Mathematical Model for Assessing the Balance of Educational Program Profiles in Higher Education Institutions

Oleh Ilarionov[1,*,†], Hanna Krasovska[1,†] , Hryhorii Hnatienko[1,†], Kateryna Krasovska[2,†] and Ravshanbek Zulunov[3,†]

[1] Taras Shevchenko National University of Kyiv, 60 Volodymyrska Street , 01033 Kyiv, Ukraine
[2] SoftServe, 20 Prosta Street, 00-850 Warsaw, Poland
[3] University Fergana branch of Tashkent University of Information Technologies named after Muhammad al-Khorezmi University of Information Technologies, 185 Mustakillik Street, 150118 Fergana, Uzbekistan

Abstract

The paper presents a formalized mathematical model for assessing the balance of educational program profiles in Ukrainian higher education institutions. The model is based on constructing a metric profile of program learning outcomes, which enables quantitative evaluation of program coherence and proportionality. The concept of a metric profile is introduced, and a method for calculating the balance coefficient of an educational program is proposed. A clustering approach for program learning outcomes is developed following the structure of the Computer Science Curricula 2023 (CS2023) framework, along with a normalization procedure for credit load comparison across programs. Examples of real educational programs are analyzed to demonstrate the model's applicability, including the use of radar (petal) charts for profile visualization. The proposed model provides a foundation for developing intelligent systems to support individual learning trajectories and can be adapted to various fields of higher education.

Keywords

educational program, metric profile, program learning outcomes, balance coefficient, individual educational trajectory, structural analysis of educational programs

1. Introduction

The requirements of the labor market, the rigid framework of educational and professional standards, and the needs of higher education students in choosing individual learning trajectories necessitate the development of tools for multidimensional evaluation of the quality of educational programs (EPs) and for the formalized comparison of their individual characteristics [1, 2]. A key challenge lies in ensuring transparency, adaptability, and balance in the mechanisms of evaluation and comparison [3, 4]. The need to formalize the structure of evaluation criteria for educational programs [5, 6] requires the establishment of clear and measurable interrelations among competencies, program learning outcomes, and educational components [7, 8]. In this context, the balance of the allocated credit load of educational components across the intended program learning outcomes should ensure the integrity of students' educational trajectories, foster their comprehensive development, and, consequently, enhance their competitiveness in the labor market.

It should be noted that the diversity of educational programs (EduProgs) within a single specialty creates significant challenges in transferring students between programs, even within the same

ITS-2024: Information Technologies and Security, December 19, 2024, Kyiv, Ukraine
* Corresponding author.
† These authors contributed equally.
oleg.ilarionov@knu.ua (O. Ilarionov); hanna.krasovska@knu.ua (H. Krasovska); hnatiienko@knu.ua (H. Hnatienko); kkraso@softserveinc.com (K. Krasovska); zulunovrm@gmail.com (R. Zulunov);
0000-0002-7435-3533 (O. Ilarionov); 0000-0003-1986-6130 (H. Krasovska); 0000-0002-0465-5018 (H. Hnatienko); 0000-0002-3468-8064 (K. Krasovska); 0000-0002-2132-0834 (R. Zulunov)

higher education institution (HEI), as well as in recognizing learning outcomes obtained through academic mobility. Therefore, the establishment of a formalized mechanism for multidimensional evaluation and comparison of EduProgs would make it possible to minimize losses during the formal recognition of learning outcomes acquired outside the HEI [9, 10]. Moreover, such a mechanism would assist students in identifying directions for the development of their individual learning trajectories and help EduProg guarantors determine pathways for further improvement and enhancement of EduProgs.

The aim of this study is to develop a mathematical model that enables the formalization of criteria for evaluating and comparing EduProgs.

2. PROBLEM STATEMENT AND MATHEMATICAL MODEL

Higher education standards define the content of learning at each educational level for every specialty in terms of an integral competence, a set of general (GC) and special (SC) competences, the formation of which is achieved through the acquisition of program learning outcomes (PLOs) prescribed by the respective standard. It should be noted that in Ukraine, the structure of all higher education standards follows a unified model established by the Order of the Ministry of Education and Science of Ukraine No. 600 of June 1, 2016, "On the Approval and Implementation of the Methodological Recommendations for the Development of Higher Education Standards."

Based on the approved higher education standards, higher education institutions develop unique educational programs (EduProgs) that differ in the structure of their educational components (EC), credit load, forms of final assessment, and the alignment of ECs with the program learning outcomes (PLO) and, consequently, with the competences defined by the standard. In addition to the sets of general (GC), special (SC) competences, and PLOs established by the standard, institutions may introduce additional components.

The model of the content of learning in the EduProg can be represented as a Knowledge Flow Structure (KFS) [11, 12], which demonstrates the logic of transferring knowledge, skills, and competencies within the educational program, presented at three logical levels (Figure 1).

