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Digital Competency and Performance Efficiency Among Statistical Educators During Covid-19 Using Hybridized DEA-ML Model: A Preliminary Study

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Abstract

The education system nowadays changes according to the development of world communication technology. Educators need to change the online system in line with the government's proposition. Thus, the primary goal was the development of a research framework to assess the digital efficiency with which teachers of STA 404 statistics operate. There are three objectives were proposed [1] to determine the digital competencies level among the STA 404 statistics educators, [2] to model the performance efficiency score among STA 404 statistics educators using the Data Envelopment Analysis (DEA) method, and [3] to predict the performance efficiency score among STA 404 statistics educators using Machine Learning (ML). 42 educators have experience teaching STA 404 but only 10 of the educators are to be sampled to evaluate the questionnaire's reliability and validity. Thus, the current work aimed to create an innovative DEA hybrid model that featured an appropriate ML algorithm with the capability to measure the digital efficiency with which teachers of STA 404 statistics operated. By applying this hybrid model, educators or researchers could generate new knowledge.

Keywords: Digital Competency, Performance Efficiency, Education 5.0, Data Envelopment Analysis, Machine Learning

Introduction

In the current situation of the Covid19 pandemic, the education system is changing in line with the development of world communication technology. The Ministries of Education and Higher Education have both determined that conventional systems of learning need to transition to online formats. However, adapting to online learning sessions is not as easy as one might think. Therefore, educators must play a role in expanding digital abilities to ensure that knowledge can be conveyed to students so that the teaching and learning process can be implemented effectively. Thus, they had to increase their teaching and learning competence specifically digital competence.

Within the eight core competencies, digital competence is a crucial element. It means using digital tools confidently and critically when dealing with information, communicating and solving fundamental problems in every aspect of life. Despite the fact that many educators at all levels recognise the importance of digital competence in enhancing the quality of teaching and learning, few have mastered it. As indicated in an existing work, whereas digital learning content is often embraced by pre-service teachers, they are frequently under-prepared to make it. While the cultivation of toleration when communicating is often demonstrated by such teachers, they tend to be unable to exhibit empathy; furthermore, despite their wish for learning management autonomy, they must be trained to digital self-present more professionally (Yakovleva, 2022).

Moreover, Zabolotska et al (2021) found that less than half (46%) of respondents used such tools regularly, indicating that the degree of knowledge and competence to use digital technology in the management of the educational process among research and teaching staff is relatively average. This situation leads to difficulties not only for educators but also for the student to manage online classes. Wahid et al (2021) indicated that both students and teachers had obstacles in adopting online teaching, but they were forced to do so since they did not experience online teaching, particularly online assessment, to the same level as face-to-face instruction (in person or classrooms).

Thus, the current study aimed to employ a Data Envelopment Analysis (DEA) approach to assess the digital efficiency with which educators of STA 404 statistics subject. To do this, the research process started with the development of the research process. Suitable inputs and outputs were identified that could be effective in conducting a performance evaluation of the decision-making unit (DMU). Data Envelopment Analysis in online learning will give a hand in identifying the digital competency of educators. Meanwhile, since big data is rapidly developing, real-world datasets are experiencing similar rapid growth. Within the context of the rapidly expanding management of data, the area of education has also experienced considerable changes. This becomes a great challenge for the researchers because they have to face complex datasets. Then, Machine Learning (ML) approaches have been developed rapidly in their capabilities to handle the massive development of data. This study is expected to guide BHEA and academics in higher education institutions in promoting best sustainable practices in online learning and to help improve a well-implemented study plan in an academic environment.

Literature Review

The Classification of Inputs and Outputs in Data Envelopment Analysis

The introduction of DEA is normally part of an approach to mathematical programming in which the relative efficiency of a DMU is measured in the presence of more than one input and output. A crucial stage to examine initially was selecting the variables for the input and output. The capacity of DEA to produce scores for efficiency while more than one input and output are accommodated is one of its key assets (Cook & Zhu, 2007). Traditionally in the DEA model, it assumes that the status of each performance factor has a predetermined whether or not as an input or output. Sometimes it is known but sometimes not known. The unclear known type of factor can be referred to as a flexible measure (Toloo et al., 2021).

