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THE EFFECT OF DIGITAL SKILLS ON E-WORKER PRODUCTIVITY AND THE MEDIATING EFFECT OF WORK EFFORT

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Abstract
This study is likely to make a positive contribution, particularly in increasing the productivity of virtual workers and as an evaluation material for companies looking to further optimize their workers' digital skills to produce more productive work results. This study used a purposive non-probability sampling method and a quantitative approach by E-survey to collect a complete dataset of 387. The SPSS 26 was used to inspect all items' validity and reliability in the research instrument. To assess the overall structural model, confirmatory factor analysis (CFA) was utilized, and to identify the amount to which all variables observed were connected to the underlying latent components, and it used a structural equation model with AMOS. The proposed theoretical model results revealed that the Goodness of Fit Index (GFI) score is 0.961 with 0.070 in RMSEA and 0.039 in RMR. The NFI value is 0.976 with an AGFI score of 0.927 and a CFA score of 0.984, which satisfy all the criterion values. It is found that digital skills do not have a significant and no direct relationship with E-worker productivity. However, digital skills are found to directly and positively impact the direction, persistence, and intensity of work effort.

Keyword :
E-Working, Remote Worker, Digital Skills, Work Effort, Productivity

1. INTRODUCTION

Working remotely using technology is now increasingly used in the world so that some jobs can be completed from anywhere and anytime. Many terms are used to depict this phenomenon, including “e-worker”, “teleworking”, “teleworker”, and “telecommuting”. In this study’s context, “remote e-worker” refers to workers or individuals who work remotely utilizing technology (electronic devices) and work from anywhere and anytime (Grant et al., 2019). Corroborates with Nilles (2007) opinion, E-working is all forms of substitution of information technology (i.e., computers and telecommunications), which transfer jobs to workers and not vice versa.

In several previous research, remote e-working has been linked to a positive effect on increasing productivity, a flexible approach to work, reducing work-life conflict, as well as increasing job satisfaction (Baruch, 2000; Fonner & Roloff, 2010; Grant et al., 2013). In addition, in several other studies, remote e-working is also associated with pressure and communication with a bad workplace, work overload, poor welfare, working more than the proper working time, all of which influence job performance and effectiveness (Barber & Santuzzi, 2015; Fonner & Roloff, 2010; Grant et al., 2013; Hartig et al., 2007; Mann & Holdsworth, 2003). Previous studies have also verified that remote working could positively influence productivity (Bloom et al., 2015).

Furthermore, it was found that the rapid changes in technology and virtual work practices were, in fact, not matched by adequate digital skills. The Collective.com (2020) states that the US economy loses nearly $1.3 trillion annually due to the digital skills gap. Meanwhile, Pirzada and Khan (2013) mentions that digital skills are the key strength to be successful in using electronic tools and communications that help individuals to increase productivity in organizations and make them better citizens.

Although productivity is an essential variable in the overall organization performance, not many studies have examined the impact of effort on productivity. One way to measure this productivity is to evaluate how employees spend their raw hours (De Mers, 2020). Workers who spend several hours using social media or checking e-mail spam with employees doing work-related tasks may have different productivity even though they both look equally busy.

The trend of working virtually with the help of technology and globalization is increasingly being applied, but not many studies have examined the significance of digital skills on the productivity of virtual workers. Thus, this study's purpose is to scrutinize the effect of digital skills on E-worker productivity with a mediator of work efforts. The urgency of this research is to make a positive contribution, especially in increasing the productivity of virtual workers and as evaluation material for companies or organizations to further optimize the digital skills of virtual workers to create more productive work results.

1. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Digital skills have become a major part of education, economy, and social life. When a person does not have digital skills, one cannot use the Internet for various purposes, which then leads to the inability to achieve the targeted results (Van Deursen et al., 2016). Although there are numerous frameworks for evaluating digital skills, the majority of them lack operational definitions. It remains at the conceptual definitions and indices or indicators level.

According to Ferrari (2012), communication, information, safety, problem-solving, and content production skills are all part of digital skills. Meanwhile, Helsper and Eynon (2013),explain that digital skills consist of four categories of skills: social, technical, creative, and critical skills.