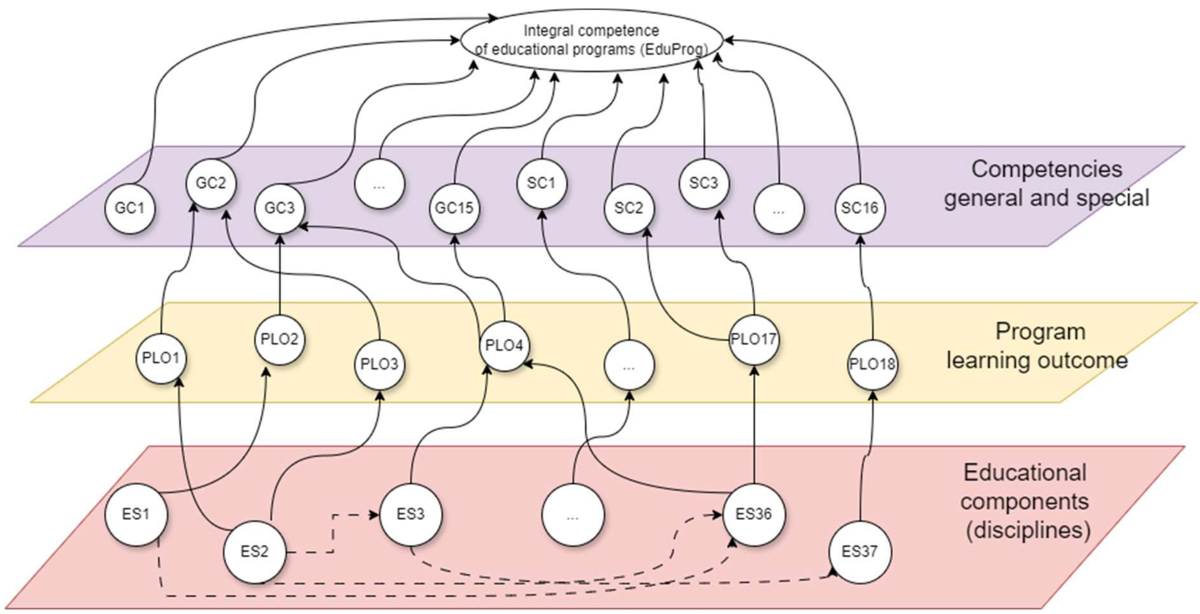


Figure 1: KFS model of the links between competencies, program outcomes, and educational components of the EduProg

1. Competency level (upper level):

- general competencies (GC1, GC2, GC3, etc.) are universal skills, knowledge, and abilities that are not tied to a specific specialty but are necessary for successful study, work, and personal development. For example, the ability to think abstractly and critically, the ability to work in a team, etc. They form the basis for interdisciplinary thinking, adaptation to change, and communication in modern society;
- special competencies (SC1, SC2, SC3, etc.) are knowledge, skills, abilities, and abilities that are directly related to a specific field of professional activity and provide students with in-depth specialized knowledge and skills necessary to perform professional tasks and solve specific problems in the relevant field;
- competencies in their entirety form an integral competence, which is the main goal of this educational program.

2. Level of program learning outcomes (middle level): program outcomes (PLO1, PLO2, PLO3, etc.) are specific knowledge, skills, abilities, ways of thinking and other qualities that a student should acquire after completing the educational program. They are the criteria for assessing the success of the student's training (i.e., they must be specific and measurable), focus on what the student will be able to do in practice, and be useful for performing professional tasks in real life.

3. Level of educational components (lower level):

- educational components (EC1, EC2, EC3, etc.) or disciplines are the structural elements of the educational program that form the basis of the educational process and ensure the achievement of program learning outcomes and competencies. These are specific disciplines, practices, term papers/projects, qualification work aimed at developing the knowledge, skills, and abilities of students;
- educational components are the basis that ensures the formation of program learning outcomes through their content, which is determined by the discipline's work program;
- educational components are interconnected in a structural and logical diagram of the educational program - this is usually a graphical representation of the logical relationships between educational components, showing how one EC creates the basis for studying another. It allows you to understand the sequence of learning, demonstrating the logical relationship between individual disciplines and between disciplines and learning outcomes, and is used to plan the learning process.

4. Connections between levels:

- the level of educational components supports the level of program results (PR) through the implementation of relevant disciplines, courses, practices, etc;
- the level of program outcomes ensures the achievement of general competencies and special competencies, which ultimately form the integral competence of the educational program.

The upper and middle levels of the KFS are determined by the standards of higher education by specialty and level: first (bachelor's), second (master's) educational levels, and third (educational and scientific) level.

Thus, the standard of higher education in the specialty 122 "Computer Science" of the first (bachelor's) level of higher education [13] defines the integral competence, general competencies GC1-GC15 ($z_1^{st} - z_{15}^{st}$), special (professional, subject) competencies SC1-SC16 ($s_1^{st} - s_{16}^{st}$), the normative content of training in terms of learning outcomes $P^{st}(p_1^{st} - p_{16}^{st})$ and the links between program outcomes and general and special competencies defined by the standard [13], which corresponds to the links between the upper and middle levels of the Knowledge Flow Structure in Fig. 1.

The list of educational components and the logical connections among them, represented at the third (lower) level of the KFS in Fig. 1, are defined by the corresponding educational programs through their component lists. The descriptions of all educational programs also include a matrix of correspondence that maps the achievement of program learning outcomes to specific educational components, which corresponds to the relationships between the lower and middle levels of the Knowledge Flow Structure in Fig. 1.

The European Credit Transfer and Accumulation System (ECTS) [14] represents a significant step toward the creation and implementation of formalized mechanisms that promote the standardization of approaches to the planning, evaluation, and quality assurance of educational programs, as well as the transparency and mutual recognition of academic results among higher education institutions across countries. ECTS provides a framework for quantifying students' academic workload in the process of achieving planned learning outcomes and ensures the transparency and comparability of EduProgs, thereby facilitating academic mobility and the recognition of qualifications [15, 16].

The credit serves as the conventional unit for measuring a student's academic workload, reflecting the amount of time required to achieve the program's intended learning outcomes. One credit corresponds to 30 hours of student workload, including both classroom instruction and independent study. This system has long ensured a unified procedure for learning assessment across universities in different countries, allowing for the measurement and comparison of students' learning outcomes and facilitating academic recognition and credit transfer among higher education institutions.

The Law of Ukraine "On Higher Education" establishes general requirements for educational programs and their volume in ECTS credits: bachelor's programs - not less than 180 and not more than 240 ECTS credits; master's program - 90-120 ECTS credits (for some specialties - not less than 60); Doctor of Philosophy (PhD) - 30-60 ECTS credits, with at least 25% of the volume of the educational program being its elective component. Thus, given that the formation of program outcomes defined by the Higher Education Standard can only be ensured by mandatory educational components of the EduProg, no more than 180 credits can be allocated for the formation of the EduProg at the bachelor's level for a 240-credit EduProg. Ideally, this credit volume should be evenly distributed among the planned learning outcomes.

Definition 1. The metric profile of an educational program is defined as a vector whose elements represent the number of credits allocated to the achievement of the respective program learning outcomes:

$$P = \left(p_j\right)_n, \tag{1}$$

where n – is the number of program results.

To determine the metric profile of an educational program, it is necessary to transform the matrix of correspondence between program learning outcomes and mandatory educational components. This transformation replaces the binary relation between ECs and PLOs with an averaged value representing the number of ECTS credits allocated by each EC to the formation of a particular PLO. As a result, the matrix is represented in the following format:

$$M = \left(m_{ij}\right)_{k \times n}, \tag{2}$$

where m_{ij} – is the average value of the number of credits allocated by the educational component i to form the program result j; k and n – are, respectively, the number of mandatory EC and PLO defined in the description of the educational program.