In general with DEA, inputs are minimised while outputs are maximised; that is, when inputs are at lower levels and outputs are at higher levels, this represents improved performance or more efficient operations. Therefore, one would have to efficiently classify these factors into input and output for use in DEA. Previous studies found that even though some researchers understand the concept of inputs and outputs, it does not guide the input and output variables (Nataraja & Johnson, 2011). Many researchers neglect to focus on this concept, frequently paying scant attention to making sure the chosen measures are a proper reflection of the process being studied to the maximum possible extent. For example, a study conducted by (Charnes et al., 1978) when developed in a ratio form of input and output; however, they provide little rationalization regarding appropriate variables (inputs and outputs) for studying student performance. Another example of unclear status (classified as input or output) of the variables is (Beasley, 1990) mentioned that in university departments' efficiency measurement, the quality of research income factor is unclear.

The determination of the role of the significant factor as input (predictor) and output (outcome) can easily be identified by using a parametric method such as regression analysis. It is the same as using the DEA method. However, the DEA formulation does not provide guidelines for selecting input and output. It will soon become more complex when it cannot identify the status of the factors. Finally, it will have an impact (Villanueva-Cantillo & Munoz-Marquez, 2021) on the efficiency score. So that such problems could be solved, the conventional model of the returns to scale was modified by Cook and Zhu (2007) in such a way that the analysis could include these flexible measures. Then, (Peyrache, Rose, & Sicilia, 2020) introduce cardinality constraints into the DEA program to automatically select the relevant input and output. Meanwhile (Toloo et al., 2021) also develop a new mixed integer linear programming (MILP) model to handle the classification of input and output factors.

Academic Achievement and Digital Competency of the Educator

Recently, it must be acknowledged that at this point, the education system must change in line with the development of the world of communication technology coupled with the current life scenario squeezed by the Covid-19 pandemic. Therefore, in addition to changes in learning methods, assessment methods also need to be changed. Student excellence should no longer be measured based on academic achievement alone.

In education studies, selecting variables that can be used in predicting academic achievement is always ambiguous. Usually, when measuring a student's achievement, the factors that are often taken into account as determinants of a student's excellence are based on their academic achievement. A previous study has shown that ever-changing factors have been taken into account to determine student excellence. All the studies make academic achievement an output. Many variables are believed to have an impact on academic achievement. The determination of the antecedents of academic achievement is based on the outcome of the educational institutions.

However, recently, the focus has begun to focus on the level of educators' digital competency as the determinant of students' academic achievement qualitatively. For example, Yakovleva (2022) analyse the value mindsets of pre-service teachers in terms of the digital learning environment (DLE) and found that pre-service teachers value digital learning content but are not sufficiently ready for its creation. Wong & Moorhouse (2021) examines the experiences of primary and secondary school English language teachers' digital competence as they navigated digital resources, teaching and learning, assessment, and empowering learners in an emergency remote teaching context.

Digital Competency

The concept of competencies in education, in higher education, emerged at the beginning of the 21st century, as a result of changing demands in the labor market. Digital competencies are a relatively new concept and refer to skills required for the utilization of digital technology in specific content (Roll & Ifenthaler, 2021). Digital competency can be defined as the range of knowledge and skillset needed to undertake a particular task involving digital technology (Rasmussen et al. 2018). Research suggests that broader experiences and having the personal capacity and confidence to undertake a particular task both enhance an individual's digital competency (Desjardins et al., 2015).

Moving towards Education 5.0 means that educators need to prepare themselves by expanding their digital competency so that there able to transmit their knowledge effectively to their students. Moreover, educators in the Science and Technology field need to enhance their digital competency more compare to other fields since they are dealing with various software and ICT tools. To improve the methods by which recently graduated teaching staff were prepared for their role in the classroom, Fallon (2020) created a framework for teacher digital competence (TDC). Therefore, it is important to know the level of digital competency of educators so that the management can plan for the course or workshop to enhance digital competency among educators.

Numerous ways to utilise digital technology and the competencies to which it is connected are conceptualised in the multidimensional framework of the GTCU (Desjardins et al., 2001). Multiple contexts are also accommodated by this framework, making it appropriate for use in all areas of life, including educational, domestic, and employment situations. According to the GTCU, all types of physically present equipment that operates via a computer and can be interconnected using a broad network are referred to as digital technology (Desjardins et al., 2001). Through the GTCU, users can employ this form of technology to engage in interaction with a digital device, inter-personal communication, the storage and retrieval of information, as well as the automation of a virtual or physical process. As stated in the GTCU, utilising digital technology for various reasons would allow any user to acquire new skills. These may differ depending on the following four orders of competency (Desjardins, 2001)

- The technical order of competency can be defined as the ways users interact with digital devices. It incorporates the skills required to operate a digital device, manage an account or system, as well as create or edit a document, sound recording, video, or multimedia item.

