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ANALYSIS OF THE COMPETENCY OF FRESH GRADUATED HIGHER EDUCATION IN SUPPORTING INDUSTRIAL ERA 4.0

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Abstract
This article analyses the need for Industry 4.0 HR competencies. The study was conducted at several tertiary institutions in Medan, where the sample was determined by purposive random sampling. The variables used in this study include; a) sense-making, b) social intelligent, c) novel and adaptive thinking, d) cross-cultural competency, e) computational thinking, f) new-media literacy, g) transdisciplinary, h) design thinking, i) cognitive load management, j) virtual collaboration. Furthermore, the data were analyzed using the Confirmatory Factor Analysis approach. The output of this research is expected to provide input and strategies for universities in strengthening the quality of the fresh graduated HR output produced. The results of this study indicate that based on the results of Confirmatory Factor Analysis, the ten variables used have a positive relationship between variables and can be an estimator to see how fresh graduated human resources are ready to face industry 4.0.

Keywords: cross-cultural competency, Industry 4.0, novel and adaptive thinking, sense-making, social intelligence

Introduction

At present, the 4.0 industrial revolution has become a new paradigm which is currently a hot topic in the world, including in Indonesia. Blanchet et al. (2014) suggested that the industrial revolution 4.0 was a development in which the strength of industrial manufacturing was optimized with the latest internet technology which was at the core of the industrial development 4.0. It is therefore natural that industry 4.0 experiences increasing attention, especially in Europe Blanchet et al. (2014)

including in Indonesia (Nurwardani, 2018a), as well as in the United States where the industrial internet has developed (Annunziata & Evans, 2012). Industry 4.0 is often compared to an increase in products such as the industrial revolution initiated by the presence of steam engines, electricity, and others. Similar to Industry 4.0, this "revolution" was started not by a single technology, but by the interaction of the number of technological advances whose quantitative effects created new modes of production.

New manufacturing technology has always been a competitive advantage for companies because it helps produce faster and more flexible, where rapid advances in manufacturing technology have also contributed to industrial development. Industry 4.0 is a term for the realistic concept of the next industrial revolution. The central vision of the 4th industrial revolution is the emergence of smart factories. In smart factories, sensors, machines, and IT systems will be connected to cyber-physical systems - CPS (Benesova et al., 2018).

The building blocks of Industry 4.0 are nine essential technologies - autonomous robots, internet of things (IoT), big data, simulations, vertical and horizontal system integration, cloud computing, cybersecurity, cybersecurity, additive manufacturing, and augmented reality. These nine technology trends will turn production into a fully integrated, automated, and optimized production flow. Smart manufacturing will help achieve a manufacturing process that is flexible, smart, and can be reconfigured to deal with dynamic markets. This industrial revolution not only had an impact on the industry but also on the labor market and education. Some professions and jobs have disappeared. The main reason for this impact is the change in educational requirements on employees. Controlling, maintaining, and operating new technology will only require qualified employees (Benesova et al., 2018; Rüßmann et al., 2015).

Along with the introduction of Industry 4.0 also introduced Education 4.0, which is a term for the concept of education in the new digital era. New technology trends, such as augmented reality will be implemented in the education system. This new education system will combine real and virtual world information (Quint, Sebastian & Gorecky, 2015). It is hoped that the number of students will increase in the field of technical studies because every company will need employees with professional education.

For this reason, young people must be educated in areas such as robotics, cybernetics, data analysis, and other mechanical or natural sciences. Future graduates must be trained in line with Industry 4.0. It is problematic because it is not clear how innovation will develop and what qualifications and future knowledge graduates need for their profession in Industry 4.0.

Collaboration between schools and universities and companies will be essential for Education 4.0. In many cases, it will be necessary to educate and retrain current company employees because their education and knowledge may not be enough for the company's future needs. At present, the lack of qualified employees is one of the highest risks for Industry 4.0. For this reason, new technological trends (virtual learning environments, factory learning, or augmented reality) must be included in education (Motyl et al., 2017).

Several studies have observed ways to transform education itself following Industry 4.0 principles, while at the same time, some recommend more

transformation of tertiary education by adjusting to the vision of Industry 4.0 and several steps to make the educational experience of students individual expertise needed in the industrial world. Coşkun et al. (2019) report on the acceptance of digital education technology especially in vocational education. They emphasized the role of digital media as a means for individualizing instruction like Industry 4.0. They created a condition variable model for education 4.0, which consisted of changes in technology and processes, changes in teaching and learning, changes in interests and economic models, and social-professional discourse. Intelligent machines, machine to machine communication (M2M), data security, big data, support systems such as mixed reality systems are the fields they emphasize in changing technology. In transforming teaching and learning, they consider individualization of learning, on-demand learning, cloud learning, and innovative learning environments such as mixed reality simulations, augmented reality, and remote laboratories.