Steyaert (2002) and Van Dijk and Hacker (2003) established the notion of digital skills as a series of three sorts of talents. Instrumental skills (technical technology operation), structural skills (information structure), and strategic skills (the basic preparedness to actively seek out information, make decisions based on that knowledge, and monitor the surroundings for pertinent data) are all defined by Steyaert.

In this regard, Van Deursen and van Dijk (2009a), Van Deursen and Van Dijk (2009b), Deursen and Van Dijk (2010) used the following domains to assess digital skill: operational (technical abilities to control digital media); formal (the ability to manage the specific digital media structures, e.g., hyperlinks and menus); information (the capability to find, choose, as well as assess digital media information; strategic (the ability to use the digital media information to achieve a specific professional or personal objective).

The framework was then completed by Van Deursen and Van Dijk (2014), who added both content development and communication skills. Skills of internet communication are characterized as the capacity to decode and encode communications to create, interpret, and exchange meaning with other people via message systems, i.e., chat rooms, instant messaging, and e-mail. It includes finding, choosing, assessing, and going to act on contacts online, decoding, encoding, as well as exchanging messages online, drawing attention online, doing profiling. It is also the ability to collect information and share meaning with others via networking that is peer-to-peer and the skill to interchange meaning to make decisions as well as complete transactions while comprehending others' meanings.

Furthermore, content creation skills, according to Van Deursen and Van Dijk (2014) are the abilities to generate acceptable quality content for publication on the Internet. Textual, picture or image, audio and video, remixed content, and multimedia are all included. Finally, in their research, Van Deursen et al. (2016) concluded that five main indicators of digital skills could be measured: social, operational, creative, information navigation, and mobile skills, and these five indicators will be used in this research construct.

Regarding this construct, showcasing digital skill mastery is a more difficult endeavor since it demonstrates productivity and competence in an indirect manner. Those who develop digital skills will have a more secure financial future and more fulfilling careers, while those who stay on the digital divide's "wrong side" will have less promising future possibilities. According to significant research material, those who utilize the Internet less tend to be less wealthy, less educated, and disadvantaged ethnic group members (Hargittai, 2010; Park, 2013). The presumption here is that people who lack these skills may find themselves in a new circle of failure if digital skills are utilized as reasons or signals for awarding advantages.

The previous study also mentioned that digital skill is one of productivity's predictors. Digital skills are important because these are a key strength to be successful in using electronic tools and communications that help individuals to increase productivity in organizations and better use of citizens (Pirzada & Khan, 2013). Furthermore, the whole process of appropriation of this new technology that has recently emerged and is growing hinges on digital abilities. In an information world, these abilities are essential for working, living, entertaining oneself, and studying. However, continuous motivation and effort are required to develop the appropriate digital skills (Van Deursen & Van Dijk, 2014). When everything runs well, and digital media usage and command are straightforward and run-in accordance with people's needs and aspirations, the stimulation is the consequence. Then, a cycle of increased effort and motivation follows. To check the relationship, following hypotheses are stated:

H1: Digital skills positively impact E-worker productivity.

H2: Digital skills positively impact work effort.

Regarding this, the productivity of employees is a topic that has received a lot of attention in the fields of management and human resources. Krol & Brouwer (2014) stated that low productive employees are linked to financial losses and greater costs to make up for the shortfall caused by poor performance, which should be factored into financial planning. For example, low production costs are expected to cost US$ 260 billion per year in the United States companies (Mitchell & Bates, 2011).

Increasing productivity is the main goal of every company, especially in the digital era where the business world and the industrial world can change very quickly. In its most basic form, work productivity refers to the output per input unit, such as manufacturing output per labor hour. Many elements (i.e., market pressures, technology) impact labor productivity at the workplace level, which includes the contribution of worker productivity individually (Beaton et al., 2009).

According to Nugroho (2012), in a company, work productivity refers to an organization's capacity to generate services and from a variety of production variables or resources to increase the work's quality and quantity performed. On the other hand, Sedarmayanti and Pd (2001) defined work productivity as a mental attitude as well as capacity to generate services and products from diverse resources with the goal of improving the work's quality and quantity done by comparing the outcomes attained (output) with the whole resources utilized (input).

