SOFT SKILLS OF HIGHER EDUCATION IN INDUSTRY 4.0 ERA USING BUCKLEY'S FUZZY-AHP

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ABSTRACT

Industry 4.0 is characterized by the digitalization of systems and processes in service and manufacturing industries and has changed the way people live. Education plays a significant role in preparing the future workforce with the necessary technological skills and competencies required by industries and institutions. Studies have shown that soft skills improve a student's ability to learn, increase their potential for success, and typically increase future economic benefits. This study aims to determine the dominant soft skills that University students in Manado should possess. The perceptions of twenty-four lecturers about four criteria and twelve sub-criteria were compared using both the Analytic Hierarchy Process (AHP) and Fuzzy Analytical Hierarchy Process (F-AHP) methods. From this, the researchers found teamwork to be the dominant skill (26%). Global analysis uncovered that integrity was the dominant factor overall (10.5% with AHP or 10.3% with F-AHP). The findings were provided to University leaders with recommendations to incorporate the elements of teamwork and integrity into their teaching materials, teaching methods, and curriculum. Students need to understand that these elements are essential to their future. This research proved that both the AHP and Fuzzy-AHP methods were effective tools in analyzing and determining the dominant factors of soft skills in the Industry 4.0 era. This research contributes to determining the priority factors related to soft skills needed by higher education graduates in the Industry 4.0 era using a combination of AHP and Fuzzy-AHP. The researchers recommended that other scholars conduct future studies using entrepreneurs or business practitioners as respondents.

Keywords: AHP; fuzzy-AHP; Industry 4.0; soft skills; La Salle; higher-education; sensitivity analysis

1. Introduction

Since the term Industry 4.0 appeared in 2011, many studies have emerged discussing this topic as it relates to different fields (Meindl et al., 2021). The fast-paced advancement of technology exhibited by Industry 4.0 has significantly changed the environment in which we live by improving the connectivity between humans, machines, and other objects (Dombrowski, Wullbrandt, & Fochler, 2019a). Real-time data is now available, globally, and to everyone online, often in excessive quantities. As a result, significant changes to the entire industrial system will be required.

Change will also be required in the world of education. Pedagogy, teaching philosophy, educational models, and learning methods will require that the exchange and transfer of information and knowledge become faster and more efficient, accessible and flexible (Miranda et al., 2021). Innovation in the field of education will improve the teaching and learning process. Distance learning, for example, is becoming more prevalent due to advances in connectivity, digitization and virtual platforms.

These changes will require that the educational sector, particularly higher education institutions, identify, rethink and address the skills and competencies required for future employees and entrepreneurs. It is through education that students will prepare to take advantage of the opportunities as well as the challenges of Industry 4.0. It is predicted that industries and companies will be looking for employees who have a high degree of technological-based expertise. To meet these needs, higher education will need to redefine itself, develop its systems, improve its internal management, and enhance its networking.

Industry 4.0 companies will still require people who have hard skills, but there will be an increasing need for a workforce with soft skills, or non-technical skills, such as teamwork, critical thinking, communication, systems thinking, and emotional intelligence to truly take advantage of these process improvements. (Fitsilis, Tsoutsa, & Gerogiannis, 2018).

This study focuses on analysis and determination of the dominant soft skills that graduates of higher education will need to thrive in Industry 4.0. The primary research question is as follows: Using AHP and Fuzzy-AHP, what are the dominant soft skills and cognitive skills that will enable students to become lifelong learners? Secondarily, the researchers seek to determine if there is a significant difference between using the AHP and Fuzzy-AHP for data analysis. The goal will be to determine what skills graduates of higher education should possess to thrive in Industry 4.0.

The study uses the Analytic Hierarchy Process (AHP) and Fuzzy-AHP methods to evaluate the perceptions of the lecturers collected through a questionnaire. Both methods have been effectively used in decision making studies with complex and multiple variables. Using a hierarchical structure, the AHP is able to simplify the analysis of the problem making it easier to understand. Fuzzy-AHP allows researchers to deal with vague and uncertain perceptions, commonly referred to the "gray area". Since there is minimal statistical data available for analysis, both methods are used to evaluate the experts' opinions.

The respondents of this study are University lecturers who each have more than twenty years of experience and doctoral degrees. The respondents understand the context of the educational system of the Universities in Manado and are involved in student activities, comprehend the current situation of the University and meet the essential criteria to be considered as respondents to the questionnaire (Raco & Tanod, 2014).

The researchers acknowledge that there are a number of articles, studies, discourses and commentaries regarding Industry 4.0. However, the existing literature focuses on descriptive, assumptive and qualitative analyses that are theoretical in nature and do not adequately consider the necessary skill sets for worker employability (Azmi, et al., 2018).

The experts of this study identified four criteria and twelve sub-criteria that had been used in previous studies for the research analysis. The criteria include communication skills, teamwork, critical thinking, and entrepreneurial skills. The research findings will be used to enhance the management of higher education in Manado. For the Universitas Katolik De La Salle (De La Salle Catholic University) of Manado-Indonesia, the results of the study will be considered as key inputs in curriculum review, reformulation of the teaching-learning systems, and processes of the school. The findings will improve the school facilities, and cooperation and networking with other schools or industries.

The structure of the study is as follows. First, the background of the study, problem formulation, objectives and limitations were developed. Second a literature review was conducted to identify findings and theories of previous studies on Industry 4.0 and its impact on higher education. Third, the methodologies were reviewed, the reasons for using each methodology were identified, and the benefits and drawbacks of each methodology were explored. Fourth, a research questionnaire was developed. Fifth, the data was evaluated. Sixth, the meaning and significance of the results as well as the limitations were discussed. Finally, the conclusions and recommendations were prepared.

2. Literature review

2.1 Characteristics of Industry 4.0

Industry 4.0 is often associated with the intelligent, digital integration of people-machine-objects, advanced computing power, augmented reality, big data analysis, horizontal and vertical system integration, autonomous robots, Internet of Things, cloud computing, and cyber-physical systems for management of business process and value creating networks (Dombrowski, Wullbrandt, & Fochler, 2019b). It serves to integrate intelligent machines, human actors, physical objects, manufacturing lines and processes into every organizational level to create systematic technical data in near real-time.

New technologies are developing at an exponential rate. A beginning to the revolution cannot be identified, rather it has had an evolutionary growth (Hussin, 2018). Industry 1.0 was characterized by the use of mechanical production assets based on water and steam power, then expanded to Industry 2.0, which was identified by the introduction of mass production techniques centered on the division of labor and the use of electrical energy. Industry 3.0 focused on the introduction of information technology and highly automated production. Industry 4.0 is identified by self-optimizing and real-time connectivity of systems. (Aulbur, Arvind, & Bigghe, 2016).

Technology will continue to develop and result in new products and services that cause disruption to the workplace and workforce which require new skills and competencies (Aulbur et al., 2016). The emergence of organizational supply chains resulting in a change from a linear and sequential model to an interconnected, open system, known as a digital supply network will require a new organizational structure and employees with a new skill set to manage them. This digitalization of the integration of vertical and horizontal value-added steps in the supply chain allows the optimization of customer integration and data access resulting in increased productivity. Smart factories using smart devices are able to self-optimize production and therefore increase productivity (Fitsilis et al., 2018). Digitalization reduces waste and promotes a circular economy and more sustainable patterns of production and consumption (Paravizo, Chaim, Braatz, Muschard, & Rozenveld, 2018). Additionally, customization increases the creation of flexible markets that are customer-oriented and can satisfy consumers' needs faster since the gap between the manufacturer and the customer is significantly reduced. Communication will take place seamlessly and require no intermediaries resulting in faster delivery of products. Industry 4.0 will create new markets such as industrial robotics design, build and installation, cyber security, Internet of Things, and 3D printing.

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In 2016, these markets were valued at $66.67 billion US, and by 2022, they are expected to reach $152.31 billion US.

Industry 4.0 has also negatively impacted industry in several ways. First, it eliminates the need for many old professions and skills (Fitsilis et al., 2018). Additionally, security risks have risen exponentially with online integration. Data leaks or loss of data, in addition to data security costs, have resulted in significant financial costs. Many organizations are reluctant to implement new digital technologies because of these risk/cost factors.

Workers are not being taught the new skills and competencies that will be required in the future such as digital communication, digital content creation, and digital problem solving (Durisova, Kucharcikova, & Tokarcikova, 2015). The development of technology has grown faster than schools are able to recognize and implement necessary training and education.