Tenberg and Pittich (2017) discuss and analyze the impact of industry 4.0, especially on vocational education. They came to the exciting conclusion that the adoption of industry 4.0 could result in a decrease in the share of vocational education for higher education if the necessary steps were not taken to change vocational education fundamentally. In the context of our work, this can be interpreted in a way that technical education in industry 4.0 cannot be imagined without linking it to practice and direct employment because there is a risk of lack of adequate sources of technical support from vocational education.

Literature Review

The concept of "Industry 4.0" first appeared in an article published by the German Government in November 2011, as a high-tech strategy for 2020. After mechanisation, electrification and information, the fourth stage of industrialisation was named "Industry 4.0". In April 2013, the term "Industry 4.0" reappeared at an industry exhibition in Hannover, Germany, and quickly emerged as a strategy of German citizens. In recent years, "Industry 4.0" has been widely used for discussion, and has become a hotspot for most global and information industries. Industry 4.0 wants to be the new industrial revolution, which wants to have a big influence on international industry (Zhou & Zhou, 2015).

Throughout history, there have been four major phases of the industrial revolution (Geissler & Horstkötter, 2014; Lasi et al., 2014). The Industrial Revolution 1.0 took place in the years 1750-1850, Industrial Revolution 2.0, known as the phase of technological change that was large in the industrial sector. The 2.0 industrial revolution took place in 1870 - 1914 (beginning of World War I). The emergence of combustion chamber combustion, power generation and motorcycles, telephones, cars, aircraft and others is a feature of the industrial revolution 2.0. The 3.0 industrial revolution was marked by the presence of digital technology and the internet. In the industrial revolution 4.0, new patterns were discovered along with the presence of disruptive technology. Industry 4.0 describes the current concept as a collective concept. The following are essential components of Industry 4.0 according to Lucke et all. (2008), among others; 1) smart factory,

2) cyber-physical systems, 3) self-organisation, 4) new systems in sales and procurement, 5) new systems in product and development services, 6) adaptation to humans, 7) corporate social responsibility.

According to Suwardana (2018), the key to the existence of change itself is innovation. Innovation is the most crucial factor in determining competitiveness. Achievement of innovation is committed to what extent a business organisation can optimise the body of knowledge, technology transfer, business incubation, science and technopark. There are five critical elements that the government will implement to stimulate the nation's economic growth and competitiveness in industry 4.0, including 1) implementing innovative learning systems; 2) review campus institutional policies to be more adaptive and responsive; 3) improving the quality of HR lecturers, researchers, and engineers; 4) research innovations that support industry 4.0; and 5) innovation and system strengthening to increase industrial output and encourage the birth of technology-based start-up (Wisnubro, 2018).

According to Mobnasesemka (2018), the Industrial IoT 4.0 instrument was recognized with IoT or Industrial Internet of Things; previously, it was beneficial for internal monitoring. Furthermore, in his scientific article Rüßmann et al. (2015) stated, there are at least nine industries 4.0 pillars, among others, reported as follows; big data and analytics, autonomous robots, simulation, horizontal and vertical integration of IT systems, the industrial internet of things, cybersecurity, the cloud, additive manufacturing and augmented reality.

Sanders et al. (2016) show six design principles, derived from Industry 4.0 technology, which support companies in identifying possible pilot projects: 1) interoperability, 2) virtualization, 3) decentralization, 4) real-time capabilities, 5) service orientation and 6) modularity. Despite growing fame, various companies are still struggling to understand the whole idea of Industry 4.0 and specific concepts and principles that are in it. Nurwardani (2018b) argues, there are at least 10 HR competencies needed during the 4.0 industrial revolution, namely: 1) sense-making, 2) social intelligence, 3) novel and adaptive thinking, 4) cross-cultural competence, 5) computational thinking, 6) new-media literacy, 7) transdisciplinary, 8) mindset design, 9) cognitive load management and 10) virtualcollaboration.

Putubuku (2008) suggests the theory of sense-making, especially to understand the search for strategic data and information. In order to use sense-making, one must master aspects of ontology and epistemology. Simply put, "ontology" is the element of "what" (the nature of phenomena) while "epistemology" is the element of "how to understand" what that element is. According to Rahim et al. (2017) social, intelligent includes; a) empathy, (b) alignment, c) empathic accuracy, d) social understanding, e) synchronization, f) presentation, g) influence and h) caring.

While novels and adaptive thinking may be easy for some people, others can strengthen their skills by practicing the following steps: a) realize, b) allow, c) control, d) be open, e) anticipate, f) ask questions, and g) assess. The National Research Council (NRC), introduces reasoning that according to the researcher

includes the ability of induction and deduction which is then added with the term adaptive logic. The researcher, namely Killpatrick et al. (2001: 116), defines adaptive reasoning (adaptive reasoning) as the ability of students to do in-depth analysis (Choiriyah, 2015).

