplinary links but also provides a means of quantitatively assessing their strength.

The interpretation of the Dice coefficient in this context is as follows:

- If $\mathrm{sim}_{Dice}(a,b)$ is less than 50%, the connection between the selected disciplines is considered weak. In such cases, it is advisable to teach these disciplines independently without emphasizing their integration.
- If the coefficient approaches 100%, this indicates a high degree of overlap between the contents of the disciplines. Despite their differing titles, the informational content is almost

identical. Under these conditions, it is rational to retain only one discipline in the curriculum to avoid redundancy.

Intelligent systems make it possible to identify relationships and patterns more effectively than traditional methods [6].

In the course of analyzing educational programs and curricula, the Dice coefficient was applied to measure the degree of overlap between instructional materials. The results can be summarized as follows:

- Minimum value – $\mathrm{sim}_{Dice}(a,b)$ = 0.12 (weak connection, almost no shared topics);
- Maximum value – $\mathrm{sim}_{Dice}(a,b)$ = 0.75 (high degree of overlap between courses);
- Average value – $\mathrm{sim}_{Dice}(a,b)$ = 0.41 (average level of interdisciplinary connection).

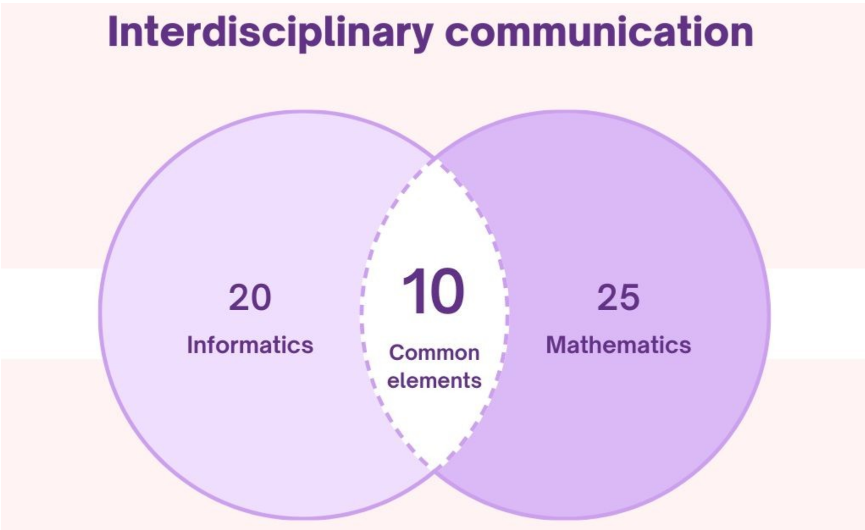

Figure 2: Visualization of interdisciplinary overlap.

Another illustrative example can be provided:

- Suppose the course Informatics includes 20 key concepts N_a = 20;
- while the course Mathematics covers 25 key concepts N_b = 25;
- Among them, 10 concepts are shared 10 $N(a) \cap N(b)$ = 10 (Figure 2).

Substituting these values into the formula gives:

$$\mathrm{sim}_{Dice}(a,b)=\frac{2*10}{20+25}\approx 0.44$$

This result indicates that approximately 44% of the course content overlaps, meaning that the interdisciplinary connection between these two courses can be interpreted as a moderate-level relationship. An additional representation of this analysis can be provided in tabular form (Table 3).

As shown in Table 3, the strongest connections were observed between the courses Mathematics and Mathematical Logic ($\mathrm{sim}_{Dice}(a,b)$ = 0,77), as well as between Information Systems and Algorithms and Data Structures ($\mathrm{sim}_{Dice}(a,b)$ = 0,69). In contrast, the courses Mathematical Logic and Pedagogy demonstrated a low level of integration, with $\mathrm{sim}_{Dice}(a,b)$ = 0,14.

Currently, interdisciplinary approaches are widely adopted in many developing countries. For instance, in Finnish schools, the concept of "phenomenon-based learning" is applied, where students study complex phenomena rather than isolated subjects. In the United States, universities have developed interdisciplinary master's programs, such as Bioinformatics and Cognitive Science [17].