Thus, the elements of the metric profile of the educational program (1) are calculated on the basis of the matrix: M:

$$P = \sum_{i=1}^{k} m_{ij}, \quad (3)$$

Let's define K_{EP} the coefficient of balance of the EduProg metric profile as the standard deviation of the credit dimension aimed at generating program results:

$$P = \sqrt{\frac{\sum_{j=1}^{n} \left(p_j - \underline{p}\right)^2}{n}} \quad (4)$$

where $\underline{p}$ – is the average value of the credit dimension for program results under the relevant EduProg.

A comparison of the balance coefficients of the metric profiles of different educational programs makes it possible to evaluate their balance, adaptability, and orientation. The generalized evaluation characteristics of EduProgs based on the analysis of their metric profiles are presented in Table 1.

It is evident that knowledge modeling cannot be fully represented by an additive model; however, the authors of this study rely on the model proposed by the Ministry of Education and Science of Ukraine (MES), which has been implemented across all higher education institutions in the country. Credits provide a convenient means of quantifying the contribution of each educational component to the learner's body of knowledge, their influence on the formation of program learning outcomes, the level of student workload, and the achievement of the required competences defined by the educational program. Therefore, the determination of a program's metric profile and its comparison with those of other educational programs can serve as an important instrument for modeling and evaluating educational program quality and for the formalized comparison of their individual characteristics, ensuring:

- an objective approach to program analysis, reducing the influence of subjective judgments;
- a simple mechanism with a high level of visual representation of the results in the form of graphs or diagrams to compare the programs of different educational institutions by a single measurable criterion;
- a simple and visual tool for tracking changes in educational programs based on the results of its implementation and monitoring;
- the ability to quickly respond to identified significant deviations already in the process of designing educational programs.

However, the comparison of programs by metric profile also has disadvantages: it does not take into account the integrity of the program, structural and logical relationships between disciplines, the level of achievement of PLO and their relevance (importance) for the labor market [17, 18]. The analysis should take into account that many professional competencies require an interdisciplinary approach (e.g., integration of statistics, machine learning and programming, etc.), so the comparison by individual PLO only ignores such interrelationships. In addition, the different number of learning outcomes and educational components for each individual PLO complicates their comparison, as it affects the distribution of credits and the alignment of components with program objectives.

Table 1
Evaluation characteristics of the EduProg based on the results of the metric profile analysis

Evaluation characteristics	Low value	High value

The balance of credit allocation	Indicates a more uniform distribution of credits among the program learning outcomes (PLOs), which demonstrates that the program aims to ensure equal development of all PLOs without placing significant emphasis on particular ones. This type of balance is characteristic of general or broad-based educational programs.	Indicates significant deviations from the mean, that is, the presence of clearly defined priorities or gaps, which may suggest either the specialization of the program in certain areas or insufficient attention to specific program learning outcomes (PLOs). At the same time, it should be taken into account that a high credit weight of an individual PLO that considerably exceeds the average value may also reflect a strength of the program, where students receive advanced or in-depth training.
Program focus and relevance to market needs	May indicate a more universal program that ensures a balanced development of skills. This type of program is typical for broad-based curricula aimed at preparing specialists with versatile professional competencies applicable across a wide range of occupations. The program is easier to adapt to changes in labor market requirements, as it provides a baseline in all areas.	Indicates that the program has a specific narrow specialization. Such a program is oriented toward the training of highly specialized professionals with in-depth knowledge in particular fields. The program has a clearer focus, although this may make it less adaptable to new labor market needs if the demand for other types of knowledge or skills changes.
Identification of potential weaknesses of the program	There is a risk of underperformance in those PLO that received fewer credits than others, which may affect the overall competence of graduates in these areas.	There is a risk that the program pays insufficient attention to certain important areas (e.g., complex tasks may be overlooked due to an attempt to distribute resources evenly).

It should be noted that the Ministry of Education and Science of Ukraine (MES) continues the reform of Ukrainian higher education in alignment with the European Higher Education Area (EHEA). As part of this process, new lists of specialties and updated approaches to the development of higher education standards by specialty have been introduced (Order of the MES of Ukraine No. 512 of March 27, 2025, “On the Approval of Methodological Recommendations for the Development of Higher Education Standards”). According to the approved recommendations, education standards will no longer include the normative content of training for students within educational programs in terms of program learning outcomes (PLOs) (with the exception of standards for regulated professions). Consequently, higher education institutions (HEIs), when developing their educational programs, will independently determine both the number and formulation of PLOs. This will significantly complicate the possibility of formalized comparison and assessment of the balance of EduProg metric profiles.

In view of this objective and comprehensive analysis, it is better to use a different approach to building a metric profile of the program, which provides a broader view of the program's balance, integration of knowledge and professional orientation.

In this study, the Computer Science Curricula 2023 (CS2023) [19] was used as a benchmark for comparing the profiles of educational programs in the specialty 122 “Computer Science.” This modern international standard reflects a consolidated vision of the structure, content, and competency framework of the computer science domain and serves as a conceptual foundation for the design and development of educational programs in this field. This choice was made due to several factors. On the one hand, its structure and content were developed taking into account global trends in the development of information technology, as well as the professional and social requirements for graduates. On the other hand, CS2023 provides a comprehensive, multi-level knowledge model that includes 17 Knowledge Areas and integrates both the knowledge-based and competency-based approaches. This makes it possible to compare educational programs both at the level of program learning outcomes (PLOs) and by generalized knowledge areas, which is consistent with the structure of educational programs in Ukraine.

The CS2023 standard distinguishes between “core” topics (CS Core), which must be included in every program, and “advanced” topics (KA Core), which may vary depending on the program’s profile. This approach is consistent with the logic of developing national higher education standards and allows for meaningful comparison regardless of the number or specificity of PLOs in a particular program.

Although there is no strict hierarchy among the 17 knowledge areas in CS2023, the authors of the document identify three competency areas, as well as a group of cross-cutting (general education) competences (Table 2), which serve as guidelines for constructing a holistic educational program profile.