Cross-cultural competence refers to knowledge, skills, and influences/motivations that enable individuals to adapt effectively in a cross-cultural environment. Cross-cultural competence is defined here as an individual's ability to contribute to intercultural effectiveness regardless of the intersection of a particular culture. Although some aspects of cognition, behavior, or influence may be very relevant in certain countries or regions, the evidence shows that a set of core competencies allows adaptation to any culture (Wiseman & Jolene, 1993). Cross-cultural competence is not an end in itself but is a set of variables that contribute to intercultural effectiveness. The results show that cross-cultural competency is needed in many ways, especially in the world of work (Daraiseh, 2018); (Perez et al., 2019); (Barzykowski et al., 2019). Leiba-O'Sullivan (1999) suggests the dimensions of cross-cultural competency include; emotional stability, extraversion (comfort interacting with others), agreeableness, openness to experience, conscientiousness.

Computational thinking is a term that is currently used to refer to ideas and concepts in the application of various fields of informatics. Internationally, there have been differences of opinion regarding the importance of computer science (as content and as one of the general capabilities). The characteristics of computational thinking include the following; "1) formulating problems with the use of computers, 2) designing logic concepts in grouping and analyzing data, 3) presenting data through abstraction models or simulations, 4) algorithmic thinking solutions (a series of steps), 5) implementing the most economical possible solutions and effective and 6) generalization" (Bocconi et al. 2016). Rojas-Lopez & Garcia-Penalvo (2018) mentioned that computational thinking skills include aspects; abstraction (understanding), decomposition (analysis process), generalization (localizing problems, solving problems, making changes), evaluation (conducting evaluation processes) and algorithmic design (comparing and looking for other alternatives in solving problems).

Media literacy is an effective and efficient skill in using mass communication (Strasburger & Wilson, 2002). Another expert Potter (2005) in Poerwaningtias et al., (2013) defines media literacy as the ability to interpret the message received and how to anticipate it. Livingstone (2004) suggests that new media literacy is a skill to access, analyze, evaluate, and create messages in various contexts. His research identifies some extraordinary problems for new media literacy that are important for policies promoting media literacy among populations. The result is to broaden our understanding of media literacy to include historically and culturally conditioned relations between three processes: (i) symbolic and material representations of knowledge, culture, and values; (ii) diffusion of interpretative skills and abilities across populations (stratified); and (iii) institutional, in particular, state management of the power that access to and use of skilled

knowledge brings to those who are 'literate'. Chen & Lee (2018) mentioned that indicators of new media literacy include; a) consuming functional literacy, consisting of absorbing skills and understanding, b) critical consuming literacy, consisting of analysis, synthesis and evaluation c) functional presuming literacy covering aspects of presuming skills, distribution and production and d) critical presuming literacy, which includes aspects participation and creation.

The meaning of transdisciplinary is; merging two or more disciplines. Transdisciplinary is an attempt to solve a problem by uniting several disciplines into a single unit or across disciplines (Nicolescu, 2002). According to Montuori (2013), complexity and transdisciplinary are very relevant in an increasingly diverse, networked, uncertain and fast-changing world. Examples are drawn from personal experience in academics, cross-cultural encounters, and the arts. Tejedor et al. (2018) bring together the elements of transdisciplinary, among others; a) transcendence and b) problem solving (real word argument and innovation argument).

The design mindset is one of the skills included in the Institute for the Future (IFTF) Future Work Skill 2020. The mindset design is a relatively new discourse but is increasingly being adopted in so many occupations and industries, even though it is not visually visible. IFTF defines the design mindset as "the ability to represent and develop tasks and work processes for desired results," while Naiman (2019) prefers to think of it as a strategy that focuses on solutions for decision making and problem-solving. This process, according to Naiman, refers to logic, intuition, imagination and systemic reasoning to explore possibilities and realize desired outputs that are beneficial to users. What is meant by design thinking is the ability to empathize, think creatively, collaborate productively, experiment with various solutions and communicate ideas, where these skills can be learned by everyone (Kelly et al., 2018).

Cognitive load management theory aims to predict learning output by considering the abilities and limitations of human cognitive architecture (Paas et al., 2004; Paas et al., 2003; Plaas et al., 2010; Plass & Kalyuga, 2019). Cognitive load management theory is a theory about the gap between task demands and one's abilities (Moray, 2013). Cognitive load theory is a theory that explains the amount of working memory to process information (Cooper, 1990). Cognitive load management is a theory that starts from teaching theory, based on cognitive architecture (Sweller, 2010). According to Sari (2012), how to manage cognitive load in learning can be divided into intrinsic cognitive load and foreign cognitive load (Tonra, 2014). Cognitive load theory, according to Sweller (2010) states that cognitive load is caused by 1) intrinsic cognitive load, 2) extraneous cognitive load, and 3) germane cognitive load.

In the work of standard forms of virtual collaboration, among others, virtual teams, virtual learning-distance education, virtual meetings (Chen et al., 2004). A number of the most important studies have been conducted related to virtual collaboration, among others, led by Beavers et al. (2017); Rennstich (2019); Zhang et al. (2018); dan Srivastava and Chandra (2018). According to Rennstich (2019),

an online collaborative creative process consists of all activities aimed at solving group problems that do not have standard solutions, which are mediated through web-based tools. Usually, such issues require interdisciplinary, lateral thinking, social empathy, and broad ideas with the aim of mutual inspiration. The processes applied are often nonlinear and depend on synchronous and asynchronous multimodal communication methods, with a particular focus on visual tools.Virtual collaboration is an activity related to the extensive use of technology channels for team members to work together on completing project tasks (Zhang etal., 2018; Peters & Manz, 2007).