2.2 Skills in Industry 4.0

Education is very important for young people and is the key to preparing present and future generations for success in a highly competitive world (Rauch, Linder, & Dallasega, 2019). Certain skills will be imperative to function in the Industry 4.0 environment. Generally, there are two kinds of skills or competencies, namely, soft skills or non-technical skills and hard skills. Examples of jobs requiring hard skills are big data analysts, software engineers, domain experts, network engineers, Information Technology architects, cyber security analysts, and location tracking technology experts. Soft skills include communication skills, ability to collaborate with others, complex problem solving, emotional intelligence, creativity, systems thinking, people management, judgement and decision making, cognitive flexibility, and teamwork. Heckman and Kautz (2012) identified soft skills as crucial for learning and success in the labor market. Cognitive skills are also shown to increase when facing more complex tasks.

Soft skills can predict success as strongly as cognitive abilities. A report detailing the economic returns resulting from soft skills in Mexico and Sweden found that soft skills can be cultivated throughout one's lifetime (Fitsilis et al., 2018). Soft skills can also contribute to an employee's economic return (Hanushek & Woessmann, 2008). Humans become more mature as they develop their cognitive skills, and they are required from the earliest stages of one's work life (Hanushek et al., 2015). The World Bank states that tertiary education is a good opportunity for people to acquire higher orders of cognitive skills. Soft skills influence a person's ability to learn (Ra et al., 2019). Neuroscience studies show that triggering one's general curiosity enables the brain to enhance learning (Gruber, Gelman & Ranganath, 2014). Heckmann and Kautz (2012) found that children who are motivated and curious tend to learn more and score higher on standardized tests. Soft skills also intensify the progress of one's cognitive abilities that further improve learning (Cunha & Heckman, 2007).

Industry 4.0 is forcing the education system to change from being facts and procedures-based to one that actively applies knowledge to collaborative problem solving in the real world. Just as the world in constantly changing, innovation and change in the education system is inevitable. The goal is to improve the quality and inclusiveness of the education

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system and these changes need to happen in pedagogy and teaching methodology (Umeda et al., 2019). Digital technology should be incorporated in both the content and process of teaching and learning activities. Educational management needs to change from deliverable-focused project management to outcome-focused product management. The educational culture has to focus on the recognition of culture's central role in digital product delivery effectiveness.

2.3 Education 4.0 in higher education

Technological developments have a major impact on the world of education. According to Miranda et al. (2021), the emergence of the industrial revolution at the end of the 18th century had a major impact on the world of education, namely through the creation of paper making machines, mechanical printing, the graphic pencil, the ballpoint pen and the typewriter. This stage in the world of education is called Education 1.0; at this stage the teacher was still the center of the education system and their job was to determine and disseminate information that students must know and learn.

In the early 20th century, industrial machines were invented, resulting in mass production, industrialization and electricity. This development penetrated the world of education where electronic devices were introduced into the teaching and learning process. Printers, calculators and computers began to enter the classroom. At this stage, teachers were still the center of knowledge development, but students began to play a role in improving their knowledge with the assistance of these electronic tools. With these electronic facilities, students began to develop study groups and peer assessments. This stage is known as Education 2.0 (Miranda et al., 2021).

At the end of the 20th century, computerization, automation and control grew rapidly and had an impact on the world of education. The teaching and learning process started to be supported by multimedia and went online. Learning resources began to be available online, and teaching and learning activities started to be carried out virtually and were able to reach more students. Teachers were no longer considered information centers because learning materials could be obtained by students online. Study materials could be prepared in advance and utilized by students through online resources. Collaboration between teachers and students became a key component in the teaching and learning process. This stage is known as Education 3.0 (Miranda et al., 2021).

The beginning of the 21st century saw digitalization enter both the industrial world and the world of education so that the digitalization of learning took place. Teaching and learning can no longer be separated from computers and the internet, and learning is no longer confined to the classroom. Physical form is replaced by digitization and there are no time limits so that teaching and learning can be carried out anywhere and anytime. The learning process changed from teaching and learning to learning and tutoring. There was massive innovation in the world of education. This is called Education 4.0 (Miranda et al., 2021). There are 4 core components in higher education at this stage. The first component is soft skills competencies such as critical thinking, cooperation, collaboration, communication, creation and innovative. These skills are in the form of training and development of functional, technical and technological knowledge and skills for successful workplace performance; promoting the capacity to research, design, creation and implementation of new technologies; and promoting the use of emerging

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technologies and adoption of best practices to promote technology-based solutions. The second component consists of the learning delivery modalities such as face-to-face-active learning, online distance learning, synchronous and asynchronous, and hybrid-blended learning needs to be combined and adapted to provide more accessible and flexible programs. Strategies to implement challenge-based learning, problem-based learning and learning by doing must be adapted to best utilize these various modalities. The third component is the use of information and communication technologies such as the Internet of Things, artificial intelligence, machine learning, cloud computing, cyber-physical systems, data science and data analytics, and mixed reality. The tools/platforms for this are web-conference platforms, learning management systems, collaborative virtual platforms, massive online open courses (MOOCs), remote and cyber-physical labs, robot teaching assistants, hologram teachers and others. The fourth component is the innovative use of infrastructure. At the classroom level, this includes the use of innovative furniture, tools, devices and equipment, and the use of specific architecture, colors, illuminations, sounds and temperature, and connected rooms. At the institutional level, this involves virtual and digital universities, sustainable universities, open innovation laboratories, and smart learning environments.

Digitalization in the modern world is changing the concept of higher education. Its pedagogical orientation leads to learning innovation to meet the needs of the technological community. Generation 4.0 knowledge goes beyond pedagogy and andragogy and leads to a combination approach between heutagogy which is the promotion of self-learning, peeragogy which emphasizes collaborative learning, and cybergogy which is a learning strategy using ICT that offers learning experiences that go beyond the limits of time and space (Miranda et al., 2021).

An important feature of digitalization is the concept of the 'digital triplet' consisting of the physical world, the cyber world and the intelligent human (Umeda et al., 2019). Previously, we studied the 'digital twins' consisting of the physical world and the cyber world. Education 4.0 will need to emphasize outcome-focused management rather than delivery-focused education (Fitsilis et al., 2018).

Hussin (2018) stated that Education 4.0 requires several things. First, it requires problem-solving such as introducing non-routine and practical problems and challenging students to solve problems collaboratively. Second, it must focus on critical reflection to reconstruct the meaning of experiences, promote responsive guidance through mentoring, and knowing/learning to value experiences whether good or bad. Third, it requires the student to learn from errors, learn something new about their own and other's practices where peers are very significant to their learning. Fourth, students need to learn together and from each other while teachers need to assume the role of facilitator (Hussin, 2018).

Learning practices need to change from being classroom-based to being able to be implemented any place and anytime. Students will determine how, when and what they want to learn. They need to be exposed to all potential fields of employment, industries or manufacturers. Internships and collaborative projects will become more relevant for learning, and assessment methods will need to change. Conventional assessment will become both irrelevant and insufficient. Assessment will need to be performed during the learning process, while the application of knowledge will need to be tested when students are working on their projects in the field. Industries will become a more important place of learning (Nyemba et al., 2019).

There are problems with the implementation of Education 4.0. First, there is a lack of digital culture and training. Second, there is a lack of a clear digital operational vision and support from top management. Third, the economic benefits of digital investment are unclear and the implementation of digitalization in some institutions, particularly educational institutions, is costly. Fourth, technologies are constantly changing (Glas & Kleemann, 2016).

2.4 The Analytic Hierarchy Process

Analysis of decision-making of multifaceted and complex problems is continuously improving and researchers, decision makers and managers are now recognizing the benefit of using various methods (Javanbarg et al., 2012). One well-known method is the Analytic Hierarchy Process (AHP) that was introduced by Thomas Saaty in the 1970s.

Advantages of the AHP include the ability to quantitatively measure subjective topics and reconstruct complex problems into a hierarchical structure to make the problem easy to solve (Ohoitimur et al., 2019). Questionnaires are designed to perform pairwise comparisons which make it easier for the respondents to determine their preferences. This method is an effective combination of quantitative and qualitative approaches (Javanbarg et al., 2012). It has proven useful for decision makers to formulate a business' management policies and is used by many researchers for scientific studies.

The AHP sorts the problem and arranges it in the form of a hierarchy to reduce the complexity of the problem which greatly facilitates the decision maker's ability to make a decision and determine the criteria to be used and the alternatives to be evaluated (Mu & Pereyra-Rojas, 2018). It is also able to handle intangible criteria such as experience, subjective preferences (Ishizaka & Labib, 2009) and intuition originating from multi-person respondents with multi-criteria input (Vrana, 2008). This method can handle qualitative and quantitative data based on individual perceptions. Finally, the mathematical formulas are not difficult, but easy to understand and use (Forbes, Hebb, & Mu, 2018).

The AHP does however have some limitations. It uses discrete numbers and does not adequately address uncertainties. Anticipating this drawback, the researchers also applied Fuzzy-AHP which can calculate and address vagueness. One of the objectives of this study was to compare the findings provided by both the AHP and ANP methods.