Moreover, Kaluarachchi (2020) state that productivity depends on good concentration, technical competence, a responsive environment, effective organization and management, and a good feeling of well-being. In detail, Kaluarachchi mention that there are several factors that affect productivity, such as human factors, system factors that affect human factors, environmental factors, and health factors.

E-worker productivity itself is referred to in the context of this study will be associated with three factors used in measuring work productivity proposed by Simamora (2004) which include: (1) work quantity, which is a collection of outcomes relating to a product's quality created by employees while technically completing work with a set of comparisons established by the firm; (2) work quantity, which is the number of results delivered by employees in contrast to current or company-set standards; (3) punctuality, which is the degree to which a task is done at the start of the time allotted; timeliness is measured from employee perceptions of the activities provided from the beginning of time to output.

Furthermore, an effort is conceptually often associated with motivation. Though the two are very different conceptually. Motivation refers to an individual psychological state or propensity in relation to behavioral decisions, whereas effort refers to the amount of energy expended on a task per time unit (De Cooman et al., 2009). There is, however, a startling dearth of research that tries to assess effort explicitly. The fact is that effort is an unseen, internal, hypothetical concept, which is indirectly observable, making it difficult to define and assess (Yeo & Neal, 2004).

Effort based on (Yeo & Neal, 2004) is also thought to be a resource with limited capacity that may be used for a variety of activities, covering off-task, on-task, as well as self-regulation. In terms of strength and durability, these allocations might differ. In addition, work effort was also defined by them as the number of visual attention resources a person devotes to job duties. There are at least three factors of work effort which then have an impact on observable performance and productivity outcomes, namely what a person does or a person's conduct to select to work in an agency (direction), how extended a person does a job or how maximum a person tries to perform the selected behavior (persistency) successfully, and how maximum a person strives to accomplish the selected behavior (intensity) (De Cooman et al., 2009).

In work-related efforts, work efforts are all behaviors that are helpful to the company, encompassing conduct required by one's official job obligations and voluntary behavior; hence, work effort is located between performance and actual motivation, according to this argument (De Cooman et al., 2009).

The degree of work effort is significant in effectiveness economic models of wage and to a few records of monetary development in the brief time frame. Along these lines, changing the intensity of work figures noticeably in specific basic records of efficiency change despite the fact that expanding the degree of work effort has been uncovered, for instance, in a diverse investigation of prosperity at work, to prompt significant decreases in prosperity, as estimated by work fulfillment and affective prosperity indicators (Green, 2004). Our hypotheses with respect to work effort, therefore, are as follows:

In efficiency economic models of wage as well as numerous theories of short-term economic development, the amount of work effort is critical. Therefore, altering work intensity plays a key role in several crucial explanations of productivity change. Nonetheless, increased labor intensity has been shown in a number of studies of workplace well-being to result in significant declines in, as evaluated by, affective well-being indices and job satisfaction (Green, 2004). The well-being hypothesis related to work effort, therefore, is as follows:

H3: Work effort has a positive effect on E-worker productivity.

It is interesting that the not working's opportunity cost amid the period away from the normal place of work has increased because of ICT. Mobile phones, laptop, as well as worldwide available connections to Internet have made it possible to work more intensively on trains, aircraft, even at home in this scenario. Work done outside of such hours can likewise be more productive thanks to information and communication technology. As a result, workers with high effort taking their jobs with them are more productive. Furthermore, it appears that people who opt to put in very little effort have productivity gains that are much smaller than those who are willing to engage with more effort-intensive technology (Green, 2004). The hypothesis involved is as follows:

H4: Digital skills positively impact E-worker productivity with work effort as a mediator variable.

For the purposes of this research, the concepts from Van Deursen et al., De Cooman et al., and Simamora will be adapted so that the theoretical framework of thinking is obtained as follows:

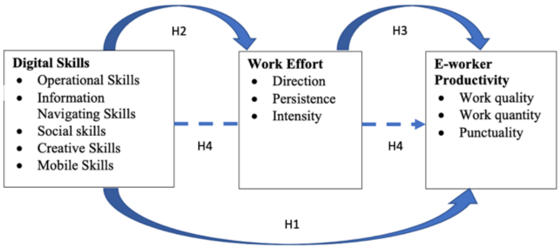

Figure 1. Theoretical framework

2. RESEARCH METHODOLOGY

This study uses a quantitative approach through surveys to respondents with question instruments referring to each research variable gauged employing a Likert scale with one being strongly agreed and five strongly disagreed. The questionnaire has been translated by a sworn translator into Bahasa Indonesia for the ease of the respondents. The research instrument will use a scale of 5 for its measurement. The media used to distribute the questionnaires is an online survey using a survey monkey. This Research and Development research was carried out with a purposive non-probability sampling method with the target profile of the respondents being workers (male/female) who have had experience working virtually (E-Working) with productive age (18-64 years) who are still active at the workplace and have a minimum education of Diploma III (polytechnic).