Tortorella and Fettermann (2018) examined the relationship between lean production (LP) and the application of industry 4.0 in Brazilian manufacturing companies. The findings show that LP practices are positively related to industry technology 4.0, and their concurrent use leads to more significant performance improvement. Furthermore, the contextual variables being investigated are indeed crucial for this association, although not all aspects are essential at the same level and effect. Anwar et al. (2018) suggested that character building is not only done in formal education (educational institutions), but non-formal education (parents, friends, and organizations) also has a significant impact on students. In the face of the industrial era 4.0, character building of parents, educational institutions and government are needed.

Motyl et al. (2017) highlight several aspects of student digital behavior and students' consideration of the industrial framework 4.0. Specifically, data describing students' relationships with digital devices and their level of knowledge on specific topics such as virtual, augmented and mixed reality, 3D printing and smart factory are very significant in understanding what students think. Coşkun et al. (2019) in his work introduces a road map consisting of three pillars that describe changes/improvements to be made in the fields of curriculum development, laboratory concepts, and student club activities related to competencies in industry 4.0. Benešová and Tupa (2017) stated that industry vision 4.0 will bring not only new approaches but also methodologies and technologies, which must be introduced to the company. The transition to such sophisticated production will not be possible immediately. The reason is the high financial costs and the lack of qualified employees.

Pfeiffer (2015) outlines specific competencies and qualification requirements concerning the four dimensions relevant to industry qualification 4.0, and, finally, uses it to make recommendations for policymakers, companies and social partners. Benesova et al. (2018) in their research, focused on the educational requirements for manufacturing electronics in modern concept 4.0. The central vision of the idea is smart factories that will be connected by physical-cyber systems. These factories will also use new technologies such as augmented reality. Employee skills and qualifications become essential because control or maintenance will only require employees with high requirements. Education 4.0 is a new concept of education that will combine real and virtual worlds.

Method

The location of this research was carried out in Medan City by taking respondents in several higher education institutions namely; Universitas Sumatera Utara (USU), Universitas Negeri Medan (UNIMED), Universitas Medan Area (UMA), Universitas Dharma Agung (UDA) and Politeknik Negeri Medan (POLMED). USU and UNIMED, in this case, represented state universities. UMA and UDA represent private universities. While Polmed represented vocational/polytechnic education.

The population in this study are all freshly graduated alumni in various tertiary education institutions in the city of Medan. The fresh graduated is obtained from the estimated number of final semester students graduating at each campus in the previous year. So that the population distribution is calculated by the Slovin formula; n = N / (1 + N. e2) = 450 respondents.

This study uses primary data, namely, data obtained from the source directly. Primary data is collected to answer/confirming research questions. Primary data are generally derived from questionnaire distribution activities (Sugiyono, 2012). The form of the questionnaire is closed in which the respondent is given alternative choices of answers to each question. All variables are measured using a Likert scale, using a 5-level range that allows respondents to provide solutions to the research questionnaire. The answer choices include; strongly agree (SS) score 5, agree (S) score 4, disagree (KS) score 3, disagree (TS) score two and strongly disagree (STS) with a score of 1. The design of this research is a quantitative research using statistical analysis (Sugiyono, 2016: 11). This study analyses the dominant factors that influence competence to enter industry 4.0. The number of estimator variables used included ten variables with the Confirmatory Factor Analysis (CFA).

The research variables consist of two types, namely the independent variable and the dependent variable. The independent variable is a variable that affects or causes changes to the dependent variable. The independent variables in this study include; 1) Sensemaking, 2) Social intelligence, 3) Novel and adaptive thinking, 4) Cross-cultural competency, 5) Computational thinking, 6) New-media literacy, 7) Transdisciplinary, 8) Design Thinking, 9) Cognitive Load Management, and 10) Virtual collaboration. The dependent variable is a variable that is influenced by the independent variable, so the amount of change in the dependent variable depends on the magnitude of the effect that is done by the independent variable. The dependent variable in this study was the readiness of students to face Industry 4.0.

The stages of data analysis in this study began with the validity test; to see how the accuracy and accuracy of measuring instruments in determining the size function (Azwar, 2009: 5). A tool is declared valid if it can measure the variables appropriately (Arikunto, 2006). Validity itself comes from the word validity, which means the extent to which an instrument has accuracy and accuracy in justifying its measurement function (Azwar, 2009: 5). After the validity test, the reliability test is then performed; to see the extent to which the results of a measurement can be trusted (Azwar, 2009: 3). Then proceed with the normality test and the data

outlier test. With univariate normality and multivariate data used in this analysis, normality tests can be tested. Testing this univariate normality is to observe the value of the skewness of the data used in the CR value in the skewness data is in the range between + 2.58 at a significance level of 0.01, then the research data used can be said to be normal. While the outlier test by looking at the value of Mahalanobis distance. If the Mahalanobis distance is higher than the chi-square value, it means that it is categorized as multivariate outliers.