Table 2
Competence areas of Computer Curricula

#	Cluster name	Frequency
1	Software Competence	SDF: Software Development Fundamentals, AL: Algorithmic Foundations, FPL: Foundations of Programming Languages, SE: Software Engineering
2	Systems Competence	AR: Architecture and Organization, OS: Operating Systems, NC: Networking and Communication, PDC: Parallel and Distributed Computing, SF: Systems Fundamentals, DM: Data Management, SEC: Security
3	Applications Competence	AI: Artificial Intelligence, GIT: Graphics and Interactive Techniques, HCI: Human-Computer Interaction, SPD: Specialized Platform Development
4	Crosscutting Core Topics	SEP: Society, Ethics, and the Profession, MSF: Mathematical and Statistical Foundations

In this study, an extended cluster model was applied to analyze educational programs (EduProgs). The model is based on the logical grouping of the CS2023 Knowledge Areas into six clusters (Table 3). According to the authors, this clustering offers several important advantages:

- it enables semantic generalization of the learning content by grouping domains that are similar in subject matter and professional orientation (for example, all topics related to algorithms, programming languages, and data structures are grouped into the Algorithmic & Programming Core cluster).
- the clusters facilitate the construction of graphical models (in particular, radar or petal diagrams), allowing for a visual representation of each program profile, identification of its strengths and weaknesses, and assessment of its balance and adaptability to labor market changes.
- the cluster structure enhances the interoperability of analysis results – it can be easily adapted for comparison among programs with different sets of PLOs, varying numbers of

educational components, or differences in their formulation, as it operates at a higher level of abstraction.

Table 3
Results of clustering knowledge domains in Computer Curricula

#	Cluster Name	Applied Domains of Knowledge (Knowledge Areas y CS2023)
1	Foundations	Mathematical and Statistical Foundations (MSF); Society, Ethics, and the Profession (SEP).
2	Algorithmic & Programming Core	Algorithmic Foundations (AL); Foundations of Programming Languages (FPL); Software Development Fundamentals (SDF).
3	Software Engineering	Software Engineering (SE); Security (SEC).
4	Systems & Infrastructure	Architecture and Organization (AR); Operating Systems (OS); Networking and Communication (NC); Parallel and Distributed Computing (PDC); Systems Fundamentals (SF); Data Management (DM).
5	Applications and platforms	Specialized Platform Development (SPD); Graphics and Interactive Techniques (GIT); Human-Computer Interaction (HCI).
6	Artificial intelligence	Artificial Intelligence (AI).

For a deeper analysis of the content structure of educational programs and their comparison with the international benchmark – Computer Science Curricula 2023 (CS2023) – this study conducted a classification of the program learning outcomes defined by the higher education standard for specialty 122 "Computer Science" according to the identified clusters. The results of this classification are presented in Table 4.

Table 4
Classification Results of Program Learning Outcomes for Specialty 122 "Computer Science"

#	Frequency	Comments
1	Foundations	PLO1, PLO2, PLO3, PLO6, PLO7, PLO8
2	Algorithmic & Programming Core	PLO5, PLO9
3	Software Engineering	PLO11, PLO15, PLO16
4	Systems & Infrastructure	PLO10, PLO13, PLO14, PLO17
5	Applications and platforms	-
6	Artificial intelligence	PLO4, PLO12

To perform the classification, a simplified expert (rule-based) approach was applied, which included the following steps:

1. Forming a list of key concepts characteristic of each cluster.
2. Comparison of key concepts with the wording of program results.
3. Conducting an expert evaluation of the domain content of each PLO to determine the most appropriate cluster for its classification.

Subsequently, the metric profile of the educational program was recalculated, taking into account the resulting classification of program results by the defined K clusters:

$$P^{cl} = \left(p_k^{cl}\right), \ \ \mathrm{k} = \overline{1, K} \tag{5}$$

where K is the number of defined clusters. Accordingly, each element of the metric profile is defined as the amount of ECTS credits allocated to achieve the relevant programmatic outcomes in the EduProg:

$$p_k^{cl} = \sum_{j=1}^{t} p_j, \tag{6}$$

Where p_j are the elements of the metric profile of the program P obtained by formula (2); t is the number of program results assigned to the corresponding cluster k.

Let's define K_{EP} (the coefficient of balance of the EduProg metric profile) as the standard deviation of the credit dimension aimed at generating program results:

$$K_{\text{EP}}^{cl} = \sqrt{\frac{\sum_{k=1}^{K}\left(p_k^{cl} - \underline{p^{cl}}\right)^2}{K}}, \tag{7}$$

Where p^{cl} is the average value of the credit dimension for the cluster of program results under the relevant EduProg.

This approach allowed us not only to quantify the weight of each training area within the program, but also to assess its balance.

To improve the accuracy of inter-program comparison of the obtained results, the credit load values for each cluster were normalized. This approach makes it possible to standardize the measurement scale and ensure objectivity in the visualization and subsequent analysis of the balance of educational programs (EduProgs). The normalized value for each cluster was calculated by dividing the actual number of credits allocated to the corresponding cluster within each program by the maximum value of that cluster among all analyzed programs:

$$P_q^{cl^H} = \left(\frac{p_k^{cl}}{\max \bigcup_q^Q P_q^{cl}}\right), k = \overline{1, K}, q = \overline{1, Q}, \tag{8}$$

where K is the number of defined clusters, Q is the number of educational programs that are compared with each other.

This approach makes it possible to assess the relative saturation of each cluster within the set of programs, independent of the total volume or absolute ECTS credit indicators. It focuses attention on the structural priorities of programs and enhances the precision of analyzing their specialization, balance, and potential content disproportions.

For a comprehensive analysis of educational program profiles and the identification of their structural balance, it is advisable to apply visual methods of multidimensional comparison, among which the radar chart (petal diagram) is one of the most illustrative and analytically effective tools.

The radar chart allows for the simultaneous visualization of the distribution of intensity across key knowledge clusters within each program while preserving their structural arrangement. It enables the identification of both absolute and relative priorities in the content composition of a program. In the case of normalized values (as shown in Table 6), the radar chart also functions as a visual normalized profile, facilitating inter-program comparison regardless of the total ECTS credit volume.