In the questionnaire, there were three constructs in the study, digital skills, work productivity and work effort. All components were assessed using items derived from prior research. Thirty-four items of the ISS Scale put forward by Van Deursen et al. (2016) were used to measure digital skills. For the dependent variable, we used a work productivity scale questionnaire adapted from by Simamora (2004) with a total of 26 items. And for the mediator variable, ten items were used to measure work effort by employing the scale of work effort developed by De Cooman et al. (2009).

Out of the 562 responses received via e-survey, 387 data could be continued to the next process while the rest were unused because the respondents did not fill in the data completely. Demographic statistics show that out of 387, 62.0% represent female respondents, whereas 38% represent male respondents. Regarding the age of the participant, 64.6% denotes 25-34 age group, 15.8% symbolizes 35-44 age group, 15% exemplifies 18-24 age group, and 2.1% signifies both 45-54 and 55-64 age groups, respectively, whereas 0.5% of respondents represent age group above 65.

On the level of education, 47.3% of respondents have an education until bachelor's degree, 37.70% belong to master's level, 12.9% have education till Diploma (polytechnic) while 2.1% obtained the degree of doctoral. On participant's domicile, 28.9% reside in DKI Jakarta, 10.6% live in Tangerang, 9% and 9.6% domiciles in Depok and Bekasi respectively, 7.5% belong Bogor, 4.1% resides in Bandung, and the remaining 30.2% located in other cities around Indonesia.

Regarding E-working, 58,4% of the respondents have worked remotely for 1-2 years. 26.6% working from home or anywhere for less than a year, while 11.6% represent people with 2-3 years of E-working experience. The rest, 3.4%, belong to respondents with more than three years of remote working.

The strength as well as the direction of a linear relationship between two variables are depicted by correlation. The correlation statistics used to determine the probable relationship between each variable: digital skills, work effort, and E-worker productivity, are shown in Table 1 below.

Before starting analysis, the validity and reliability of all items in the research instrument are checked using the SPSS 26 program. Validity is a metric that indicates whether or not a measuring instrument measures what it claims to be measured (Sugiyono, 2013). In factor analysis, the item validity test is a data instrument test that determines how reliable a data instrument is in determining what it is aimed to measure. If an item has a substantial connection with the total score, it is considered valid; it suggests that the item has support in disclosing something that needs to be disclosed. Items are usually in the form of questions or statements addressed to respondents using a questionnaire to reveal something.

In testing the validity of the factor analysis method, if a variable fits the requirements, it is deemed valid and can be further investigated, namely if the KMO (Keiser-Meyer-Olkin) MSA (Measures of Sampling Adequacy) number in the KMO as well as Barlett's Test columns is higher than or equal to 0.500. Meanwhile, the significance level (sig) must be less than or equal to 5% (0.05).

The MSA value in the Anti Image Correlation column may then be used to determine if each item is valid. If the MSA value is more than 0.5, the item is valid and can be further investigated. Meanwhile, reliability is a metric that indicates how much a measuring device can be trusted or depended upon. It demonstrates how consistent the measurement findings are when performed twice or more for the same symptoms using the same measuring device (Notoatmodjo, 2005). When a measuring device delivers the same result again and over again, it is considered to be reliable. After examining all data, it was determined that the data were normally distributed, and the overall instrument's reliability was Cronbach's alpha > 0.5.

Data analysis was conducted employing a structural equation model (SEM) with AMOS, through confirmatory factor analysis (CFA) to inspect the overall structural model as well as find out the amount to which all observable variables are linked to the latent components.