After passing the testing stages, the data are then analyzed using Confirmatory Factor Analysis (CFA). Where Brown and More in Hoyle (2012: 361) suggest that CFA is a type of structural modeling equation that specifically addresses measurement models, that is, the relationship between observed steps or indicators (for example, test items, test scores, behavior observation ranks) and latent variables or factors. CFA is a technique used to look for factors that can explain the relationship or correlation between various independent indicators that are observed (Widarjono, 2010:235). Because the indicators used are derived from existing theoretical foundations, this factor analyst is a confirmatory factor analysis, which is an analysis that aims to test the theory empirically or confirm the structure of existing factors (Gudono, 2011: 207).

Findings and Discussion

The composition of respondents by sex is spread proportionally between men and women. From a total of 450 research respondents, consisting of 225 male respondents (50%) and 225 (50%) female respondents. Likewise, the composition of respondents based on the origin of higher education is spread proportionally. The number of respondents from USU totaled 97 respondents (20.8%), from UNIMED 94 respondents (20.2%), from UMA as many as 88 respondents (18.9%), from UDA 92 respondents (19.7%) and Polmed 95 respondent (20.4%).

The sense-making variable (X1) in this study was measured using three items based on three leading indicators. The overall average value of 4.270. Of the three indicators used, the indicator with the highest average value is X1.1 (perspective) with a value of 4.293, while the lowest value is X1.2 (self-meaning) with a value of 4.252. The social intelligence (X2) variable in this study was measured using three statements based on three leading indicators. The overall average score is 4,302. Of the three indicators used, the indicator with the highest average value is X2.1 (empathy) with a value of 4.332, while the lowest value is X2.3 (influence in groups) with a value of 4.329.

Novel and adaptive thinking (X3) variables in this study were measured using three items based on three leading indicators. The overall average score is 4,281. Of the three indicators used, the indicator with the highest average value is X3.3 (concept and procedure) with a value of 4.421 while the lowest value is X3.2 (prediction) with a value of 4.288. The cross-cultural competence (X4) variable in this study was measured using three statements based on three leading indicators. The overall average value of 4.220. Of the three indicators used, the indicator with the highest average value is X4.2 (extraversion/comfort interacting with others)

with a value of 4.292, while the lowest value is X4.3 (openness to experience) with a value of 4.160.

The computational thinking (X5) variable in this study was measured using three items based on three leading indicators — the overall average value of 4.190. Of the three indicators used, the indicator with the highest average value is X5.2 (abstraction and decomposition) with a value of 4.240, while the lowest value is X5.3 (algorithmic design) with a value of 4,165. The new media literacy (X6) variable in this study measured using three statements based on three leading indicators. The overall average value of 4.217. Of the three indicators used, the indicator with the highest average value is X6.1 (functional and critical consuming literacy) with an amount of 4.240 while the lowest value is X6.3 (critical presuming literacy) with an amount of 4.184.

Transdisciplinary variables (X7) in this study were measured using 3 statements based on three leading indicators. The overall average score is 4.261. Of the three indicators used, the indicator with the highest average value is X7.3 (problem-solving - innovation argument) with a value of 4.240, while the lowest value is X7.1 (transcendence) with a value of 4.251. The design thinking variable (X8) in this study was measured using three statements based on three leading indicators. The overall average value of 4.184. Of the three indicators used, the indicator with the highest average value is X8.2 (courage to experiment) with a value of 4.204 while the lowest value is X8.1 (communication of ideas) with a value of 4.162.

Cognitive load management (X9) variables in this study were measured using three statements based on three leading indicators. The overall average value of 4.083. Of the three indicators used, the indicator with the highest average value is X9.2 (extraneous cognitive load - extrinsic cognitive load complexity due to distortion of expectations and reality) with a value of 4.117 while the lowest value is X9.1 (intrinsic cognitive load - complexity of cognitive load intrinsically) with a value of 4.076. The virtual collaboration variable (X10) in this study was measured using three statements based on three leading indicators. The overall average value of 4.046. Of the three indicators used, the indicator with the highest average value is X10.1 (virtual team) with a value of 4.047, while the lowest value is X10.3 (virtual meeting) with a value of 4.033. While the readiness to face the industry 4.0 variable in this study was measured using three statements based on three leading indicators — the overall average value of 4,372. Of the three indicators used, the indicator with the highest average value is Y1.3 (skill readiness and competence) with a value of 4.047, while the lowest value is Y1.1 (mental readiness) with a value of 4.033. Based on the mean results of the data processing, it can be arranged the number of respondents' preferences for the research variables, as presented in Table 1.