3. Computational Experiment

To verify the hypothesis regarding the adequacy and sensitivity of the proposed formal model for assessing the balance of educational program (EduProg) profiles, a computational experiment was conducted. Within its framework, several bachelor's EduProgs in the specialty 122 "Computer Science", implemented by different higher education institutions (HEIs) of Ukraine, were analyzed. To illustrate the obtained results, examples of calculations are provided for three of these programs. In the following sections, these programs are referred to by the conventional identifiers EduProg1, EduProg2, and EduProg3. The initial calculation data for the selected programs are presented in Table 5.

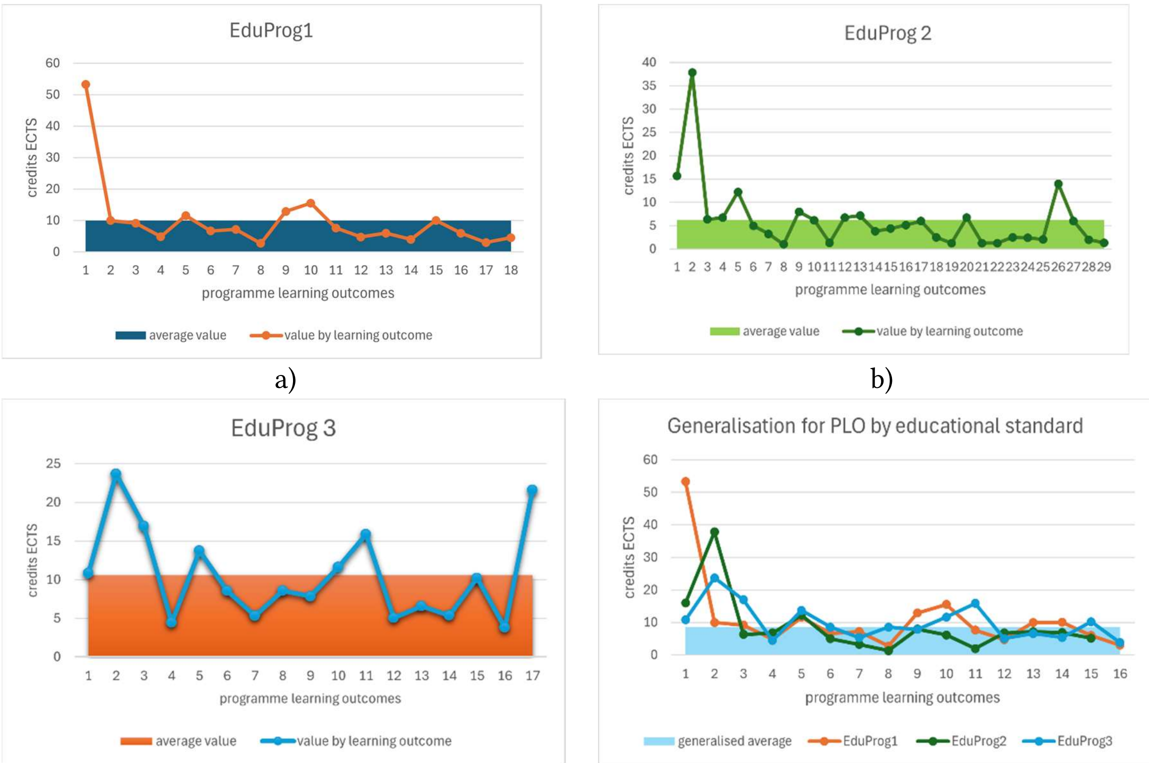
The metric profiles were constructed based on the matrices linking the program learning outcomes (PLOs) with the mandatory educational components (EduComps), followed by clustering according to CS2023, normalization of the credit load, and calculation of balance coefficients (standard deviations).

All calculations and visualizations (radar charts) were performed using Microsoft Excel, which ensured reproducibility of procedures and transparency of algorithmic steps. The obtained results were used to evaluate the structural balance of the programs, identify knowledge cluster priorities and deficiencies, and verify the consistency of the program profiles with the CS2023 core framework.

Table 5
General characteristics of the educational programs.

Educational program	Number of credits		Number of PLO	Number of mandatory EduProg
	general	mandatory EduProg		
EduProg1	240	180	18	37
EduProg2	240	180	29	32
EduProg3	240	180	17	39

The graphical interpretation of the constructed metric profiles of the educational programs EduProg1-EduProg3 is presented in Figures 2, a) - c). Also in Figure 2, d) for comparison, generalized metric profiles of these EduProg are presented only taking into account the program learning outcomes (P^{st}), which are defined by the standard of higher education in the specialty 122 "Computer Science" of the first (bachelor's) level.



a) b) c) d)

Figure 2: Metric profiles of educational programs and their generalization for program outcomes defined by the higher education standard (P^{st}).

The results of the metric profile analysis for the selected educational programs (EduProgs) are presented in Table 6. The first part of the table shows the maximum, minimum, and average values of the credit load derived from the EduProg metric profiles, as well as the corresponding balance coefficient. The second part of the table presents the total number of credits allocated for the formation of the standard program learning outcomes P^{st}, along with the metric profile indicators and balance coefficient values calculated only for these PLOs.

Table 6
Results of the analysis of the metric profile of the educational programs.

Educational program	p_j max	p_j min	p_j mid	K_{EP}	Credits Allocated for the Achievement of Standard p_j	p_j^{st} max	p_j^{st} min	p_j^{st} mid	K_{EP}^{st}
EduProg1	53,3	2,73	10	11	175	53,3	3	11	11,5
EduProg2	37,8	1,25	6,2	7	137	37,8	2	8,5	8,5
EduProg3	23,7	3,8	10,6	5,8	158	23,7	3,8	9,9	5,3

The classification of program learning outcomes according to the defined clusters was carried out for all PLOs specified in the educational programs (Table 7).

Table 7
Distribution of ECTS credits of different EduProg by clusters

#	Title	EduProg1	EguProg2	EduProg3	CS Core
1	Foundations	89,06	101,1	95,48	49
2	Algorithmic & Programming Core	24,58	20,21	21,6	64
3	Software Engineering	23,7	14,69	31,43	8
4	Systems & Infrastructure	28,56	20,52	21,99	41
5	Applications and platforms	4,56	0	0	11
6	Artificial intelligence	9,643	23,52	9,492	8

The normalized values are shown in Table 8.

