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Decision Support Model for Determining Priorities of Non-Academic Competencies Using Content Analysis & Weighted Mapping Approaches

Hendra Jatnika[1]; Purwanto P Purwanto[2]; Dinar Mutiara Kusumo Nugraheni[3]*

[1]Information Systems Doctoral Program, Postgraduate School, Universitas Diponegoro Semarang Indonesia.
Faculty of Energy Telematics, Institut Teknologi PLN Jakarta Indonesia.
[2]Information Systems Doctoral Program, Postgraduate School, Universitas Diponegoro Semarang Indonesia.
Department of Chemical Engineering, Faculty of Engineering, Universitas Diponegoro Semarang Indonesia.
[3]Department of Informatics, Faculty of Science and Mathematics Universitas Diponegoro Semarang, Indonesia

[*)]Email: hendrajatnika@students.undip.ac.id

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ABSTRACT

This study formulates a Decision Support model to determine the priority of students' non-academic competencies as a basis for improving the concept of link and match between higher education and industry needs. Data were collected from the 21st Century Skills Framework, the WEF Future of Jobs Reports (2020, 2023, 2025), and tracer study alumni of the Institut Teknology PLN (ITPLN) (2022, 2024). The method used is a mixed analytical method including Content Analysis to extract and consolidate competencies, accompanied by Weighted Mapping consisting of Frequency Weight (FW), Correlation Weight (CW), Normalized Weight (NW), and Final Priority Score (FPS). The results of the study identified eight main non-academic competencies which relational structure was analyzed through a correlation matrix and a priority model. The findings indicate that Information and Communication Technology (ICT) Literacy, Critical Thinking, and Communication competencies are the highest priority competencies. The resulting model can be used as a basis for strategic recommendation in compiling work programs related to students' non-academic competencies as university graduates who will face the industrial world.

Keywords: *Non-Academic Competencies, Decision Support Model, Content Analysis and Weighted Mapping, 21st Century Skills and Future of Jobs, Link And Match*

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1. INTRODUCTION

The development of digital technology in the Industry 4.0 era has driven significant transformation in various sectors, including the world of work which demands human resources capable of adapting to rapid changes [1][2][3][4]. Higher education, as providers of educated workers also face challenges in ensuring the relevance of graduate competencies by strengthening the concept of link and match with industry needs [5]. In 2019, an international report addressed the future of education and the workforce [6] and emphasizes that non-academic competencies such as leadership skills, adaptability, creativity and problem solving as well as social and emotional skills are key factors for the success of the modern workforce. In 2018, the OECD released the Future of Education and Skills 2030 report, which discusses the vision and strategies for education in the future, emphasizing the importance of holistic learning, transformative competencies, and the adaptive capabilities of young people [7]. 2021 McKinsey & Company [8] reports indicate a gap between industry needs and job seekers' skills, particularly in soft skills and employability. 2020/2023 and 2025 World Economic Forum (WEF) Future of Jobs report emphasizes that analytical thinking, creativity, collaboration, communication, and technology literacy are core competencies in facing automation disruption [9][10][11]. Similarly, in 2015, the 21st Century Skills framework emphasized the importance of developing non-academic competencies, such as social and emotional skills, creativity, collaboration, communication, and leadership. These competencies are considered key to preparing students to face challenges in the workplace and in everyday life [12]. In 2023, through the 21st Century Skills Framework, it was emphasized that non-academic competencies are very important for the success of students in facing the challenges of the world of work in the 21st century, as well as for achieving success in the academic world and in social and professional environments [13]. In the national context, the results of the 2022 ITPLN alumni Tracer Study questionnaire for 725 respondents from 2020 graduates and 593 respondents from 2024 indicate that industry in Indonesia demands strengthening of non-academic competencies such as work ethic, adaptability, decision-making, and Information and Communication Technology (ICT) literacy [14][15].

However, released reports or previous research generally only use one analytical perspective or one framework, such as 21st Century Skills [16][17]. WEF Future of Jobs [18][19], OECD [20][21], or McKincey & Company [22], or just evaluate industry perceptions of the soft skills of student graduates [23][24][25]. These analyses and approaches do not yet provide an integrative mechanism for formulating various sources of global, national, and empirical competence in a comprehensive manner. This situation creates a research gap, particularly regarding the need to integrate various sources of non-academic competencies into a single, objective, data-driven prioritization model. Furthermore, most studies have not utilized institutional tracer study data as empirical evidence in the competency alignment process. This gap gives rise to the main research question: what non-academic competencies should be prioritized to assist stakeholders in decision-making, when various global sources and results of tracer studies of higher education alumni as empirical and theoretical data are systematically formulated in one analytical framework?