Table 1. Ranking of respondents' answer preferences on research variables

No	Indicators	Mean	Rank
1	X1 Sense making	4,270	4
2	X2 Social intelligence	4,302	2
3	X3 Novel and adaptive thinking	4,281	3
4	X4 Cross cultural competency	4,220	6
5	X5 Computational Thinking	4,190	8
6	X6 New Media Literacy	4,217	7
7	X7 Transdisciplinary	4,261	5
8	X8 Design Thinking	4,184	9
9	X9 Cognitive Load Management	4,083	10
10	X10 Virtual Collaboration	4,046	11
11	Y1 Readiness to enter industry 4.0	4,372	1

A validity test is done by a convergent validity test, which is testing the construct (indicator) whether it has a high proportion of variance or not. Meet the criteria if the value of C.R. > 1.96, while the loading factor or standardized loading estimate > 0.5. The results of data analysis showed that the CR values of all question items > 1.96 and loading factor values > 0.5 so that it can be concluded that all items used in this study were valid. The reliability test is carried out by using the construct reliability test, which is testing the reliability and consistency of the data. Meet the criteria if Construct Reliability > 0.7. Construct Reliability values between 0.6 to 0.7 can still be accepted, provided that the construct validity (indicator) in the model is good.

Ghozali (2013) explains that indicators of variables are called reliable if the value of AVE ≥ 0.05 and CR ≥ 0.07. The reliability test results of all variables declared valid. Testing the next data is to analyze the level of normality of the data used in this study. Based on data analysis obtained that there is no CR value outside + 2.58 so that it can be concluded that univariate is good. The normality test is carried out using a critical ratio criterion of ± 2.58 at a significance level of 0.01 (Ghozali, 2004: 105) so that it can be concluded that there are no distorted data. Whereas the multivariate outliers test can be seen in the Mahalanobis distance at the level of $p < 0.05$. Based on the Chi-square value with 360 degrees of freedom at a significance level of 0.001 which is 405.24, the Mahalanobis value that exceeds or is above 405.24 identifies the presence of multivariate outlier's data. Based on the data, it appears that the highest value lies in the 464 observation of 265,288 which is still below 405.24 and it can be concluded that there are no multivariate outliers from the data used in this study.

As stated in this study using Confirmatory Factor Analysis (CFA), Hoyle (2012:361) argues that CFA is a type of structural modeling equation that addresses the measurement model explicitly, that is, the relationship between the observed steps or indicators (for example, test items, test scores, behavioral observation ratings) and latent variables or factors. CFA is a technique used to look for factors that can explain the relationship or correlation between various independent indicators that are observed (Widarjono, 2010:235). Because the indicators used

are derived from existing theoretical foundations, this factor analyst is a confirmatory factor analysis, which is an analysis that aims to test the theory empirically or confirm the structure of existing factors (Gudono, 2011:207). Furthermore, to see whether or not the CFA result can be seen from the size of the loading factor (estimate) of each variable construct. It can also be seen from the value of Average Variance Extracted (AVE) which must be ≥ 0.05 and CR value ≥ 0.07. In addition, observations are also used on the output goodness of fit. Related to the output results, the CR and AVE values have been stated previously, where the variables and constructs have met the specified criteria. Furthermore, based on Figure 1, it is found that all-important indicators report that the model used is good and meets the required goodness of fit criteria. A loading factor value of > 0.5 indicates that all constructs used to meet the criteria and the variables used are representative enough to be an industry competency model 4.0.