The results of the analysis of the metric profile of clusters for the selected educational programs are presented in Table 9. The first part of the table provides the maximum, minimum, and average values of the credit dimension of the EduProg clusters based on their metric profiles, as well as the obtained values of the profile balance coefficient K_{EP}^{cl} without normalization and $K_{EP}^{cl^H}$ with normalization of the credit dimension of the clusters taken into account.

Table 8
Normalized ECTS credit distribution across CS2023 clusters for three CS programmes

#	Title	EduProg1	EguProg2	EduProg3	CS Core
1	Foundations	1	1	1	0,766
2	Algorithmic & Programming Core	0,275	0,2	0,226	1
3	Software Engineering	0,266	0,145	0,329	0,125
4	Systems & Infrastructure	0,321	0,203	0,23	0,641
5	Applications and platforms	0,051	0	0	0,172
6	Artificial intelligence	0,108	0,233	0,099	0,125

Table 9
Results of the analysis of the metric profile of the educational programs clusters

Educational program	p_k^{cl} max	p_k^{cl} min	p_k^{cl} mid	K_{EP}^{cl}	$K_{EP}^{cl^H}$
EduProg1	89,06	4,56	30	27,75464	0,311701
EduProg2	101,1	0	30,01	32,704	0,323487

EduProg3	95,48	0	29,99	30,94343	0,324151
CS Core	64	8	30,17	22,23673	0,347514

The radar charts, constructed based on the normalized values, make it possible to visualize the distribution of knowledge cluster weights within the structure of the analyzed educational programs (EduProg1, EduProg2, and EduProg3) (Figures 3–6).

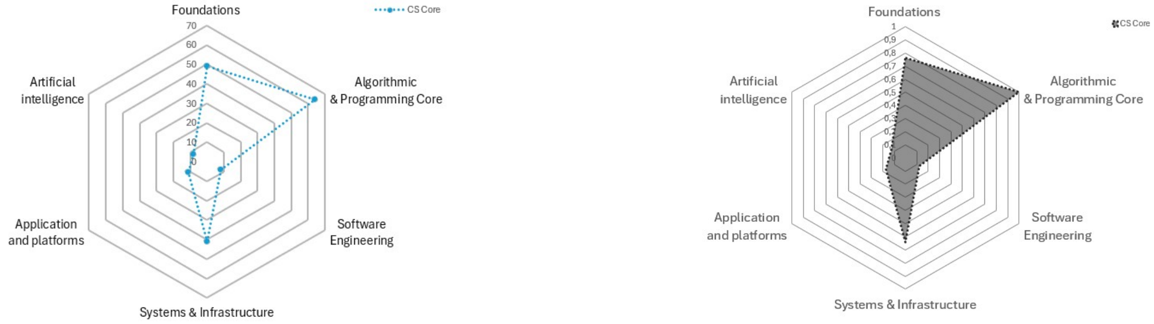


Figure 3: Clustering of CS2023 knowledge domains for Core. a) without data normalization; b) normalized data.

The educational program EduProg1 is characterized by a relatively uniform distribution across the knowledge clusters. Four of the six clusters have values within the 0.25–0.32 range (Algorithmic Core, Software Engineering, Systems & Infrastructure, and AI), which indicates a tendency toward broad-based training. The highest values are observed in Foundations (1.0), Systems & Infrastructure (0.321), and Algorithmic Core (0.275), suggesting a high content density in the fundamental, infrastructural, and algorithmic components that form a solid basis for a universal educational trajectory. The moderate coverage of the AI domain (0.108) and the low representation of Application & Platforms (0.051) indicate potential areas for further program development.

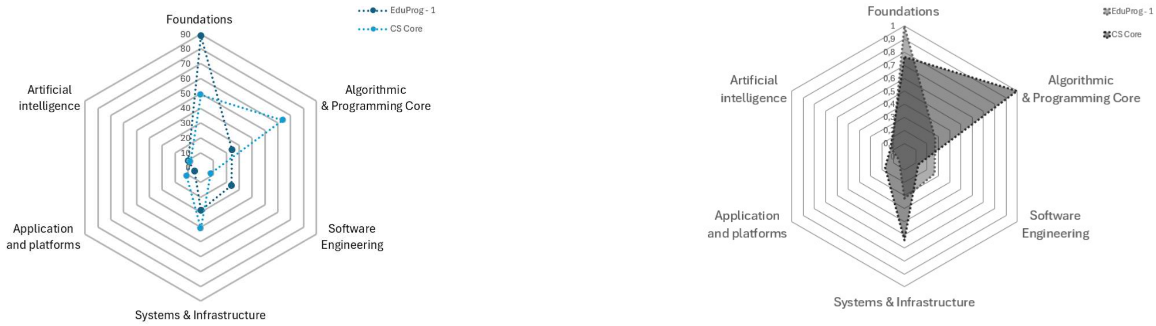


Figure 4: Radar chart of the educational program EduProg1. a) without data normalization; b) normalized data.

The profile of EduProg2 demonstrates a distinct dominance in the Artificial Intelligence cluster (0.233) – the highest value among all analyzed programs. This allows EduProg2 to be interpreted as a program oriented toward training specialists in the fields of Data Science and Machine Learning (ML). At the same time, the considerably lower values in Software Engineering (0.145) and Algorithmic Core (0.200) indicate a less pronounced engineering component. The Application & Platforms cluster is completely absent, which may potentially limit graduates' competences in UX/UI design, cross-platform applications, or interactive technologies.

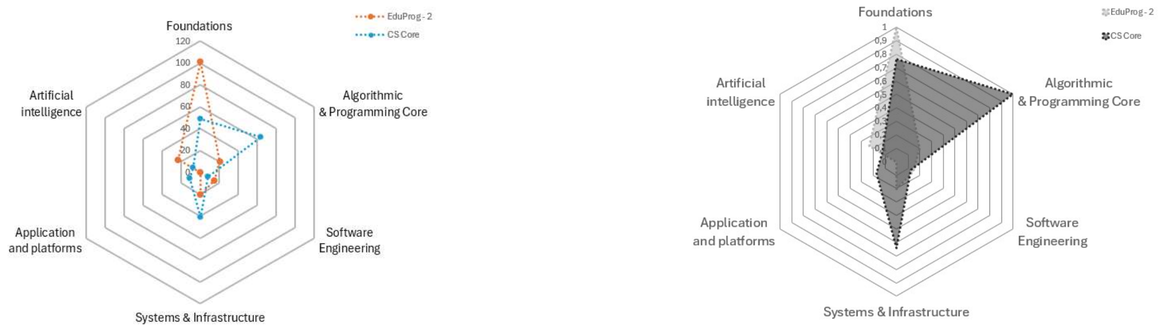


Figure 5: Radar chart of the educational program EduProg2. a) without data normalization; b) normalized data.