To answer this question, this study formulated a Decision Support Model based on Content Analysis and Weighted Mapping [26][27] to determine non-academic competency priorities objectively, consistently, and data-driven. The resulting model is in the Information Systems domain, specifically the field of decision support systems [28] which relies on modeling, weighting, and visualization of information to support strategic decision making in curriculum design, student activities, and competency development. Thus, this model not only produces academic contributions in the form of an integrated analytical approach, but also becomes a practical Information System

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artifact that can be implemented to strengthen the link and match process between higher education and the dynamics of industrial needs.

2. RESEARCH METHODS

This study uses a Mixed Analytical Method approach in analyzing data [29], an approach taken by combining content analysis and weighted mapping [30][31][32][33], In this study, it was used to determine the priority of non-academic competencies based on data from several sources. The research subjects included three main groups: (1) 21st Century Skills Framework as a conceptual source of core competencies, (2) World Economic Forum Future of Jobs Report (2020, 2023, and 2025) as a representation of global competency needs, and (3) ITPLN Tracer Study (2022, 2024) as an empirical source of competencies needed by industry and mastered by graduates who are already working. The data used is in the form of a list of competencies, competency indicators, and levels of industrial needs obtained from documents, official publications, and reports from higher education institutions.

The sampling technique uses purposive document sampling [34][35], namely selecting documents that are directly relevant to the needs of competency mapping. The content analysis method is used to extract competency terms from each source, followed by a coding process, grouping, and forming eight main non-academic competencies. The analysis design includes: (1) compiling a Frequency Matrix to calculate Frequency Weight (FW), (2) compiling a Correlation Matrix to calculate Correlation Weight (CW), (3) normalizing weights through Normalized Weight (NW), and (4) calculating the final priority score through Final Priority Score (FPS) as a basis for decision making.

The variables measured consisted of: the level of competency occurrence in various sources (frequency), the strength of the relationship between competencies (correlation), and the priority weight resulting from the integration of the two variables. The analysis was conducted using the FW–CW–NW–FPS formula and visualization through heatmaps, bar charts, and network graphs to illustrate the structure of relationships between competencies. All analysis results were combined to produce a Decision Support Model that displays the priority weights and interconnectedness of non-academic competencies. The general flow of the research, from data collection, competency extraction, weight calculation, to the preparation of the Decision Support Model, is shown in Figure 1, which illustrates all procedural stages of the research from input to output of the priority model.

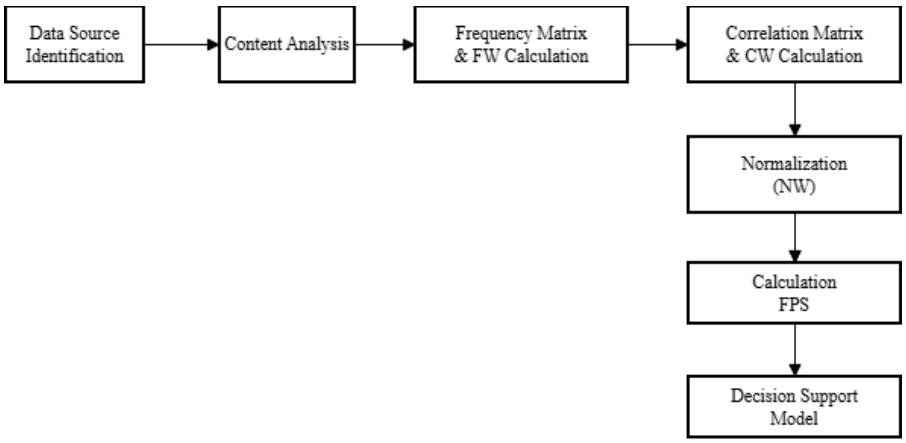

Figure 1. Research method

The detailed research stages were as follows:

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First, we implemented a content analysis method on three primary sources: the 21st Century Skills Framework, the WEF Future of Jobs reports from the past three years, and the ITPLN Tracer Study covering two periods. This process involved several key steps, such as competency term extraction, keyword identification, coding, data reduction, and categorization. Each step was designed to produce eight systematically integrated non-academic competencies. During this process, we collected documents from these three sources to identify key concepts related to non-academic competencies. After data extraction, we conducted an in-depth analysis to code the obtained information so that it could be clearly categorized. The data reduction stage was crucial for filtering relevant information, ensuring that only the most significant competencies were considered in the final analysis. The detailed flow of the content analysis process is shown in Figure 2, which shows all stages, from document collection, concept extraction, and consolidation of the results into integrated competencies. This figure provides a clear picture of how each step is interrelated and contributes to mapping the skills needed for students to face the challenges of the 21st century.