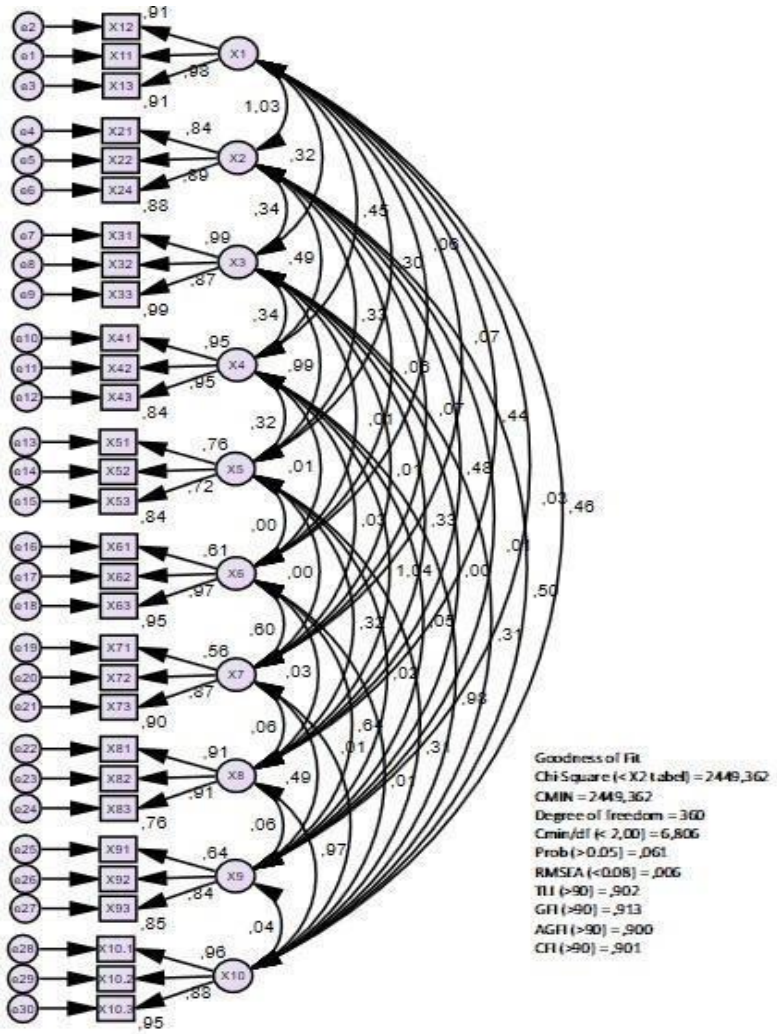


Figure 1. Output Confirmatory Factor Analysis (CFA)

Furthermore, after all the validity of the variables is proven, the next step is to analyze the effect of each of these variables on the dependent variable, namely the readiness of students to enter industry 4.0. Estimation results are presented in Figure 2.

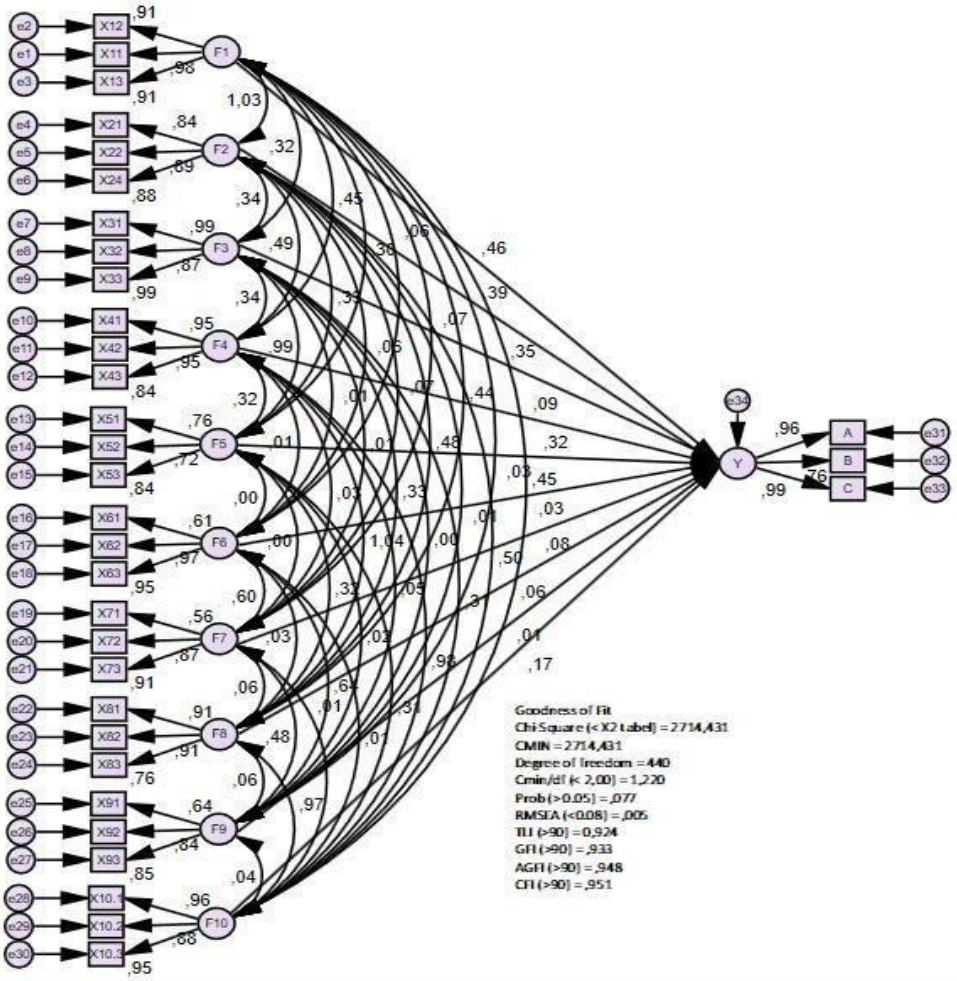


Figure 2. Output Full Model Readiness to Enter Industry 4.0

From Table 24, it can be seen that this human resource competency model has met the criteria for the goodness of fit. This is indicated by the value of TLI, CFI, and GFI which are close to 1. The TLI value is 0.924, and the CFI value is 0.951 while the GFI value is 0.933.