The steps of the AHP are as follows. It begins with determining the research goal, then criteria and sub-criteria are determined, including alternatives. Next, the criteria and alternatives are structured in a hierarchy.

2.5 Fuzzy-AHP

It has been determined that when the preferences are uncertain and not easily determined using exact numerical values, the AHP is insufficient (Javanbarg et al., 2012). Human understanding of certain complex issues is imprecise (Wang & Chen, n.d.) because the

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real world is highly ambiguous and difficult to understand quantitatively (Javanbarg et al., 2012).

To address these problems Zadeh (1965) introduced a fuzzy method to rationalize uncertainties in relation to vagueness and thus make them applicable to human thought. Fuzzy methods continue to develop, and today there are many fuzzy methods, one of which is Fuzzy-AHP which this study applies based on Buckley's method.

In Fuzzy-AHP, the pairwise comparison matrices are formed with Triangular Fuzzy numbers (TFN) and obtained by appropriate fuzzification of Saaty's scale (Lavic et al., 2018). The Fuzzy-AHP used in this study is Buckley's Fuzzy-AHP which presents a three-step decision-making process. This process involves finalizing the weights, then normalizing the weights for all the attributes/factors and finally ranking the alternatives (Lohan, Ganguly, & Kumar, 2020).

Application of the fuzzy AHP method makes decisions possible by taking into account the importance of criteria and their relative priority that is needed in the study of determining soft skills (Zavadskas et al., 2020).

Under certain conditions, the fuzzy set formed in the real numbers is called the fuzzy number. Due to the uncertainty of information and the complexity of the decision-making problem, it is difficult for decision makers to express their preferences using exact numbers. In these cases, we can use fuzzy numbers to reduce the complexity. Fuzzy numbers plays a vital role in many decision making applications.

Triangular fuzzy numbers can not only be used to express the vagueness and uncertainty of information, but can also be used to represent fuzzy terms in information processing. Besides being integrated into decision-making, triangular fuzzy numbers have been applied in many disciplines such as performance evaluation, forecast, and matrix games (Zhang, Ma, & Chen, 2014). A triangular fuzzy number not only covers interval questions, but also medians and shows the most probable relationship between indicators. The triangular fuzzy number reflects the evaluator's subjective understanding of the important relationships between indicators (Lu & Zhu, 2018).

2.6 Sensitivity analysis

A sensitivity analysis is a fundamental step in Multi-Criteria Decision-Making (MCDM) methods to measure stability, consistency, and robustness in the selection of the optimal solution. It is used in the event of a change in policy or additional information that requires the decision maker to change a policy that results in a change in the priority order.

The sensitivity analysis is also called a 'what if analysis', meaning that the final result will change if there is a change in the criterion weights (Mu & Pereyra-Rojas, 2018). The more sensitive a parameter, both criteria and sub-criteria, the poorer the criteria or sub-criteria will be because it will affect the order of priority. Sensitivity is determined based on the smallest range value of several criteria. The decision maker can make better decisions if he or she can determine how critical each criterion is. In other words, it is

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important to know how sensitive the actual ranking of the sub-criteria is to changes in the weights of the current decision criteria.

A sensitivity analysis is a dynamic element of a hierarchy. This means that the initial assessment is maintained for a certain period of time and then a change in policy or sufficient action is altered and the sensitivity analysis determines the effects that occur. A sensitivity analysis helps decision makers understand the strength of the decision (Raco et al., 2021). This is an important part of the decision-making process and no final decision should be made without conducting a sensitivity analysis (Mu & Pereyra-Rojas, 2018). Therefore, to ensure the robustness of the criteria, the researcher conducted a sensitivity analysis.

3. Methodology

This research was conducted by following several steps that appear in Figure 1. The first step was to determine the research objective, namely the determination of the dominant soft skills that graduates of higher education will require in Industry 4.0 using the AHP and Fuzzy-AHP. The second objective of this research is to determine if there is a significant difference between using the AHP and Fuzzy-AHP for the data analysis.

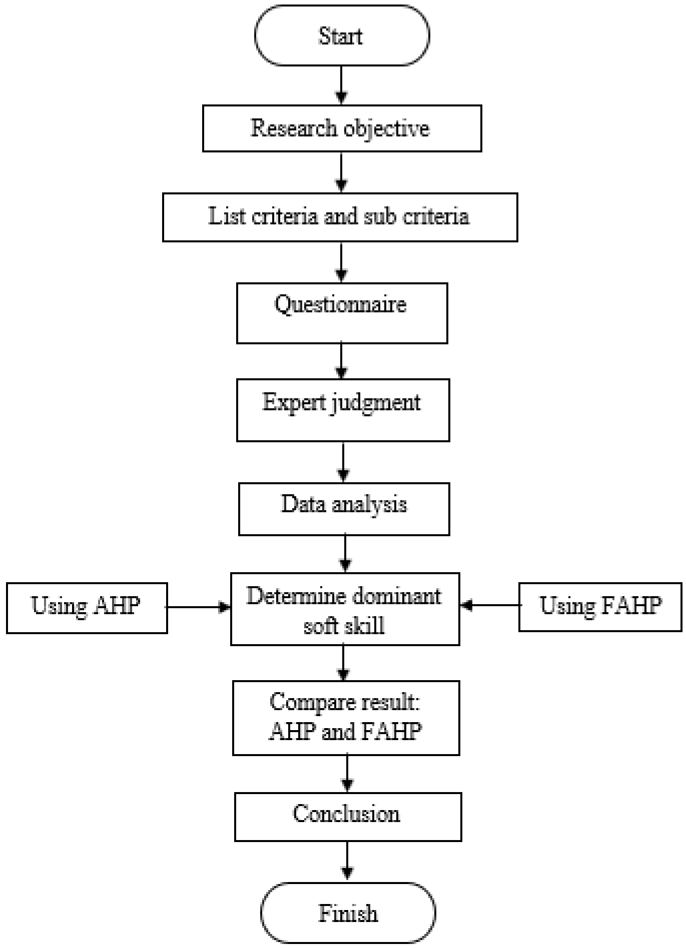

Figure 1 Research flowchart

The objective of the research is displayed in a hierarchical form as shown in Figure 2.

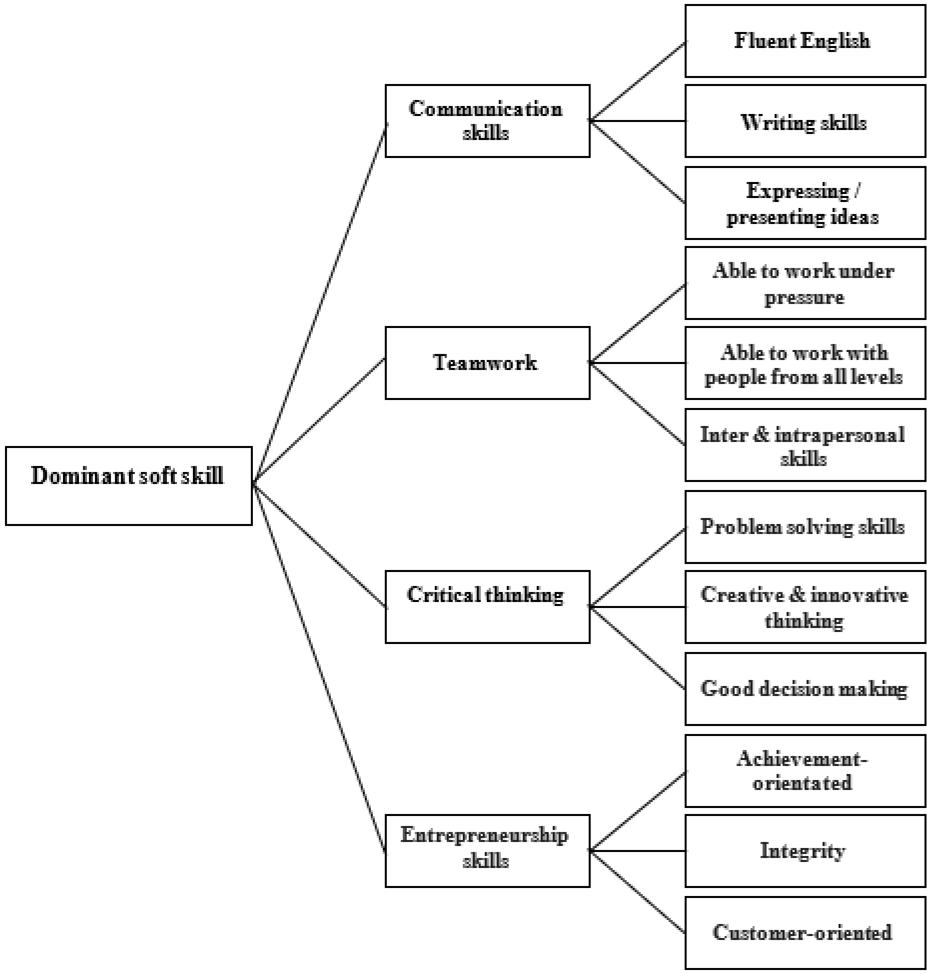

Figure 2 Hierarchy structure

The second step was to determine the criteria and sub-criteria based on the results of the literature review. There were 5 criteria used in this study, namely communication skills, teamwork, critical thinking and entrepreneurship skills. Communication skills are defined as the ability to speak English fluently, the ability to write well and the ability to express ideas or thoughts. Teamwork is defined as the ability to work under pressure, the ability to work with others at all levels and intra/extra personal skills. Critical thinking is defined as skills in problem solving, innovative and creative thinking, and the ability to make good decisions. Entrepreneurship skills are defined as being achievement-oriented, customer-oriented and having integrity.