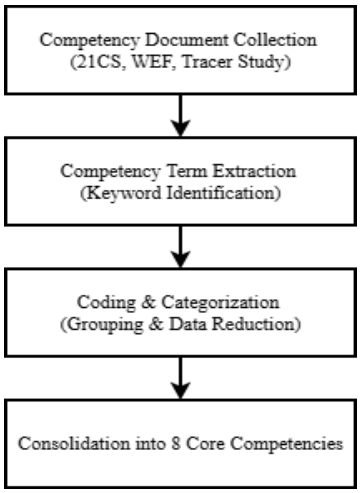

Figure 2. Content Analysis Stages

The second stage is the implementation of the Weighted Mapping method, which is an analytical process for calculating competency priorities based on frequency and correlation weights. This stage begins with the preparation of a frequency matrix that produces a Frequency Weight (FW), followed by the preparation of a correlation matrix to obtain a Correlation Weight (CW), then normalizing the weights through Normalized Weight (NW), and producing a final priority score through the Final Priority Score (FPS). The complete flow of the weighting process is shown in Figure 3. Thus, this research method provides not only a qualitative approach through content analysis but also a structured quantitative approach through weighted mapping.

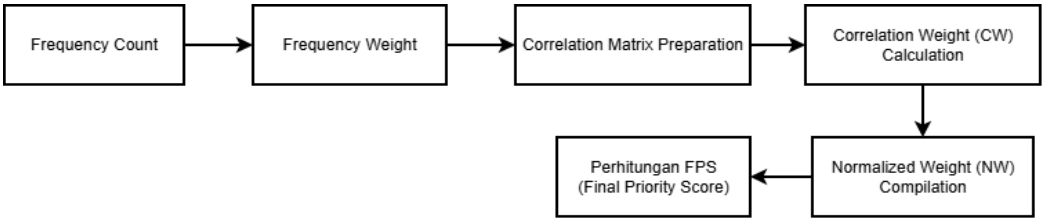

Figure 3. Weighted mapping stages

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3. RESULTS AND DISCUSSION

The results of the study indicate that eight non-academic competencies have varying levels of priority when analyzed using the Content Analysis and Weighted Mapping approach, which integrates various global and empirical competency sources into a single analytical framework. Based on the Final Priority Score (FPS) calculation, ICT Literacy, Critical Thinking, and Communication consistently ranked highest in priority compared to other non-academic competencies. This finding reflects the shift in industry needs toward a workforce that is not only able to adapt to digital technology but also possesses analytical thinking capacity for decision-making and effective communication skills in complex and collaborative work environments. The visualization of the results in Figure 4 presents a quantitative and easily interpretable hierarchy of competency priorities, providing a strong evidentiary basis for policymakers in higher education.

From an Information Systems perspective, this priority model serves as a decision support artifact that can be utilized in the institutional strategic planning process, particularly in establishing policies for developing student non-academic competencies, aligning learning outcomes, and designing integrated non-academic competency strengthening programs. FPS-based priority information enables higher education leaders to allocate resources more rationally, determine the most impactful learning interventions, and continuously monitor the alignment between graduate competencies and industry needs. Thus, this research not only provides a conceptual contribution but also offers a data-driven decision-making framework that supports the implementation of link and match policies in a systematic, measurable, and adaptive manner to the changing dynamics of the industrial world.