Table 3
Dice Similarity Coefficient between pairs of courses

Course A	Course B	The number of elements $N(b)$	The number of elements $N(a)$	The number of elements $N(a) \cap N(b)$	$\text{sim}_{Dice}(a,b)$
Computer science	Information systems	22	18	12	0.63
Philosophy	Psychology	20	24	14	0.61
Pedagogy	Psychology	15	20	5	0.29
Algorithms and Data structures	Information Systems	25	28	18	0.69
Mathematical logic	Mathematics	30	32	24	0.77
Database	Algorithms and Data structures	22	26	10	0.41
Information Systems	Programming	30	24	16	0.59
Mathematical Analysis	Database	18	24	6	0.28
Mathematical logic	Pedagogy	30	24	4	0.14

A comparative analysis indicates that Kazakhstan possesses favorable conditions for the implementation of similar models in higher education, particularly given its ongoing digitalization initiatives. However, several key steps must be undertaken to ensure successful adoption:

1. Conduct an audit of existing curricula to identify duplicated content;
2. Develop a comprehensive database of interdisciplinary links across all fields of study;
3. Introduce software systems to automate the analysis of academic programs;
4. Provide training for faculty members in the use of digital tools;
5. Implement the model initially in pilot universities, followed by large-scale deployment.

6. Discussion

The conducted study has demonstrated that the automation of interdisciplinary connection detection based on information technologies is an effective tool for modernizing educational programs. The developed system formalized the process of curriculum analysis, identified intersections between courses, and provided a quantitative assessment of integration using the Dice coefficient. These results confirm that digital tools can significantly enhance the transparency and manageability of the educational process [6,10].

A comparison with previous research shows that the findings are consistent with international experiences of integrating disciplines in the context of educational digitalization. For instance, Finland has implemented phenomenon-based learning, where interdisciplinarity is realized through the comprehensive study of phenomena [14]. Similar approaches can be found in the United States and South Korea, where artificial intelligence algorithms are actively integrated into educational platforms for curriculum analysis [2,16]. Our results confirm the applicability of such approaches in the Kazakhstani context [5].

At the same time, certain limitations were identified. First, the effectiveness of the system largely depends on the quality and completeness of the initial curricula [12,17]. Second, while the Dice coefficient helps formalize connections, it does not account for the semantic depth of course integration, which requires expert input from subject specialists [9,14]. Furthermore, the implementation of automated systems necessitates methodological training for instructors and adaptation to digital tools [17].

Despite these limitations, the study highlights the strong potential of automation for advancing interdisciplinary integration. The use of big data analytics, machine learning algorithms, and artificial intelligence technologies can not only identify overlaps between disciplines but also predict potential areas of integration [7,10]. This opens opportunities for the development of adaptive learning trajectories, integrated curricula, and the transition toward the "smart university" model [15].

In conclusion, this research contributes to the methodology of analyzing interdisciplinary connections in higher education, demonstrating that automation can significantly improve the quality of the educational process and align it with the challenges of the digital economy [2,4].

Future research directions may include:

- Developing adaptive systems that recommend personalized courses for students;
- Applying big data analytics to study learning trajectories;
- Employing machine learning to uncover hidden patterns within curricula;
- Designing a dedicated interdisciplinary integration platform for Kazakhstan.

7. Conclusion

Ultimately, it becomes evident that at a new stage of education, interdisciplinary connections acquire a special context and play an important role in the training of highly qualified specialists. In higher education institutions, interdisciplinary integration contributes to the consolidation and systematization of scientific knowledge, the development of a scientific worldview, and the optimization of the learning process. Moreover, it enables each student, guided by their own value orientations, to reveal and realize their potential [5].

For example, information and communication technologies (ICT) represent a profound and complex scientific domain. Mastering this field requires extensive work involving electronic educational resources, the potential of the Internet, as well as accumulated theoretical and practical experience. The rapid development of ICT, the growth of human knowledge and cognition, the expansion of business practices, and their application in society necessitate the transition to a new stage of advancing and refining interdisciplinary approaches.

Studying this domain within the framework of a single discipline is a significant mistake. It must instead be approached through interdisciplinary methods, fostering interdisciplinary thinking. Furthermore, ICT in practice makes it possible to achieve real integration of academic disciplines, identify intersections between general and specialized courses, and thereby ensure the consolidation of various fields of education and the implementation of interdisciplinary links.

The conducted study has demonstrated that automating the identification of interdisciplinary connections through digital technologies reduces duplication of educational material, reveals integrative opportunities between courses, and supports the development of adaptive learning trajectories.

The practical significance of this research lies in the fact that the developed system can be implemented not only in Kazakhstani universities to improve the quality of educational programs and to realize the concept of a "smart university," but also internationally as a successful example of integrating interdisciplinary connections with digital tools. In universities across different countries, such systems support the construction of educational trajectories where students' knowledge is shaped not in isolation but through diverse integration of disciplines, which aligns with employers' expectations and competency requirements in the rapidly changing digital economy [18].

Future research prospects are associated with the application of machine learning methods and big data analysis to predict new areas of disciplinary integration, support adaptive selection of educational content, and develop individualized student trajectories based on their interests and labor market needs.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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