- The social order of competency can be defined as the ways a user interacts with other people through the use of emails, text messaging, spoken chatting, video conferencing, social media, tools used to collaborate, and shared media.
- The informational order of competency can be defined as the ways a user employs digital technology to interact with information. It incorporates skills like seeking a journal article, video, movie, song, or eBook, as well as using a digital map and numerous types of aggregators.
- The epistemological order of competency can be defined as the ways a user employs digital technology to interact with processes. It incorporates computer-linked skills like how to program, perform a mathematical operation, analyse data, map concepts, share calendars and create diagrams.

Distance Learning

During mid of the year 2019, our education landscape shifted into a new normal landscape. The traditional class (face-to-face method) had to be replaced with distance learning where the process of transmitting information was done by using technology to control the spread of Covid 19. Thus, two entities that have mostly been affected by this situation are educators and students. Both of these entities had to accept and adapt to this new learning environment. The development and organisation of students' digital material need to be linked to specific courses. By 2000, Wang (2012) stated, digital materials would be utilised in interactive learning as part of the development of the principal approaches to learning. To evaluate distance learning performance a few issues had been pointed out by (Xiaoming, Shieh, & Wu, 2014) which are digital material and resources, teaching innovation, student learning abilities, the knowledge management platform, and the acquisition of information and teaching materials. Thus, this study attempts to measure the performance of digital competency of educators during online learning by using data envelopment analysis.

Combination of DEA method and Machine Learning algorithm

Meanwhile, since big data is rapidly developing, real-world datasets are experiencing similar rapid growth. Within the context of the rapidly expanding management of data, the area of education has also experienced considerable changes. This becomes a great challenge for the researchers because they have to face complex and big datasets. Then, Machine Learning (ML) approaches have been developed rapidly in their capabilities to handle the massive development of data. A machine learning algorithm uses sample data (also called "training data'') to build a mathematical model that can predict or decide, despite not containing an explicit program that performs such tasks. Recently, the key drivers of machine learning progression have been the creation of innovative theories and algorithms; the continual expansion in the ways data is accessible online; and the falling costs of computation. In scientific, technological, and commercial settings, data-intensive approaches to machine learning have been adopted, resulting in decisions increasingly being made based on evidence in many areas, such as healthcare, manufacturing, educational facilities, financial models, the police, and product promotion (Jordan & Mitchell, 2015). Operational research studies are not left behind for synergy with ML algorithms. Traditionally, the DEA method had to re-calculation and re-run the efficiency of all DMUs if a new DMU is added. Since nowadays we are facing numerous numbers of datasets growing up quickly, re-calculation or re-run of the process of obtaining efficiency of the DMUs will become a tedious and never-ending story.

Research Methodology

To achieve these three objectives, this study will propose five phases. Phase 1 to phase 3 will be answered by objective 1 while phase 4 will be answered by objective 2. Meanwhile, the last phase (phase 5) will be covered in objective 3. The details are illustrated in Figure 1.