The third step was to develop a questionnaire in the form of pairwise comparisons. This questionnaire facilitated the respondents ability to choose because there were only two choices given for each question (Raco et al., 2020). The formulation of the pairwise questionnaire used Saaty's comparative scale (1987) shown in Table 1.

Table 1
Saaty's comparative scale

Intensity of Importance on an Absolute Scale	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgment strongly favor one activity over another
5	Essential or strong importance	Experience and judgment strongly favor one activity over another
7	Very strong importance	An activity is strongly favored and its dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When compromise is needed

The next step involved expert judgments consisting of 24 experienced educators in Manado City. In this study, researchers used the aggregation of individual judgments and calculated them manually using the geometric mean (Equation 1). According to Basak & Saaty (1993) and Mu & Pereyra-Rojas (2018), the geometric mean is the correct way to synthesize judgments given by the experts as reciprocal matrices.

Next, the data processing was carried out using the AHP and Fuzzy AHP, and the results were compared. Finally, the conclusions were drawn.

The steps of data analysis using the AHP are as follows:

The questionnaire was completed by the experts and aggregated applying Equation 1.

$$GM = \sqrt[n]{(x_1)(x_2)\ldots(x_n)} \tag{1}$$

The aggregated results were then arranged in the matrix of pairwise comparisons utilizing Equation 2.

$$A = [a_{ij}], a_{ij} = w_i/w_j, a_{ji} = 1/a_{ij}, a_{ii} = 1 \tag{2}$$

The pairwise comparison matrix was normalized using Equation 3.

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{3}$$

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The priority weight was established using Equation 4.

$$w_i = \frac{\sum_{j=1}^{n} b_{ij}}{n} \tag{4}$$

The researchers set up the consistency index as follows:

- Calculate the Maximum (Principal) Eigenvalue using Equation 5.

$$\lambda_{max} = \sum_{i=1}^{n} \frac{(Aw)_i}{nw_i} \tag{5}$$

- Calculate the consistency index applying Equation 6.

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{6}$$

- Then, calculate the consistency of ratio utilizing Equation 7.

$$CR = \frac{CI}{RI} \tag{7}$$

The Ratio Index for each n object is shown in Table 2.

Table 2
Ratio index

N	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

The conversion of the AHP to the Fuzzy-AHP scale is shown in Table 3.

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Table 3
Scale AHP and Fuzzy-AHP

Linguistic variables	AHP Scale	Fuzzy AHP Scale	
		TFNs	Reciprocal TFNs
Equal Importance	1	(1, 1, 1) diagonal	(1, 1, 1)
Intermediate	2	(1, 2, 3)	(1/3, 1/2, 1)
Moderately more important	3	(2, 3, 4)	(1/4, 1/3, 1/2)
Intermediate	4	(3, 4, 5)	(1/5, 1/4, 1/3)
Strongly more important	5	(4, 5, 6)	(1/6, 1/5, 1/4)
Intermediate	6	(5, 6, 7)	(1/7, 1/6, 1/5)
Very strongly more important	7	(6, 7, 8)	(1/8, 1/7, 1/6)
Intermediate	8	(7, 8, 9)	(1/9, 1/8, 1/7)
Extremely more important	9	(8, 9 ,9)	(1/9, 1/9,1/8)

The steps to determine the weight of respondents' perceptions using fuzzy AHP according to Buckley's AHP are as follows:

Step 1. Compile a pairwise comparison matrix of criteria and sub-criteria as follows:

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ 1/\tilde{a}_{12} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\tilde{a}_{1n} & 1/\tilde{a}_{2n} & \cdots & 1 \end{bmatrix} \quad (8)$$

With,

$$\tilde{a}_{ij} = \begin{cases} \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}, \textit{criterion i is relative importance to criterion j} \\ 1, \ i = j \\ \tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1}, \textit{criterion i is relative less importance to criterion j} \end{cases}$$

Step 2. Calculate the geometric mean of the fuzzy comparison value of criterion *i* to each criterion using Equation 9.

$$\tilde{r}_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \cdots \otimes \tilde{a}_{in})^{1/n} \quad (9)$$

Where, $\tilde{a}_{in}$ is the fuzzy comparison value of criterion *i* to criterion *n*.

Step 3. Determine the fuzzy weight of each criterion indicated by the triangular fuzzy number.

$$\widetilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \cdots \oplus \tilde{r}_n)^{-1} \quad (10)$$

Where, $\widetilde{w}_i$ is the fuzzy weight of the i^{th} criterion and can be indicated using a triangular fuzzy number, $\widetilde{w}_i = (Lw_i, Mw_i, Uw_i)$. Lw_i, Mw_i *and* Uw_i are the lower, middle and upper values of the fuzzy weight of the i^{th} criterion.

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Step 4. The process of defuzzification used the Center of Area method to obtain the weight of the Best Nonfuzzy Performance (BNP) applying Equation 11.

$$BNP_{w_i} = [(Uw_i - Lw_i) + (Mw_i - Lw_i)]/3 + Lw_i \quad (11)$$

Several studies show that fuzzy AHP, in comparison to the AHP with crisp numbers, gives more complete, flexible and realistic results. Unlike with other MCDM methods, it is not necessary to know the exact numerical values of the factors being considered, but it is enough to assess a good value of comparisons.

This is important for application in the construction industry, where in the first phase of a construction project that includes realization and preparation of preliminary feasibility studies, many important data concerning costs, time of work execution and others, are not precisely known, but the values of comparison of important factors could be better assessed. Since these values cannot be expressed precisely by crisp numbers, it is necessary to use fuzzy numbers. The usage of verbal judgements ("equal", "equal/moderate", "moderate" to "extreme") for mutual comparison of criteria, sub-criteria and alternatives is more accurate than comparison with integers or crisp numbers. At each level, the comparisons may be expressed numerically or linguistically. Non numerical values are transformed to numerical ones according to the corresponding scale. The absence of units in comparison values is an important advantage since these values are quotients of two quantities of the same kind. Application of fuzzy numbers instead of crisp numbers gives more realistic results and better ranking of alternatives. (Praščević & Praščević, 2016).

The sensitivity analysis calculation is used to assess the robustness of the priority factors in the event of a change in the criteria. If there is a change in the criteria and the priority factors do not change, it can be said that these priority factors can be used in policy making. However, if there is a change in the criteria and the priority factors do change, then policymakers must be careful when using these priority factors. It is important to always pay attention if there is a change.

4. Results

The goal of this research was to determine the dominant soft skills that graduates should possess in the Industry 4.0 era using the AHP and Fuzzy-AHP methods. Another objective of this study was to compare the results analysis using both methods. The respondents, who were considered the experts in this study, were lecturers in Manado who have more than twenty years' experience teaching in University and hold doctoral degrees. Based on previous studies, four criteria and twelve sub-criteria were included. The criteria were communication skills, teamwork, critical thinking, and entrepreneurship skills. Each criterion had three sub-criteria; therefore, the total number of sub-criteria was twelve. The goal, criteria and sub-criteria were structured in a hierarchy form (Figure 2).

4.1 Weighting of criteria and sub-criteria using AHP method

Weighting of criteria and sub-criteria in the AHP method was calculated using Equations 1 – 7. Following a consistency test, the pairwise comparison matrix and the weight of criteria and sub-criteria are presented in Table 4.

The opinion of each respondent, according to Saaty, was used as the opinion of the group by combining these opinions using the geometric mean (Saaty, T.L., 2013). Moreover, this method must satisfy each individual's opinion (Saaty, R., 1987). Saaty (2008) added that the geometric mean is the best way to combine the opinions of each individual.

Table 4
Matrix of pairwise comparison and priority weight of the criteria

	C1	C2	C3	C4	Priority Weight
C1	1.000	1.056	1.105	0.727	0.238
C2	0.947	1.000	1.352	0.957	0.260
C3	0.905	0.739	1.000	1.607	0.257
C4	1.375	1.045	0.622	1.000	0.246
$\lambda_{max} = 4.104, CI = 0.035, CR = 0.039$					

Criteria symbols
C1: Communication skills
C2: Teamwork
C3: Critical thinking
C4: Entrepreneurship skills

The priority weights of the criteria are shown in Figure 3.