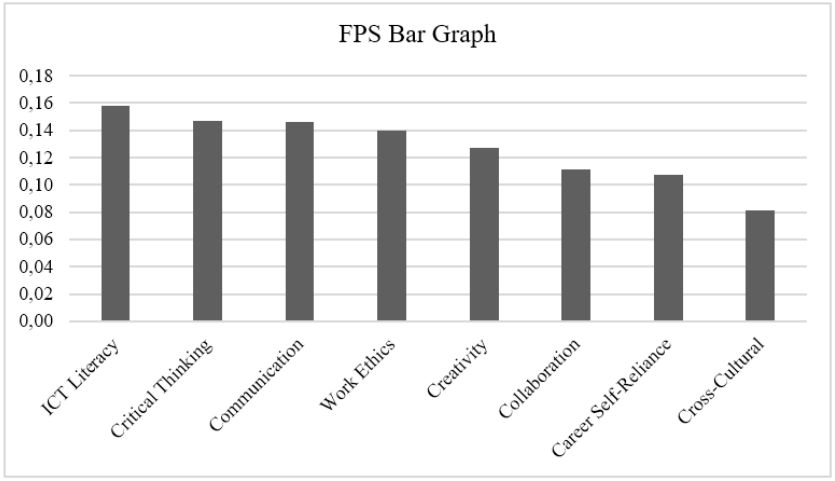

Figure 4. Final Priority Score

Next, an analysis of the relationship structure between competencies was conducted by constructing a correlation matrix. The results are visualized in the form of a heatmap in Figure 5, which shows that ICT Literacy, Critical Thinking, and Communication have the strongest correlations with the other competencies. Darker colors on the heatmap indicate the intensity of the relationship. Conversely, Cross-Cultural Understanding appears to have a weaker correlation pattern, thus tending to be more independent compared to the other competencies in the system.

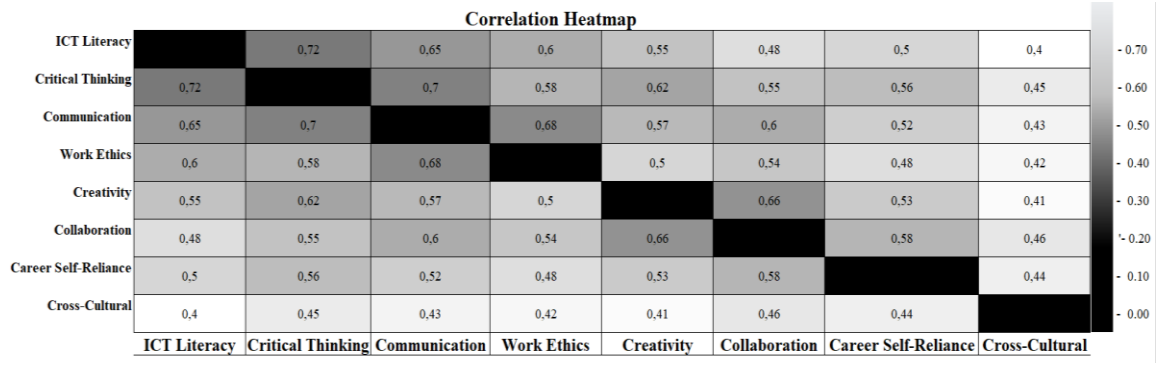

Figure 5. Correlation Matrix between non-academic competencies

To understand the structural interrelationships between competencies, the Network Graph shown in Figure 6 is used. This network model shows the priority relationships between non-academic competencies with arrows based on the Final Priority Score (FPS). Arrows indicate that high-priority competencies influence lower-priority competencies. Cross-Cultural Understanding and Career Self-Reliance are conceptually added using dotted lines from the most relevant competencies, namely Communication and Collaboration. This reflects that these two competencies still have a supporting contribution in the competency ecosystem even though their level of connection is lower than core competencies such as ICT Literacy, Critical Thinking, and Communication.

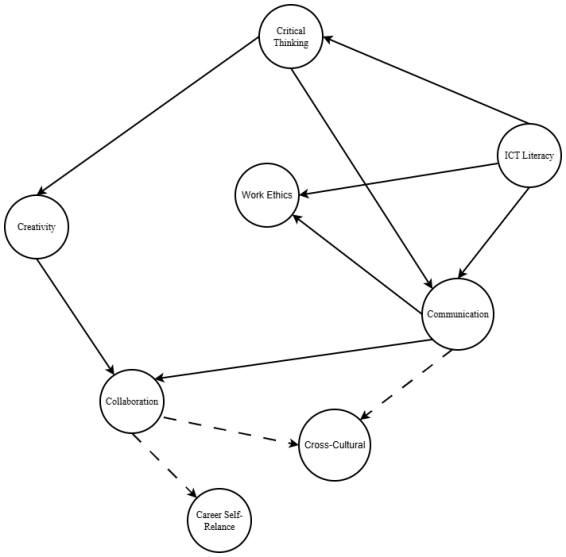

Figure 6. Network Graph between non-academic competencies

The subsequent analysis integrated frequency weights (FW), correlation weights (CW), normalized values (NW), and final priority scores (FPS) into a single model. This model is presented in Figure 7, the Priority Competency Model, which shows the prioritization model for non-academic competencies based on FPS weights and the strength of relationships between competencies. Larger nodes indicate higher priorities, while thicker lines represent stronger correlations. Dashed lines were added to connect Cross-Cultural Understanding with the most conceptually relevant competencies, indicating lower-level but still significant relationships within the competency structure. This

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visualization allows for the identification of dominant competency clusters and the position of supporting competencies within the non-academic ecosystem.