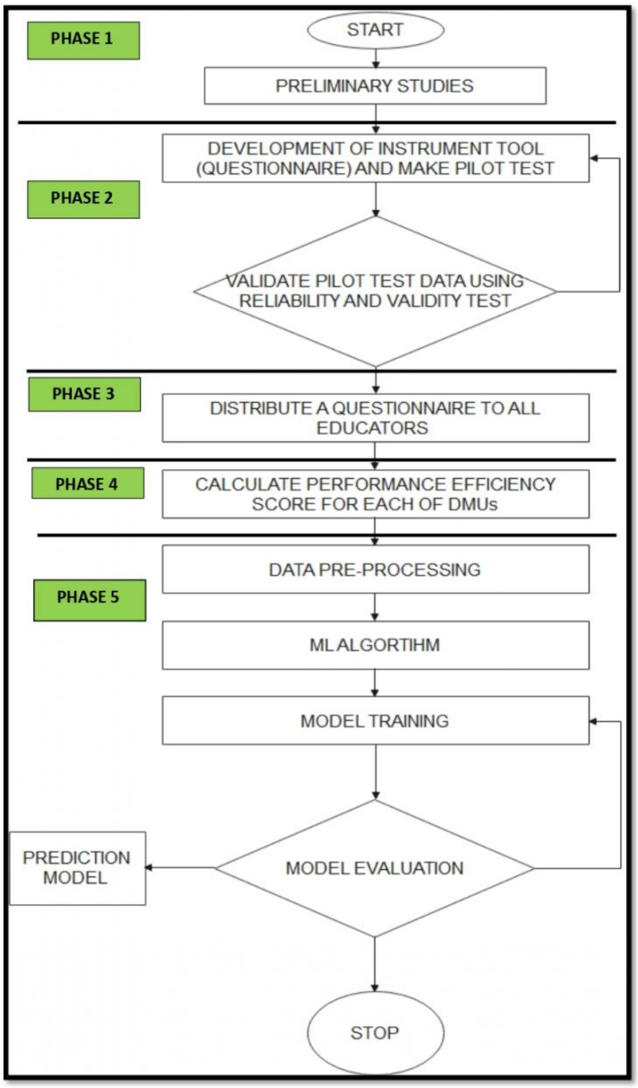

Figure 1. Overall research framework

Research Framework

As seen in Figure 1, this study involves a five-phase method. This study will start preliminary studies by reviewing previous studies related to digital competency. By identifying what is/are the factor(s) that contribute to digital competency, by understanding the elements that influence digital competence among educators, the questionnaire may be better constructed. The total educators included in this study are 42 statistics educators that have experience teaching STA 404. In addition, a preliminary study will be done to collect at least 10 samples to evaluate the questionnaire's reliability and validity. The process of evaluating the questionnaire will be conducted by using Reliability Analysis. Once the questionnaire is found to be reliable and valid, the process data collection method will be implemented. Next, the variable selections undergo a classification of input and output variable procedures. This study uses a direct questionnaire to gather the information needed. Further explanations regarding the phases involved in this study are explained in detail in the next section below.

Data Analysis Procedure

Based on the research framework in Figure 1, the following describes more details on the data analysis procedure of this research.

- Phase 1: Selection of Inputs and Outputs for Digital Competency

  When applying DEA, selecting the inputs and outputs is the principal complication. These are selected using somewhat subjective criteria, and the selection process is not determined by any particular rules. Experts could be requested to choose the most vital inputs and outputs, thus reducing the overall count to more manageable levels.

Screening procedures could also be used as part of both quantitative and qualitative methods.

  Thus, to screen the inputs and outputs, the authors chose the panel expert review. A correlation analysis is performed to test the reliability of the selected indicators. The indicators that are very positively correlated will be selected (with a score higher than 0.90). Thus, this study decided to use personnel expenses, cost of equipment input and output used in this study are described below:

- Phase II: Development of the Research Instrument and Development

  In this stage, the research instrument will be developed. The instrument consists of a series of survey questions that are based on factors in the framework found during Phase 1.

  Before distributing the instrument to the respondents, the instrument will be revised and pilot-tested. Ambiguous survey questions were to be eliminated and the instrument's reliability improved through the pilot test. The pilot study produced findings and feedback that were employed to modify the survey questionnaire. The target respondents are focused educators that teach statistical course (STA 404) at Universiti Teknologi MARA. A questionnaire was conducted and distributed to the respondents. Closed-ended construct-related questions, ten-point Likert scales, and a semantic differential scale were included in the questionnaire. In the current research, ten-point Likert scales were employed, ranging from (1) for *strongly disagree* to (10) for *strongly agree*. The Statistical Package for the Social Sciences (SPSS) v28 was used to analyse the data.

- Phase III: Validating instrument design

  The instruments will be tested using pre-tested through a pilot study. The total of respondents during the pilot survey is 10. The target respondents are focused educators that teach statistical courses (STA 404) at Universiti Teknologi MARA. Besides, exploratory factor analysis (EFA) will be conducted to explore the items and dimensions between variables and respondents. EFA is used to assess the reliability and to select items for measuring the construct. Finally, after the entire relevant tests are performed and verified, the model will be proposed. In this stage, the convenience sampling method will be used in this study.

- Phase IV: Analysing distance learning efficiency by using Data Envelopment Analysis

With DEA, input and output orientation are the two orientation options. The aim of the former is to keep all inputs at given levels of output to a minimum, while the latter aims to keep the output at given levels of input to a maximum. Input orientation was utilised in the current work since the assumption was that digital competency-related inputs could be controlled, unlike the output of academic achievements. The same orientation is used by (Vallespín, 2003).

Evaluating learning through the DEA model is intended to pinpoint teachers who operate efficiently and to examine teachers' digital competency-related performance inefficiencies in the context of attaining the performance goals expected of them. Therefore, the DEA model used two output variables: the value of anticipated performance goals and student performance. These were assessed using individual STA 404 course grades and the ratio of these to the real (attained) values of the performance goals. Then, the efficiency score will be evaluated by using the below information.