Table 1. Correlation Matrix Among Research Variables (n=387)

	Mean	Std.D	KDop F1	KDso F3	KDse F5	UKke F1	UKar F2	UKin F3	PKkn F1	PKkl F2	PKkw F3
KDopF1	**4.635946**	**0.519787**	**1.000**	.687**	.597**	.554**	.540**	.508**	-.182**	-.179**	-.163**
KDsoF3	**4.459087**	**0.549486**	.687**	**1.000**	.641**	.533**	.553**	.547**	-0.009	-0.013	0.003
KDseF5	**4.294574**	**0.751848**	.597**	.641**	**1.000**	.400**	.396**	.401**	0.047	0.070	0.084
UKkeF1	**4.271318**	**0.654158**	.554**	.533**	.400**	**1.000**	.773**	.713**	-.130*	-.108*	-.123*
UKarF2	**4.304048**	**0.602005**	.540**	.553**	.396**	.773**	**1.000**	.750**	-0.091	-0.073	-0.089
UKinF3	**4.213824**	**0.625181**	.508**	.547**	.401**	.713**	.750**	**1.000**	0.013	0.035	0.013
PKknF1	**2.646856**	**1.188076**	-.182**	-0.009	0.047	-.130*	-0.091	0.013	**1.000**	.931**	.905**
PKklF2	**2.581395**	**1.176129**	-.179**	-0.013	0.070	-.108*	-0.073	0.035	.931**	**1.000**	.903**
PKkwF3	**2.683032**	**1.183273**	-.163**	0.003	0.084	-.123*	-0.089	0.013	.905**	.903**	**1.000**

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 2: Confirmatory Factor Analysis (CFA) Model Results

Indicators	Standardize Loading	Error Variance	t-value	*p*	R^2	CR	AVE
Construct: Digital Skills							
Operational skills (KDopF1)	0.815	0.010	14.704	***	0.664	0.843	0.643
Information Navigation Skills (KDinF2)	0.098	*Omitted due to bad factor loading*					
Social Skills (KDsoF3)	0.861	0.010	15.196	***	0.742		
Creative Skills (KDkrF4)	0.470	*Omitted due to bad factor loading*					
Mobile Skills (KDseF5)	0.723	0.023	A	***	0.523		
Construct: Work Effort							
Persistence (UKkeF1)	0.862	0.012	A	***	0.744	0.898	0.747
Direction (UKarF2)	0.895	0.009	22.183	***	0.800		
Intensity (UKinF3)	0.835	0.118	20.256	***	0.697		

Indicators	Standardize Loading	Error Variance	t-value	*p*	R^2	CR	AVE
Construct: Work Productivity							
Work Quantity (PKknF1)	0.966	0.013	A	***	0.933	0.969	0.913
Work Quality (PKklF2)	0.964	0.013	47.798	***	0.929		
Punctuality (PKklF3)	0.937	0.016	41.228	***	0.878		

Notes $\chi 2$/d.f (69.889/24) = 2.912, GFI = 0.961, AGFI = 0.927, RMR = 0.309, p = 0.000.
Notes: ***p<.001; **p<.01; *p<.05, significant at a t-value >1.96. A regression weight was fixed at 1.00
CR=Composite Reliability (Cronbach's alpha); C.R=Critical Ratio (C.R=t-value); AVE= Average Variance Extracted.

3. RESULT AND DISCUSSION

The confirmatory factor analysis (CFA) is carried out using a measurement model. The parameters are calculated using the maximum likelihood technique. The findings of the CFA Model are shown in Table 2, and the overall CFA is shown in Figure 2. Because a predetermined measuring scale is utilized, confirmatory factor analysis is more exploratory. Even if the model is adopted, it is checked for validity and dependability since it is being evaluated in a new industry, new environment, with a new sample. It expresses how successfully the three constructions were estimated by the items (shown in Table 2).