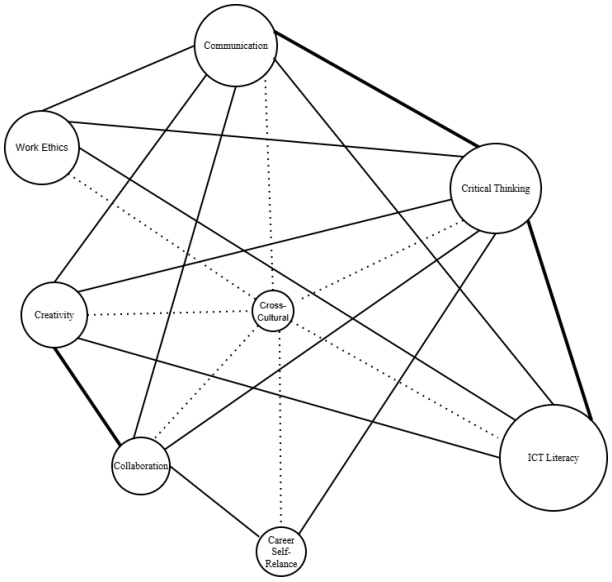

Figure 7. Priority Competency Model

Finally, the NW and FPS values obtained from the weighting process are displayed in a concise table in Table 1. This table presents numerical data as objective evidence of competency priorities, while also strengthening the overall research results. Thus, all of these visualizations complement each other and clarify that ICT Literacy, Critical Thinking, and Communication competencies must be the main priority for higher education in developing student work programs related to non-academic competencies and strategies or mechanisms for improving the concept of link and match with the industrial world.

Table 1. Normalized Weight (NW) and Final Priority Score (FPS) Values

No	Competence	NW	FPS
1	ICT Literacy	0,1547	0,1573
2	Critical Thinking	0,1445	0,1469
3	Communication	0,1440	0,1464
4	Work Ethics	0,1381	0,1404
5	Creativity	0,1239	0,1260
6	Collaboration	0,1096	0,1114
7	Career Self-Reliance	0,1051	0,1069
8	Cross-Cultural	0,0802	0,0815

4. CONCLUSION AND SUGGESTIONS

This research produces a Decision Support Model capable of objectively determining the priority of non-academic competencies through the integration of content analysis and weighted mapping. This model directly addresses the research objective, which is to identify the competencies most important for the readiness of college graduates to face industry needs. The findings indicate that ICT Literacy, Critical Thinking, and Communication are the three competencies with the highest

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priority based on a combination of frequency weighting and correlation. This implies that strengthening digital literacy competencies, analytical thinking skills, and effective communication and integrity needs to be a primary focus in developing student activities related to non-academic competencies. Meanwhile, the competencies of Work Ethics, Creativity, Collaboration, Career Self-Reliance, and Cross-Cultural Understanding show a lower level of connectedness and priority, so they can be developed as supporting competencies.

Based on the results of this study, several suggestions can be put forward. First, higher education need to use this priority model as a basis for decision-making in developing student activities related to non-academic competencies. Second, further research can expand the scope of the data, including involving tracers to active students to evaluate student activities related to the needs of the industrial world, involving relevant departments within higher education in managing student activities, conducting industry surveys to obtain input on workforce needs related to the characteristics of college graduates, or comparing between institutions to strengthen the validity of the model. Third, the application of this model can be further developed in the form of an information system-based decision support system in the form of an application that utilizes developments in science and information technology to facilitate data collection and validation of non-academic student competencies that are in line with career needs in the industrial world on an ongoing basis.

Thus, the resulting model not only provides academic contributions but also practical benefits, enabling educational institutions to formulate competency development strategies that are more focused, evidence-based, and responsive to actual industry needs. This data-driven approach also strengthens the implementation of the link and match concept between higher education and the business and industrial worlds, as non-academic competency priorities can be determined objectively, measurably, and aligned with job market demands.

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