Table 1
The Efficiency Score

Categorize	Efficiency score	Slack variable
Strong efficiency	1	All the slack variables are 0
Marginal efficiency	1	At least 1 slack variable not being 0
Marginal inefficiency	0.9	
Obvious inefficiency	<0.75	

- Phase V: Predicting efficiency using DEA model with ML algorithm

In this phase, the selection of the combination between the DEA model and ML algorithm is discussed in the following: First, each DMU in the training datasets was assessed for its efficiency using the DEA model. As a result, marks could be given for a specific DMU based on its technical efficiency (that is, the target variable was DEA efficiency, while the feature variables were the DEA model's input and output indicators). Each DMU marked as efficient by DEA was parsed using the ML algorithm; from this, the rules were learned. ML consists of five phases which are:

Table 2
Phases using Machine Learning (ML) approach

Phase	Description
1	Data pre-processing. Mainly refers to data standardization processing.
2	ML algorithms selection.
3	Model training. Use the training datasets with DMUs "marked" by its DEA efficiency to learn the rules from them, namely what kind of input/output combination can be got the corresponding DEA efficiency?

4	Standard judgments. If the model satisfies the evaluation standard, namely the accuracy and stability of the model meet the requirements, then the trained ML model is obtained. Otherwise, continue training the model.
5	Model prediction. The DEA efficiency of a new DMU can be predicted through the trained ML model. To predict the efficiencies of the DMUs, we just need to add the new DMUs that need to predict efficiency into the testing datasets and run the Python program, then the Python software can automatically calculate its prediction efficiency.

Results and Discussion

Related Studies on Digital Competency Among Educators

This section presents the proposed research framework's new contributions, as presented in the section before. According to our best knowledge based on literature studies, the research framework fills the following research gaps the previous study revealed that the target population for these studies was categorized into three different groups which are educators (teachers, teachers' trainees, pre-service teachers), administration and students (including university students).

Table 3 describes the target population of the studies related to evaluating digital competency among both educators and students. Most of the studies conducted are empirical studies with various numbers of sample sizes. The focus of these studies is on educator experience and difficulties (Wong & Moorhouse, 2021; Mutohhari et al., 2021; Wahid et al., 2021; Chan et al., 2022), investigating the effectiveness of digital competencies among educators (Fahrurrozi et al., 2020; Jorge-Vázquez et al., 2021; Sánchez-Cruzado et al., 2021; Domínguez-Lloria et al., 2021) and identifying level digital literacy in education sectors(Tabieh et al., 2021; Nabhan, 2021; Diz-Otero et al., 2022; Núñez-Canal et al., 2022). Based on here, it was found that the exploration of digital competencies in the education field is still vague and there was much room for exploration that can be done to explore for example in terms of evaluating the efficiency of digital competency among educators or students.

Table 3

Findings of previous research based on target population, sample size, and research method

Author	Target population		Sample size	Type of study		Research Method used	
	Educators	Students		Empirical study	Review	Qualitative	Quantitative
(Bartkowiak et al., 2022)	/		39	/		/	
(Pérez-Sanagustín et al., 2022)	/	/	83	/		/	/
(Yakovleva, 2022)	/	/	200	/		/	
(Núñez-Canal et al., 2022)	/		251	/		/	
(Montiel & Gomez-Zermeño, 2022)	/				/	/	
(Zabolotska et al., 2021)	/	/	650	/		/	

(Wong & Moorhouse, 2021)	/		83	/		/	
(De la Calle et al., 2021)	/				/		/
(Roll & Ifenthaler, 2021)		/	222	/		/	
(Mutohhari et al., 2021)	/	/	178	/			/
(Wahid et al., 2021)	/	/	170	/		/	/
(Zimmer & Matthews, 2022)	/	/	311	/		/	/
(Diz-Otero et al., 2022)	/		166	/			/
(Estrada-Domínguez et al., 2022)	/			/			/
(Tabieh et al., 2021)	/		212	/		/	/
(Nabhan, 2021)	/		107	/			/
(Hämäläinen et al., 2021)	/	/	2590	/			/
(Domínguez-Lloria et al., 2021)		/		/		/	/
(Hizam et al., 2021)	/		238	/			/
(Mendoza Velazco et al., 2021)	/			/		/	/
(Ogodo et al., n.d.)	/	/	109	/		/	
(Sarango-Lapo et al., 2021)	/		271	/		/	/
(Tomczyk, 2021)	/	/	123	/			/
(Sánchez-Cruzado et al., 2021)	/		4883	/			/
(Záhorec et al., 2021)	/		280	/		/	
(Karunaweera & Wah, 2021)	/		40	/			/
(Badran et al., 2021)	/		221	/			/
(Fahrurrozi et al., 2020)		/	72	/			/
(Chan et al., 2022)		/	142	/		/	/