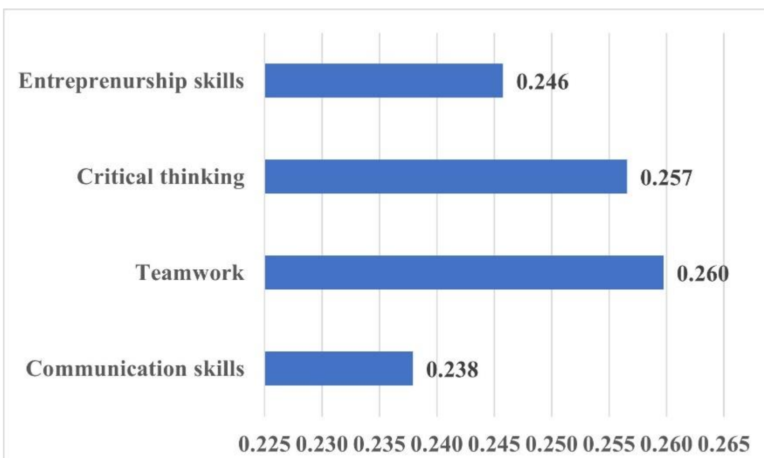

Figure 3 Priority weight of the criteria

From the AHP calculation of the criteria, the results were as follows. First the consistency index $(CI = 0.035)$ and consistency ratio $(CR) = 0.039 < 0.1$, which means the results were consistent. The results, shown in Table 4 and Figure 3, show that the criteria teamwork (0.260) was ranked the highest, followed by the criteria critical thinking (0.257), then entrepreneurship skills (0.246), and lastly, communication skills (0.238).

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The pairwise comparison matrix and priority weights of the sub-criteria of communication skills are displayed in Table 5.

Table 5
Pairwise comparison matrix and priority weights of the communication skill sub-criteria

	SC1.1	SC1.2	SC1.3	Priority Weight
SC1.1	1.000	1.997	0.851	0.386
SC1.2	0.501	1.000	0.714	0.231
SC1.3	1.175	1.401	1.000	0.383
$\lambda_{max} = 3.030, CI = 0.015, CR = 0.026$				

Sub-criteria Communication skills symbols
SC1.1: Fluent English
SC1.2: Writing skills
SC1.3: Expressing/presenting ideas

The pairwise comparison matrix and priority weights of the sub-criteria of teamwork are shown in Table 6.

Table 6
Pairwise comparison matrix and priority weights of the teamwork sub-criteria

	SC2.1	SC2.2	SC2.3	Priority Weight
SC2.1	1.000	0.891	0.486	0.250
SC2.2	1.122	1.000	1.420	0.381
SC2.3	2.058	0.704	1.000	0.369
$\lambda_{max} = 3.103, CI = 0.051, CR = 0.089$				

Sub-criteria Teamwork symbols
SC2.1: Able to work under pressure
SC2.2: Able to work with people from all levels
SC2.3: Inter & intra personal skills

The pairwise comparison matrix and priority weights of the sub-criteria of critical thinking are shown in Table 7.

Table 7
Pairwise comparison matrix and priority weights of the critical thinking sub-criteria

	SC3.1	SC3.2	SC3.3	Priority Weight
SC3.1	1.000	0.918	1.016	0.322
SC3.2	1.089	1.000	1.596	0.396
SC3.3	0.984	0.627	1.000	0.281
$\lambda_{max} = 3.015, CI = 0.007, CR = 0.013$				

Sub-criteria Critical thinking symbols
SC3.1: Problem solving skills
SC3.2: Creative & innovative thinking
SC3.3: Good decision making

The pairwise comparison matrix and priority weights of the sub-criteria of entrepreneurship skills are found in Table 8.

Table 8
Pairwise comparison matrix and priority weights of the entrepreneurship skills sub-criteria

	SC4.1	SC4.2	SC4.3	Priority Weight
SC4.1	1.000	0.788	1.034	0.305
SC4.2	1.269	1.000	1.772	0.428
SC4.3	0.967	0.564	1.000	0.267
$\lambda_{max} = 3.010, CI = 0.005, CR = 0.009$				

Sub-criteria Entrepreneurship skills symbols
SC4.1: Achievement-orientated
SC4.2: Integrity
SC4.3: Customer-oriented

Calculations using the AHP method for each of the sub-criteria showed that the experts' assessments were consistent because the Consistency Ratio (CR) of each of the sub-criteria and were < 0.1 as shown in Tables 5-8.

4.2 Weighting of criteria and sub-criteria using Fuzzy-AHP method

The weighting of criteria and sub-criteria in the Fuzzy-AHP method was performed using the Equations 8-11. The results of the twenty-four experts were transferred into a pairwise comparison matrix as shown in Table 9. The assessment of twenty-four experts was aggregated using the arithmetic mean and the results are shown in a fuzzy pairwise comparison matrix in Table 9.

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Table 9
Fuzzy pairwise comparison matrix for criteria

Crite-ria	C1			C2			C3			C4		
	l	M	U	L	m	u	L	M	u	l	M	U
C1	1.000	1.000	1.000	0.764	1.056	1.421	0.928	1.105	1.341	0.612	0.727	0.891
C2	0.704	0.947	1.310	1.000	1.000	1.000	1.029	1.352	1.646	0.837	0.957	1.091
C3	0.745	0.905	1.078	0.607	0.739	0.972	1.000	1.000	1.000	1.260	1.607	1.986
C4	1.122	1.375	1.634	0.917	1.045	1.195	0.504	0.622	0.794	1.000	1.000	1.000

Determine the geometric mean of fuzzy comparison value of criteria using Equation 9,
$\tilde{r}_{c1} = (\tilde{a}_{11} \otimes \tilde{a}_{12} \otimes \tilde{a}_{13} \otimes \tilde{a}_{14})^{1/4}$
$= ((1 \times 0.764 \times 0.928 \times 0.612)^{1/4}, (1 \times 1.056 \times 1.105 \times 0.727)^{1/4}, (1 \times 2.421 \times 1.341 \times 0.891)^{1/4})$
$= (0.812, 0.960, 1.142)$

Obtain the value of the geometric means for other criteria using the same method,
$\tilde{r}_{c2} = (0.882, 1.052, 1.238)$
$\tilde{r}_{c3} = (0.869, 1.018, 1.201)$
$\tilde{r}_{c4} = (0.848, 0.973, 1.116)$

Determine the weight of each criterion based on Equation 10,
$\tilde{w}_{C1} = \tilde{r}_{C1} \otimes (\tilde{r}_{C1} \oplus \tilde{r}_{C2} \oplus \tilde{r}_{C3} \oplus \tilde{r}_{C4})^{-1}$
$= (0.812, 0.960, 1.142) \otimes \big(1/(1.142 + 1.238 + 1.201 + 1.116), 1/(0.960 + 1.052 + 1.018 + 0.973) + 1/(0.812 + 0.882 + 0.869 + 0.848)\big)$
$= (0.173, 0.240, 0.335)$

The weights of the other criteria are obtained using the same method,
$\tilde{w}_{C2} = (0.188, 0.263, 0.363)$
$\tilde{w}_{C3} = (0.185, 0.254, 0.352)$
$\tilde{w}_{C4} = (0.181, 0.243, 0.327)$

The next step is to determine the best nonfuzzy performance (BNP) value using Equation 11,
$BNP_{C_1} = [(Uw_{C1} - Lw_{C1}) + (Mw_{C1} - Lw_{C1})]/3 + Lw_{C1}$
$= [(0{,}335 - 0{,}173) + (0{,}240 - 0{,}173)]/3 + 0{,}173$
$= 0{,}249$

The weights of the other criteria are obtained using the same method,
$BNP_{C_2} = 0.271$
$BNP_{C_3} = 0.264$
$BNP_{C_2} = 0.250.$

The results of the calculations of the Fuzzy-AHP for the criteria are shown in Table 10.

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Table 10
Results of Fuzzy AHP for criteria

Criteria		Weight	
		Fuzzy	BNP and Normalized
Communication skills	C1	(0.173, 0.240, 0.335)	0.241
Teamwork	C2	(0.188, 0.263, 0.363)	0.262
Critical thinking	C3	(0.185, 0.254, 0.352)	0.255
Entrepreneurship skills	C4	(0.181, 0.243, 0.327)	0.242

The resulting calculations of the Fuzzy-AHP for criteria showed that the criteria teamwork received the highest value (0.262), followed by critical thinking (0.255), then entrepreneurship skills (0.242), and lastly, communication skills (0.241).

The fuzzy pairwise comparison matrix and the weights for each sub-criteria are listed in the following tables.