Table 1. The Goodness of Fit Model HRD Competency to Face Industry 4.0

Indicators of Goodness of Fit	Rule of Thumb Goodness of Fit	Result	Conclusion
Chi square (Cmin)	Smaller is better	2714,431	Fit
Degree of freedom	The value should be +	440	Fit
Probability	> 0,05	0,061	Fit
RMSEA	0,05≤RMSEA≤0,08	0,005	Fit
Tucker Lewis Index (TLI)	0,80≤TLI≤1	0,924	Fit
Composite Fit Index (CFI)	0,80≤CFI≤1	0,951	Fit
Goodness of Fit Index (GFI)	0,80≤GFI≤1	0,933	Fit

The results of hypothesis testing prove that the coefficient estimation of the sense-making variable (X1) is positive at 0.355. This variable has a positive influence on the readiness of HR competencies facing industry 4.0 (Y). Statistically, the effect was significant because of p-value 0.006 <0.05 and CR value
2.772> 1.96. The estimated coefficient of social intelligence (X2) is positive by 0.311. This variable has a positive influence on the readiness of HR competencies facing industry 4.0 (Y) and statistically, the effect is significant because the p-value is 0.031 <0.05 and the CR value is 2.157> 1.96. The estimated coefficient of the novel and adaptive thinking (X3) variable is positive at 0.421. This variable has a positive influence on the readiness of HR competencies facing industry 4.0 (Y), and statistically, the effect is significant because the p-value is 0.048 <0.05 and the CR value is 2.192> 1.96.

The estimated coefficient of the cross-cultural competence (X4) variable is positive at 0.068. This variable has a positive influence on the readiness of HR competencies facing industry 4.0 (Y), and statistically, the effect is significant because the p-value is 0.028 <0.05 and the CR value is 2.632> 1.96. The estimated coefficient of the conceptual thinking variable (X5) is positive at 0.396. This variable has a positive influence on the readiness of HR competencies facing industry 4.0 (Y) and statistically, the effect is significant because the p-value is 0.003 <0.05 and the CR value is 2.176> 1.96. The estimated coefficient of the new media literacy (X6) variable is positive at 0.025. This variable has a positive influence on the readiness of HR competencies facing industry 4.0 (Y) and statistically, the effect is not significant because the p-value is 0.491> 0.05 and the CR value is 0.689 <1.96.

Furthermore, the estimated coefficient of the transdisciplinary variable (X7) is positive at 0.056. This variable has a positive influence on the readiness of HR competencies facing industry 4.0 (Y), and statistically, the effect is significant because the p-value is 0.003 <0.05 and the CR value is 2.632> 1.96. The estimated coefficient of design thinking variable (X8) is positive at 0.047. This variable has a positive influence on the readiness of HR competencies facing industry 4.0 (Y) and statistically, the effect is not significant because the p-value is 0.892 <0.05 and the CR value is 0.136 <1.96. The estimated coefficient of cognitive load

management (X9) is positive at 0.011. This variable has a positive influence on the readiness of HR competencies facing industry 4.0 (Y) and statistically, the effect is significant because the p-value is 0.035 <0.05 and the CR value is 2.208> 1.96. The estimated coefficient of the virtual collaboration variable (X10) is positive at 0.147. This variable has a positive influence on the readiness of HR competencies facing industry 4.0 (Y) and statistically, the effect is significant because the p-value is 0.010 <0.05 and the CR value is 2.373> 1.96.

Table. 3 Hypothesis testing with CR value and probability

			Estimate	S.E.	C.R.	P	Label
Y	<---	X1 Sense making	,355	,128	2,772	,006	Sig
Y	<---	X2 Social intelligence	,311	,144	2,157	,031	Sig
Y	<---	X3 Novelty Adaptive	,421	2,195	2,192	,048	Sig
Y	<---	X4 Cross Cultural Com	,068	,108	2,632	,028	Sig
			Estimate	S.E.	C.R.	P	Label
Y	<---	X5 Computational Thinking	,396	2,254	2,176	,050	Sig
Y	<---	X6 New Media Literacy	,025	,036	,689	,491	Not sig
Y	<---	X7 Transdisciplinary	,056	,034	2,632	,003	Sig
Y	<---	X8 Design Thinking	,047	,346	,136	,892	Not sig
Y	<---	X9 Cognitive Load Mgt	,011	,051	2,208	,035	Sig
Y	<---	X10 Virtual Collaboration	,147	,395	2,371	,010	Sig

Conclusion

The results of this study indicate that based on the results of confirmatory factor analysis - CFA, ten variables used have a positive relationship/correlation between variables and can be an estimator to see how fresh human resources are prepared in facing industry 4.0. The results of the analysis using the SEM method show that there are eight variables that are positive and significantly affect the readiness of industrial 4.0 human resources, namely; sense-making, social intelligence, novel and adaptive thinking, cross-cultural communication, computational thinking, transdisciplinary, cognitive load management and virtual collaboration. Whereas the two insignificant variables are new media literacy and design thinking.

The recommended recommendations related to this research are theinstitutions providing higher education, in an effort to encourage improvement in the quality of human resources, especially in anticipating industry 4.0 to notice andmaximize aspects; sense-making, social intelligence, novel and adaptive thinking, cross-cultural competency, computational thinking, new media literacy, transdisciplinary, design thinking, cognitive load management, and virtual collaboration. Other researchers who will continue this research with the same theme are expected to be able to develop this research model to become more complex, such as adding new variables and carried out on different objects from previous research so that other studies will be created in the future.

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