The profile of EduProg3 shows the highest value in the Software Engineering cluster (0.329), which is almost twice as high as the corresponding values for EduProg1 and EduProg2. This provides grounds to position the program as engineering-oriented. The high values in Systems & Infrastructure (0.230) and Algorithmic Core (0.226) further confirm its technical training profile. At the same time, the low value in Artificial Intelligence (0.099) and the complete absence of Application & Platforms (0.000) indicate a lack of content in areas related to interactivity, UX, and modern interface design, which may affect the program's adaptability to emerging challenges in digital product development.

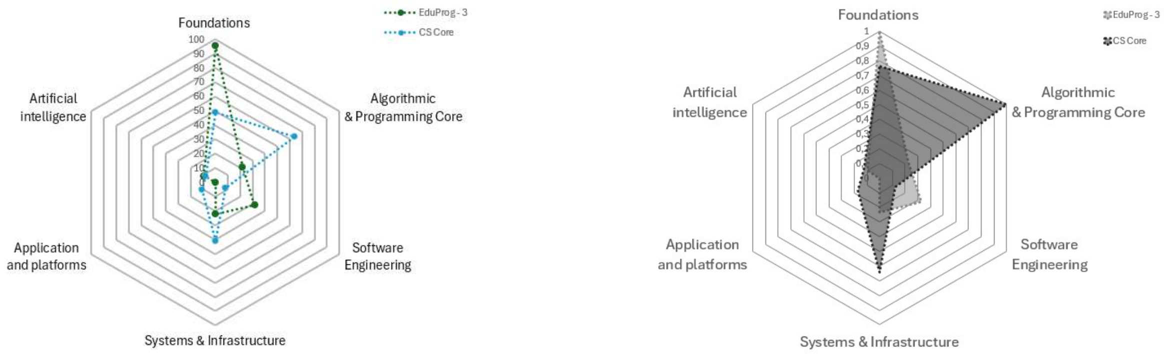


Figure 6: Radar chart of the educational program EduProg3. a) without data normalization; b) normalized data.

For an objective assessment of the development directions of educational programs (EduProgs), it is appropriate to compare them with a reference model that reflects the recommendations of the international academic community. In this study, such a reference was represented by the core curriculum profile (CS Core) in accordance with the Computer Science Curricula 2023 (CS2023), which defines the fundamental knowledge and skills that should be ensured by any computer science program.

Table 6 and Figure 3(b) present the normalized CS Core profile across six knowledge clusters. According to this profile, the clusters with the greatest weight are:

- Algorithmic & Programming Core - 1.0;
- Systems & Infrastructure - 0.641;
- Foundations - 0.766.

Other clusters have smaller but still significant intensity – specifically Artificial Intelligence (0.125), Software Engineering (0.125), and Application & Platforms (0.172) – which together represent the minimum essential content for a modern, comprehensive computer science curriculum.

A comparison of real educational programs with this model shows the following:

- EduProg1 is the closest to the CS Core: it covers all clusters and demonstrates high values in Foundations, Algorithmic Core, and Systems & Infrastructure – the three fundamental areas. This indicates a strong alignment with international benchmark recommendations
- EduProg2 exhibits significant deviations: the *Algorithmic Core* cluster has a low value (0.200) while *AI* shows a high emphasis (0.233), which does not correspond to the recommended balance of the core. This may indicate insufficient fundamental engineering training compared to the analytical component.
- EduProg3, on the other hand, exceeds the benchmark values in Software Engineering (0.329) but completely lacks coverage of Platforms & UX, while AI is represented only minimally. The program is thus more technically specialized but less comprehensive in the area of digital technology applications.

4. Conclusions

The paper presents a formalized approach to assessing the balance of educational programs (EduProgs) through the construction of a metric profile and its interpretation via a balance coefficient. The proposed model is based on the Knowledge Flow Structure (KFS) framework and enables the formation of a matrix of weighted relationships between educational components and program learning outcomes. This provides a means for quantitative evaluation of the distribution of credit load across learning outcomes.

The computation of the metric profile and the corresponding coefficient allows for the assessment of the uniformity of PLO formation, the identification of program priorities, and the detection of potential risk areas. The semantic grouping of PLOs according to the cluster model derived from the Computer Science Curricula 2023 (CS2023) ensures the possibility of comparing EduProgs even when they have different sets of PLOs. The constructed radar charts visually illustrate the distribution of knowledge and reveal the strengths and weaknesses of each program.

The developed mathematical model for assessing the balance of educational program (EduProg) profiles is grounded in the principles of mathematical modeling, cluster analysis, and data normalization, which are fundamental to the field of computer science. The model is universal and can be adapted to various specialties and educational levels, demonstrating both flexibility and cross-disciplinary applicability. It is particularly relevant for disciplines characterized by rapid technological change, such as information technology.

Within the framework of this study, Microsoft Excel was used to verify the hypothesis concerning the adequacy, sensitivity, and practical applicability of the proposed formal model for assessing EduProg balance. This tool enabled the implementation of algorithms for metric profile formation, CS2023-based clustering, normalization of credit load indicators, and calculation of balance coefficients, thereby ensuring automation of computations, algorithmic transparency, and reproducibility of results. The obtained calculations confirmed the validity of the hypothesis and demonstrated the analytical capability of the model to identify structural disproportions and patterns within educational program profiles. This provides a solid foundation for further software implementation of the model in the form of a specialized analytical application or an intelligent decision-support system designed for analyzing, comparing, and optimizing educational programs across different levels and specialties.

Beyond its analytical potential, the proposed approach can be applied to the development of an intelligent adaptive system for managing individual learning trajectories, personalizing curricula, detecting knowledge gaps, and enhancing the flexibility of educational programs.