Table 11
Pairwise comparison matrix for Fuzzy-AHP of sub-criteria of communication skills

Sub-criteria	**SC1.1**			**SC1.2**			**SC1.3**		
	L	**m**	**u**	**l**	**m**	**U**	**l**	**m**	**u**
SC1.1	1.000	1.000	1.000	1.542	1.997	2.390	0.827	0.851	0.972
SC1.2	0.418	0.501	0.648	1.000	1.000	1.000	0.609	0.714	0.933
SC1.3	1.029	1.176	1.209	1.072	1.401	1.642	1.000	1.000	1.000

Table 12
Weight of sub-criteria of communication skills

Sub-criteria		Weight	
		Fuzzy	BNP and Normalized
Fluent in English	SC1.1	(0.316, 0.387, 0.481)	0.389
Writing skills	SC1.2	(0.185, 0.230, 0.307)	0.237
Expressing/presenting ideas	SC1.3	(0.302, 0.383, 0.457)	0.374

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Table 13
Pairwise comparison matrix of Fuzzy-AHP for sub-criteria of teamwork

Sub-criteria	SC2.1			SC2.2			SC2.3		
	L	m	u	l	m	u	l	m	u
SC2.1	1.000	1.000	1.000	1.542	1.997	2.390	0.827	0.851	0.972
SC2.2	0.418	0.501	0.648	1.000	1.000	1.000	0.609	0.714	0.933
SC2.3	1.029	1.176	1.209	1.072	1.401	1.642	1.000	1.000	1.000

Table 14
Weight of sub-criteria of teamwork

Sub-criteria		Weight	
		Fuzzy	BNP and Normalized
Able to work under pressure	SC2.1	(0.197, 0.248, 0.324)	0.251
Able to work with people	SC2.2	(0.304, 0.382, 0.473)	0.379
Inter & intra personal skills	SC2.3	(0.280, 0.370, 0.484)	0.370

Table 15
Pairwise comparison matrix of Fuzzy-AHP for sub-criteria of critical thinking

Sub criteria	SC3.1			SC3.2			SC3.3		
	l	M	u	L	m	u	l	m	u
SC3.1	1.000	1.000	1.000	0.780	0.918	1.078	0.718	1.016	1.421
SC3.2	0.928	1.089	1.281	1.000	1.000	1.000	1.204	1.596	2.079
SC3.3	0.704	0.985	1.384	0.481	0.626	0.831	1.000	1.000	1.000

Table 16
Weight of sub-criteria of critical thinking

Sub-criteria		Weight	
		Fuzzy	BNP and Normalized
Problem solving skills	SC3.1	(0.230, 0.322, 0.450)	0.322
Creative & innovative	SC3.2	(0.289, 0.397, 0.542)	0.394
Good decision making	SC3.3	(0.194, 0.281, 0.410)	0.284

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Table 17
Pairwise comparison matrix of Fuzzy-AHP for sub-criteria entrepreneurship skills

Sub-criteria	SC4.1			SC4.2			SC4.3		
	L	m	u	l	m	u	l	m	u
SC4.1	1.000	1.000	1.000	0.675	0.788	0.941	0.851	1.034	1.263
SC4.2	1.062	1.269	1.480	1.000	1.000	1.000	1.303	1.772	2.239
SC4.3	0.792	0.967	1.175	0.447	0.564	0.767	1.000	1.000	1.000

Table 18
Weight of sub-criteria of entrepreneurship skills

Sub-criteria		Weight	
		Fuzzy	BNP and Normalized
Achievement-oriented	SC4.1	(0.236, 0.305, 0.399)	0.305
Integrity	SC4.2	(0.317, 0.428, 0.562)	0.424
Customer-oriented	SC4.3	(0.201, 0.267, 0.364)	0.270

4.3 Comparison analysis of the calculated results of AHP and Fuzzy-AHP methods

A comparison of the calculated results of the AHP and Fuzzy-AHP for the criteria are shown in Table 19 and Figure 4.

Table 19
Comparison analysis results of the AHP and fuzzy AHP for criteria

Criteria		Weight (AHP)	Weight (F-AHP)
Communication skills	C1	0.238	0.241
Teamwork	C2	0.260	0.262
Critical thinking	C3	0.257	0.255
Entrepreneurship skills	C4	0.246	0.242

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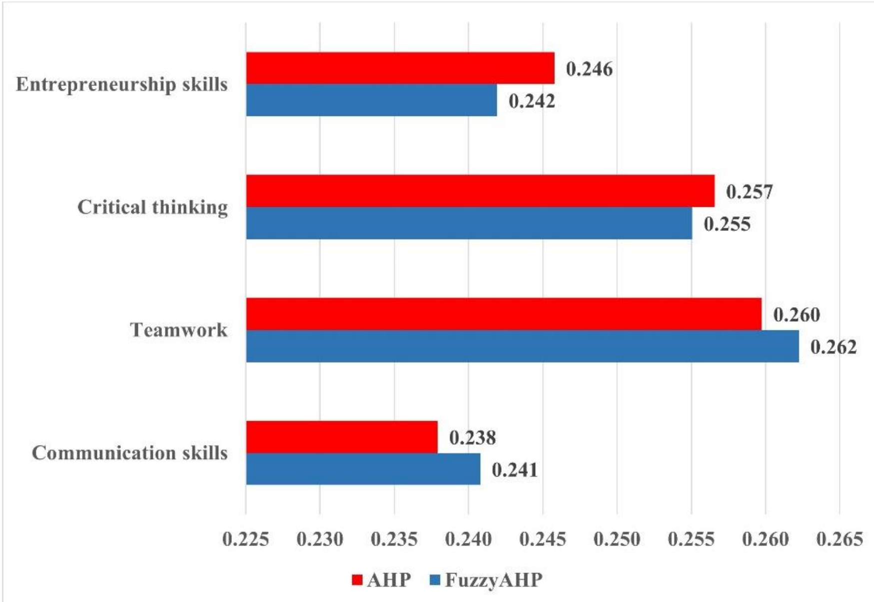

Figure 4 Comparison analysis results of the AHP and the Fuzzy-AHP for criteria

From the results in Table 19 and Figure 4, we concluded that there were no differences in the results between the two methods. Teamwork was ranked first and received the highest weight, followed by critical thinking, then entrepreneurship skills and lastly, communication skills. The differences in the results of the AHP and Fuzzy-AHP were quite small. For example, the difference in the results of the teamwork criteria between the AHP and Fuzzy-AHP was only 0.0439; for the critical thinking, the difference was 0.0075. This was also true for the comparison between the criteria. For example, the difference between the teamwork criteria (Fuzzy-AHP 0.2456) and the critical thinking criteria (Fuzzy-AHP 0.2224) was only 0.0232.

The comparison of the results of analysis for each of the sub-criteria is shown in the following tables and figures.

Table 20
Comparison analysis of sub-criteria of communication skills

Criteria		Weight (AHP)	Weight (F-AHP)
Fluent in English	SC1.1	0.386	0.389
Writing skills	SC1.2	0.231	0.237
Expressing/presenting ideas	SC1.3	0.383	0.374

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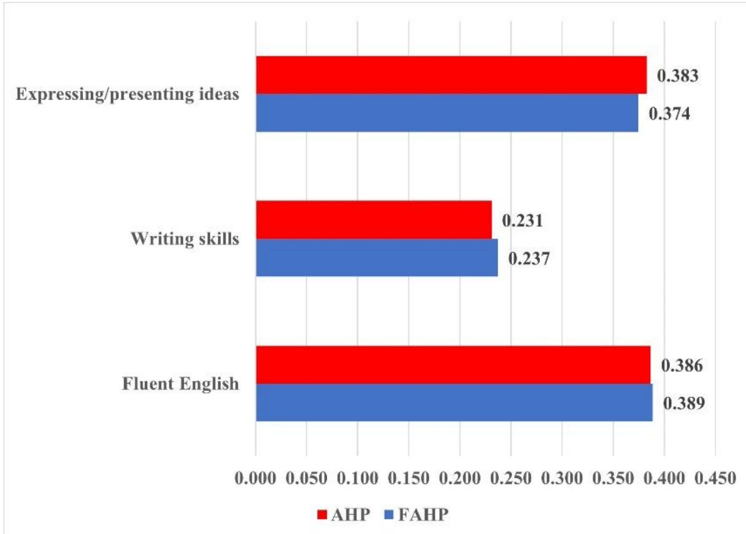

Figure 5 Comparison of the results analysis of the AHP and Fuzzy AHP for sub-criteria communication skills

Table 21
Comparison of the results analysis of the sub-criteria of teamwork

Criteria		Weight (AHP)	Weight (F-AHP)
Able to work under pressure	SC2.1	0.250	0.251
Able to work with people from all levels	SC2.2	0.381	0.379
Inter & intra personal skills	SC2.3	0.369	0.370