Variables involved in these studies were age, gender, working experience, self-evaluation, psychological well-being, Quality of work life, attention, relevance, satisfaction, digital learning values and opportunities, training received, attitude towards technology, creativity skills, critical thinking, problem-solving, communication, literacy, functional skills, digital competency, online safety, digital culture, collaboration, finding information and professional identity skills. Some variables from the listed research frameworks can be considered, but additional literature also is required. overall, there is room for improvement instead of focusing on the determinants of digital literacy among educators, one of the aspects that need to focus on is by measuring performance efficiency. There is no single study that measures digital performance efficiency among the research framework listed in Table 4.

Therefore, the intention of this study is to focus on measuring digital competency by considering four inputs namely total costs of equipment invested during e-learning (Facilities, Materials, Courses), amount spend on digital equipment number of gadget used, the number of hours spend on e-learning training while two outputs number of student enrolled in the class and students' achievement in the STA 404.

Related studies on integration data envelopment analysis with machine learning

Table 5

Related studies ML DEA prediction

Related Studies	DMUs	DEA model	Machine Learning Method			ML algorithm		
			Prediction	Classification	Clustering	k-mean	RF	REG
Hoz et al., 2021	254 programs	DEA-CCR		√	√	√	√	
Solanki & Virparia.,2021	Institutions		√					√
de Abreu & Kimura, 2020	Financial Institutions	NDEA		√				√
Rebai et al., 2020	Secondary Schools	DDF	√				√	√

Based on Table 5, there were few studies in the field of education that measured performance efficiency utilising a hybridised DEA model with ML technique. Despite the many ML algorithms that could be utilised when measuring performance efficiency in the educational context - including the Decision Tree (DT), Neural Networks (NN), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbour (KNN), Genetic Algorithm Neural Network (GANN), Back Propagation Neural Network (BPNN), Incremental SVM (ISVM) and Logistic Regression - these algorithms have not been extensively applied. Apart from that, the use of DMUs focuses organisations (homogenous groups) rather than individuals. Therefore, this study intends to develop a novel DEA hybrid model employing a machine learning (ML) algorithm capable of measuring the digital efficiency of STA 404 statistics educators.

Conclusion

This new study methodology is designed to add to educators' fundamental understanding of digital competencies. Moreover, given the recent changes in the education sector, this study will be able to quantify explicit input and output in order to measure the level of digital efficiency among STA 404 statistics educators. In applying the hybrid (DEA-ML) prediction model to predict digital competencies, educators or researchers could generate new knowledge.

Table 4
Results of variables involved in measuring digital literacy efficiency

Research framework	Bartkowia	Velaora et	Pérez-	Yakovleva	Núñez-	Montiel &	Zabolotska	Wong &	De la Calle	Roll &	Mutohhari	Wahid et	Zimmer &	Diz-Otero	Estrada-	Tabieh et	Nabhan	Choi et al.,	Hämäläine	Domíngue	Hizam et	Mendoza	Ogodo et	Sarango-	Záhorec et	Tomczyk	Sánchez-	Jorge-	Karunawe	Badran et	Belikova &	Fahrurrozi	Chan et
Variable																																	
Self - evaluation	√																																
Psychological well-being	√																												√				
Quality of work life	√																												√				
Attention		√																															
Relevance		√																															
Confidence		√																															
Satisfaction		√																															
Digital Learning Values				√																													

Digital Learning Opportunities				√																													
Knowledge about technology					√		√					√		√					√		√												
Training received					√								√																				
Attitude towards technology					√			√											√														
Creativity Skills											√						√																
Critical thinking											√						√																
Problem solving skills											√																						
Communication skills											√						√																
Age														√																			
Gender														√														√					

Work experience														√									√										
Literacy skills																√																	
functional skills																√	√																
Digital competency																√		√			√		√			√	√	√					
Online safety																	√																
Digital Culture																	√																
Collaboration																	√																
Finding information																	√																
Professional identity (skills)																		√	√		√												

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