For further development of the model, both cardinal and ordinal measurement scales may be employed. In particular, weighting coefficients of significance for all model components – competences, program learning outcomes, and educational components – can be defined using expert methods. The relative importance of these components can then be determined through ranking of alternatives, pairwise or multiple comparisons, and various clustering techniques for result aggregation [20, 21].

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] R. Luczak, R. Erwin, *Mathematical modeling: a study of multidisciplinary benefits in the math classroom*, *Teaching Mathematics and Its Applications: An International Journal of the IMA*, 42(4), 325–342 (2023). DOI:10.1093/teamat/hrac021

[2] A. Bray, B. Tangney, “Technology usage in mathematics education research – A systematic review of recent trends,” *Computers & Education*, 114, 255–273 (2017). DOI:10.1016/j.compedu.2017.07.004.

[3] H. Hnatiienko, V. Snytyuk, N. Tmienova, O. Voloshyn, *Application of expert decision-making technologies for fair evaluation in testing problems*, CEUR-WS Proc., Vol-2859, 46–60 (2021). URL: https://ceur-ws.org/Vol-2859/paper5.pdf.

[4] H. Hnatiienko, T. Babenko, *Quantitative Assessment of the Criticality Level of Organizational System Elements*, CEUR-WS Proc., Vol-3503, 62–81 (2022). URL: https://ceur-ws.org/Vol-3503/paper7.pdf.

[5] C. Derouet, C. Kuzniak, D. Laval, E. Montoya-Delgadillo, L. Moutet, A. Nechache, B. Parzysz, L. Vivier, *Modeling tasks and mathematical work*, in: Proc. CERME-10, Dublin (2017). URL (PDF): https://www.academia.edu/129850219/Modeling_tasks_and_mathematical_work

[6] F. K. Lester Jr., *On the theoretical, conceptual, and philosophical foundations for research in mathematics education*, ZDM – Mathematics Education, 37, 67–85 (2005). DOI: 10.1007/BF02655854.

[7] F. Aydin-Güç, A. Baki, *Evaluation of the learning environment designed to develop student mathematics teachers’ mathematical modelling competencies*, Teaching Mathematics and Its Applications, 38(4), 191–215 (2019). DOI: 10.1093/teamat/hry002.

[8] P. Biccard, D. Wessels, *Six principles to assess modelling abilities of students working in groups*, in: G.A. Stillman, W. Blum, G. Kaiser (eds.), *Mathematical Modelling and Applications. Crossing and Researching Boundaries in Mathematics Education*, Springer, 589–599 (2017). DOI: 10.1007/978-3-319-62968-1_49.

[9] Rommel AlAli, Ali Al-Barakat. Using Structural Equation Modeling to Assess a Model for Measuring Creative Teaching Perceptions and Practices in Higher Education. Education Sciences. 2022, 12(10), 690. pp.1-17; https://doi.org/10.3390/educsci12100690

[10] J.-B. Lagrange, J. Huincahue, G. Psycharis, *Modeling in Education: New Perspectives Opened by the Theory of Mathematical Working Spaces*, in: *Mathematical Work in Educational Context*, Mathematics Education in the Digital Era 18, Springer, 247–266 (2022). DOI: 10.1007/978-3-030-90850-8_11.

[11] V. Skrbinjek, V. Dermol, “Designing a Programme Profile: An Example of a Bachelor Business Study Programme,” *International Journal of Management, Knowledge and Learning*, 5(1), 123–136 (2016). URL: https://www.issbs.si/press/ISSN/2232-5697/5_123-136.pdf

[12] A. de Janvry, F. Finan, E. Sadoulet, *Using a Structural Model of Educational Choice to Improve Program Efficiency*, Working Paper, 38 p. (2005). URL: https://gspp.berkeley.edu/assets/uploads/research/pdf/ProgresaWP-2005.pdf

[13] Ministry of Education and Science of Ukraine, *Standard of Higher Education in Specialty 122 “Computer Science” for the First (Bachelor’s) Level of Higher Education*, Order No. 962 dated July 10, 2019. Official PDF: https://mon.gov.ua/static-objects/mon/sites/1/vishcha-osvita/zatverdzeni%20standarty/2019/07/12/122-kompyut.nauk.bakalavr-1.pdf

[14] European Commission, *European Credit Transfer and Accumulation System (ECTS).* URL: https://education.ec.europa.eu/education-levels/higher-education/inclusive-and-connected-higher-education/european-credit-transfer-and-accumulation-system

[15] R. Borromeo Ferri, *Mathematical Modelling in European Education*, Journal of Mathematics Education at Teachers College, 4(2), 18–24 (2013). DOI: 10.7916/jmetc.v4i2.624.

[16] J. Check, R. K. Schutt, *Survey Research*, in: *Research Methods in Education*, SAGE (2012/2017 online). Chapter DOI: 10.4135/9781544307725.n8; Book DOI: 10.4135/9781544307725.

[17] H. Hnatiienko, O. Hnatiienko, O. Ilarionov, O. Ivanchenko, V. Snytyuk, *The Method of Determining the Priority of Candidates by Means of Preferential Voting Based on an Algebraic Approach*, CEUR-WS Proc., Vol-3538, 232–244 (2023). URL: https://ceur-ws.org/Vol-3538/Paper_21.pdf.

[18] A. F. Voloshin, G. N. Gnatienko, E. V. Drobot, *A Method of Indirect Determination of Intervals of Weight Coefficients of Parameters for Metricized Relations Between Objects*, Journal of Automation and Information Sciences, 35(1–4) (2003). DOI: 10.1615/JAutomatInfScien.v35.i3.30.

[19] *Computer Science Curricula 2023 (CS2023): Curriculum Guidelines for Undergraduate Degree Programs in Computer Science*, DOI: 10.1145/3664191

[20] V. Snytyuk, *Evolutionary technique for complex objects clustering*, in: *2017 IEEE 4th International Conference on Actual Problems of Unmanned Aerial Vehicles Developments (APUAVD), Kyiv, Ukraine, Oct 17–19, 2017*, IEEE Proc. DOI (proceedings): 10.1109/APUAVD41319.2017.

[21] M. Antonevych, N. Tmienova, V. Snytyuk, *Models and evolutionary methods for objects and systems clustering*, CEUR-WS Proc., Vol-3018, 37–47 (2021). URL: https://ceur-ws.org/Vol-3018/Paper_4.pdf