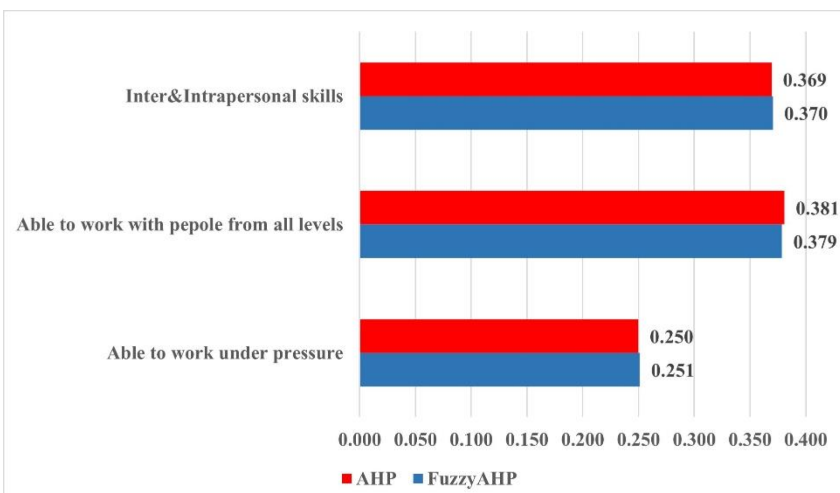

Figure 6 Comparison of the results analysis of AHP and Fuzzy AHP for sub-criteria of teamwork

Table 22
Comparison of the results analysis for sub-criteria of critical thinking

Criteria		Weight (AHP)	Weight (F-AHP)
Problem solving skills	SC3.1	0.322	0.322
Creative & innovative thinking	SC3.2	0.396	0.394
Good decision making	SC3.3	0.281	0.284

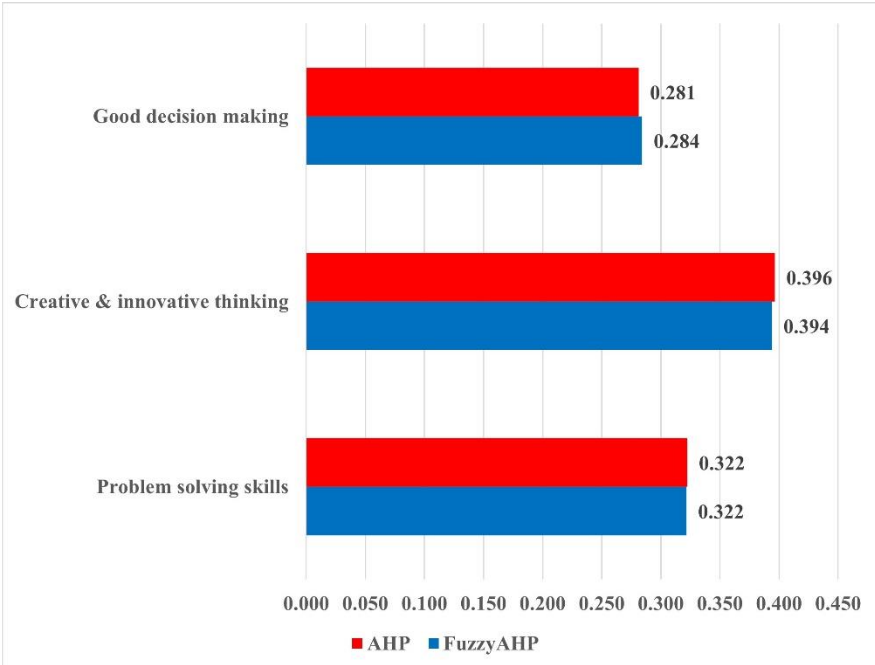

Figure 7 Comparison of the results analysis of sub-criteria of critical thinking

Table 23
Comparison of the results analysis of sub-criteria of entrepreneurship skills

Criteria		Weight (AHP)	Weight (F-AHP)
Achievement-orientated	SC4.1	0.305	0.305
Integrity	SC4.2	0.428	0.424
Customer-oriented	SC4.3	0.267	0.270

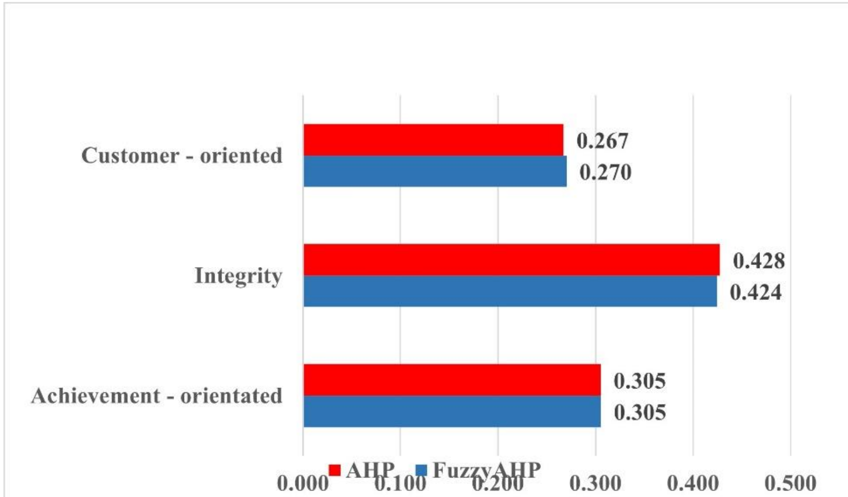

Figure 8 Comparison of the results analysis of the sub-criteria of entrepreneurship skills

4.4 Global calculation results

The global results or global weight of the dominant factor of soft skills that the graduates at the University in Manado should possess based on the assessment of 24 experts was obtained by multiplication between the criteria and each sub-criterion. Based on the calculation, the results of the global weights are shown in Table 24.

Table 24
Global weights

Criteria/Sub-criteria		Local Weight		Global Weight	
		AHP	F-AHP	AHP	F-AHP
Communication skills	C1			0.238	0.241
Teamwork	C2			0.260	0.262
Critical thinking	C3			0.257	0.255
Entrepreneurship skills	C4			0.246	0.242
	Sum			1.000	1.000
Fluent in English	SC1.1	0.386	0.389	0.092	0.094
Writing skills	SC1.2	0.231	0.237	0.055	0.057
Expressing/presenting ideas	SC1.3	0.383	0.374	0.091	0.090
	Sum	1.000	1.000	0.238	0.241
Able to work under pressure	SC2.1	0.250	0.251	0.065	0.066
Able to work with people from all levels	SC2.2	0.381	0.379	0.099	0.099
Inter & intra personal skills	SC2.3	0.369	0.370	0.096	0.097
	Sum	1.000	1.000	0.260	0.262
Problem solving skills	SC2.1	0.322	0.322	0.083	0.082
Creative & innovative thinking	SC3.2	0.396	0.394	0.102	0.100
Good decision making	SC3.3	0.281	0.284	0.072	0.072
	Sum	1.000	1.000	0.257	0.255
Achievement-orientated	SC4.1	0.305	0.305	0.075	0.074
Integrity	SC4.2	0.428	0.424	0.105	0.103
Customer-oriented	SC4.3	0.267	0.270	0.066	0.065
	Sum	1.000	1.000	0.246	0.242

The global weights revealed that integrity was the soft skills dominant factor. The result of the calculations for integrity was the highest for both the AHP (10.5%) and Fuzzy-AHP (10.3%).

A sensitivity analysis was carried out with the help of SuperDecisions software using the steps in Mu & Pereyra-Rojas (2018).

The weight of the criteria and sub-criteria for the original results, scenario 1 and scenario 2, and the results of the sensitivity analysis are listed in Table 25. The original results show that the largest criterion weight is teamwork in the AHP (26%) and in Fuzzy-AHP (26.2%). However, the greatest weight for the sub-criteria is integrity in the AHP (10.5%) and in Fuzzy-AHP (10.3%).

The first scenario in the sensitivity analysis involved making the criteria weights equal, in this case each criterion was given a weight of 0.25. The results of this first scenario show that the largest sub-criteria weight remains integrity (10.6%).

Table 25
Weight of criteria and sub-criteria of sensitivity analysis

Criteria / Sub-criteria	Weight		
	Original	Scenario 1	Scenario 2
Communication skills	0.23754	0.25	0.238
Teamwork	0.26014	0.25	0.240
Critical thinking	0.25782	0.25	0.278
Entrepreneurship skills	0.24451	0.25	0.244
Fluent in English	0.09192	0.09674	0.09210
Writing skills	0.05467	0.05754	0.05478
Expressing/presenting ideas	0.09094	0.09572	0.09112
Able to work under pressure	0.06440	0.06189	0.05941
Able to work with people from all levels	0.09942	0.09555	0.09173
Inter & intra personal skills	0.09632	0.09257	0.08886
Problem solving skills	0.08312	0.08060	0.08962
Creative & innovative thinking	0.10229	0.09919	0.11030
Good decision making	0.07241	0.07021	0.07808
Achievement-oriented	0.07460	0.07627	0.07444
Integrity	0.10464	0.10699	0.10442
Customer-oriented	0.06527	0.06674	0.06514

The second scenario involved changing the weights of the two highest criteria, namely teamwork and critical thinking. The weight value of the teamwork criteria was reduced by 2% and the weight of the critical thinking criteria was increased by 2%. The value for the criteria for communication skills and entrepreneurship skills remained the same as in the original results. This resulted in a change in the weight of the sub-criteria, in this case the highest sub-criteria weight became creative and innovative thinking with .1103.

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5. Discussion

The AHP and Fuzzy-AHP methods were used to determine the soft skills dominant factors that the graduates in Manado need to possess to be able to compete in the Industry 4.0 era. The research findings will be used to improve the curriculum and the teaching-learning systems of higher institutions, particularly at Universitas Katolik De La Salle Manado (De La Salle Catholic University of Manado-Indonesia). The criteria and sub-criteria were determined by the experts based on previous studies. The researchers designed questionnaires in the form of a pairwise comparison matrix. The analysis of consistencies verified that the results were consistent and considered scientifically acceptable.

The results proved, as shown in Table 24, that teamwork was the dominant factor, followed by critical thinking, then entrepreneurship skills and lastly, communication skills. The research findings for both AHP and Fuzzy-AHP were the same. The differences in the results between the criteria in the AHP and Fuzzy-AHP were small. For example, the gap between the AHP and Fuzzy-AHP for both the teamwork and critical thinking criteria was only 0.002. This was also true for the resulting gap between the criteria themselves. For example, the difference between the teamwork criteria (Fuzzy-AHP 26.2%) and critical thinking criteria (Fuzzy-AHP 25.5%) was only 0.07%. The differences are understandable because the Fuzzy-AHP uses triangular fuzzy numbers unlike the AHP which uses a single value.

The global analysis (Table 24) shows that integrity was the dominant factor. The findings recommend that in the Industry 4.0 era, the higher institutions in Manado need to provide students with teamwork skills. Teamwork skills should appear in the curriculum and the teaching-learning system, and faculty and teaching methods must focus on providing teamwork skills. The sectoral ego will not be effective in the Industry 4.0 era. Everyone needs to work together to be successful. However, other skills such as critical thinking, entrepreneurship and communication must also be considered because these criteria also support the future success of the graduates. The combination of these criteria is larger than the teamwork criteria. Failure to acknowledge the importance of them would cause the graduates' competencies to suffer.

The study advocates that whatever the profession or job chosen by the graduates, teamwork must be given priority during their education. The interconnection and interdependency between human beings, machines and objects in the Industry 4.0 era requires workers to be team players. Compatibility of products, systems and services are only possible if teamwork exists.

The overall result or global weight shows that integrity has the highest score in the AHP (10.5%) and Fuzzy-AHP (10.3%) which means that the superior skill in Industry 4.0 is integrity.

To determine if integrity is a robust result, a sensitivity analysis was conducted by changing the criteria. The value of the original result criteria was changed by 2%. In this case, the weight of the teamwork criteria was reduced by 2% and the weight of the critical thinking criteria was increased by 2%. Meanwhile, the weights of the criteria for

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communication skills and entrepreneurship skills did not change. As a result, with a weight change of 2%, the weight of the teamwork criteria becomes 24% and the weight of the critical thinking criteria becomes 27.8% while the weights of the sub-criteria change with the largest weight being the creative and innovative thinking sub-criteria at 11.03% and the integrity sub-criteria being 10.4%. Therefore, a 2% decrease in the value of the teamwork criteria and a 2% increase in weight of the critical thinking criteria will cause a change in the position of the highest sub-criteria, namely, creative and innovative thinking. This means that the integrity sub-criteria is very unstable, not robust or fragile.

This study shows that integrity is the most important factor in higher education in the Industry 4.0 era. Integrity is defined as conformity between words and action, rather than manipulation. Integrity is a key to success in Industry 4.0 and must be incorporated into the curriculum, teaching-learning materials, studying system and educational processes. Integrity means to behave in an honest, fair, and ethical manner. Mondal (2015) mentioned that integrity is the ability to act with honesty and be consistent in whatever it is one is doing based on one's own particular moral, value or belief compass. Covey defined integrity as "honestly matching words and feelings with thoughts and actions, with no desire other than for the good of others" (Pillay, 2014). The Latin word "integritas" denotes wholeness or unity. It means that to attain integrity, someone must be whole and undivided. In the scholarly discourses, this position is called "integrated-self view" and implies that "integrity is a matter of persons integrating various parts of their personality into a harmonious, intact whole (Schottl, 2015).

These findings are in line with the LaSallian expected qualities known as ELGA (Expected Lasallian Graduate Attributes). These attributes include being an effective communicator, critical and creative thinker, lifelong learner, service driven-citizen, steward of the environment and entrepreneurial spirit.

The AHP and Fuzzy-AHP methods were appropriate for this study. The rankings produced by both of these methods were the same even though there were numerical differences between them. This is because AHP uses discrete numbers while Fuzzy-AHP applies triangular fuzzy numbers so it can capture the uncertainties or vagueness of the perceptions of the experts. It was important to keep in mind that the AHP and Fuzzy-AHP were not competing with each other. The AHP was used if the evaluation or information was definite. However, if the information or evaluation was blurred and uncertain Fuzzy-AHP was used.

The AHP is a good methodology to use when there is a lack of statistical data and researchers have to rely on the experts' choice. For the experts or respondents, the AHP questionnaire, in the form of a pairwise comparison matrix is quite helpful since they only need to compare two options. One of the limitations of this study was the respondents' unfamiliarity with the AHP method. There was some confusion about answering the questionnaire which required the researchers to assist the respondents in making their choices. Most of the experts felt indifferent about the options and thought that there was little difference between the criteria or sub-criteria.

Previous studies have used Pareto (Raco et al., 2020) to explore the capabilities of the fuzzy method paired with the AHP.

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One limitation of the AHP is that it cannot evaluate vagueness since it uses crisp numbers, while in the real-world problems are not always represented by crisp numbers. In reality, all things are not black and white.

6. Conclusions

The study aimed to determine the soft skills dominant factors that the graduates of higher education should possess to be successful in Industry 4.0 and to compare the results of the AHP and Fuzzy-AHP.

The results of the study showed that the teamwork criteria had the highest priority of 26% in AHP and 26.2% in F-AHP, followed by critical thinking with a priority of 25.7% in AHP and 25.5% in F-AHP, entrepreneurial skills at 24.6% in the AHP and 24.2% in F-AHP and communication skills at 23.8% in the AHP and 24.1% in F-AHP. Moreover, the global weight calculation showed that the element of integrity was the highest factor, followed by the ability to work with people of all levels, then having intra-extra personal skills, followed by creative and innovative thinking and lastly, fluency in English (Table 24).

The results of the sensitivity analysis show that the integrity factor is fragile because when the teamwork criteria is reduced by 2% and the critical thinking criteria is increased by 2%, the highest sub-criteria value then becomes creative innovative thinking (11.03%) followed by integrity (10.4%).

While teamwork was the most dominant and integrity had the top global weight, other criteria and elements should not be ignored. Teamwork and integrity will be effective and successful when combined with other criteria and elements. Moreover, the numerical differences between the criteria were quite small, which was also true with other elements of the global weights. Failing to consider other criteria and sub-criteria could jeopardize the findings because if those criteria with smaller numerical results were combined they would yield a significant number and hold greater weight.

The results of this research must be conveyed to students by qualified lecturers to prepare for their future (Lazarević, 2019). The findings might be different than other research that is conducted in different situations. The researchers suggest caution when implementing the results. Factors such as lack of knowledge and undistinguished opinions about the options among the respondents should be seriously taken into consideration.

The calculation of the Fuzzy-AHP method took longer, but had higher accuracy than the AHP. It is able to deal with the vagueness in human thinking and effectively solve multi-criteria decision making problems.

The results of the study have implications for management. First, the dominant criteria should be used as guidelines for decisions by management when making changes. According to this study, the greatest attention should be given to teamwork and integrity. Second, there were only small numerical differences between the criteria and the global weight results. The study suggests a need to do comparative research with other institutions to determine whether there would be different results. Since changes are happening fast, this research needs to be conducted regularly. Third, every researcher has different interpretations, so a narrative of the background and ranking methodologies is necessary.

This study was done in Indonesia with Indonesian subjects. Cross cultural analysis in different countries is required to ensure generalizability of the results. The researchers recommend future studies using the same or different soft skills criteria using entrepreneurs, owners or business management as respondents.

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