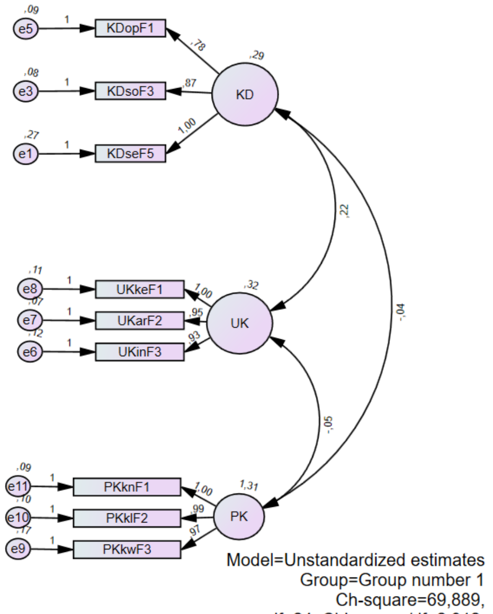

Figure 2. The overall CFA

To get to the measurement model, several analyses were carried out. To begin, CFA was done with Amos-22 to see if the given theoretical model was appropriate. The model's overall fit is almost satisfactory and acceptable. Secondly, before analyzing the validity and reliability, the researcher checked for unidimensionality. All the three variables on the model of measurement, CFI was used for each for this purpose. Each construct with a CFI of 0.6 to 1.00 has a good fit, indicating unidimensional (Hair et al., 2014; Sureshchandar et al., 2002).

Then, the study employed squared multiple correlations (R^2) for each assessment item, average variance extracted, as well as composite reliability for each element to examine the construct reliability. The (R^2) for each item varies from 0.523 to 0.933, indicating high reliability (Holmes-Smith, 2001); it reflects the variation in the variable supplied by the latent construct. As a result, all structures fit nicely and are one-dimensional. Then, the Cronbach's alpha values were computed to determine the constructions' reliability. It was found out that all numbers are in the range of 0.843 to 0.969, indicating strong reliability as well as internal consistency. The composite reliabilities range from 0.843 to 0.969, indicating that the measurements are valid (Anderson & Gerbing, 1998).

Fourthly, the factor loadings and composite reliabilities were used to determine the measuring items' convergent validity. The standardized factor loadings range from 0.723 to 0.966, are much higher than the indicated limit of 0.35, and are significant; these are definitely excellent CFA indications (Hair et al., 2014). Even though two indicators from digital skills, which are information navigation skills and creative skills, must be omitted due to bad factor loading since the t-value for CFA is suggested > 1.96, so the t-value in the author's CFA model is above the standard with the score of P-value < 0.05. Before doing the overall CFA, the author performs factor analysis first and then calculates the means score for each factor used for the overall CFA analyses.

Table 3: Fit indices of Structural Equation Modeling (SEM)

Fit Index		**Observed Scores**	**Criterion Values**
Absolute fit measures	Chi-square	69.889	Near to degree of freedom
	df	24	The greater, the better
	Chi square/ df (CMIN/df)	2.912	<2;<3or<5
	GFI	0.961	>0.90
	RMR	0.039	<0.05
	RMSEA	0.070	<0.08
Incremen-tal fit measures	NFI	0.976	>0.90
	AGFI	0.927	>0.90
	CFI	0.984	>0.95
Sources: Hair et al., 2014. and Anderson & Gerbing, 1998			

Structural equation modeling: Table 3 provides the fit indices for structural equation modeling. The absolute fit indices assess the compatibility of the suggested and observed variance-covariance matrices. The suggested theoretical model's results revealed that the goodness of fit's chi-square was 2.912, with a CMIN of 69.889 and 24 degrees of freedom. This is the first statistic which provides information about the fit of data with the model.

In this case, CMIN is a chi-square statistic that measures how well the data fits the model. Meanwhile, the Goodness of Fit Index (GFI) indicates how much variation in the matrix of sample variance-covariance is described by the model; in this example, the GFI score is 0.961, which is good. Then, RMSEA stands for root mean square error of approximation; its number is 0.070, which is good. In addition, RMR means root mean square residual; it is a measure of the difference between the estimated variance and covariance and the actual variance; the lower the difference, the better. Its value of 0.039 is acceptable in this circumstance.

The incremental fit indices make a comparison between the theoretical and null models (independent models). Then, the Normed Fit Index (NFI) is the difference between the two models, calculated by dividing the independent model's chi-square by the dependent model's chi-square; in this example, the NFI value is 0.976, which is satisfactory. Moreover, AGFI stands for "adjusted GFI Index," an alternative GFI index whose value is altered for the parameters' number in the model. The AGFI will be closer to the GFI if in the model, the parameters' number is reduced. In this situation, both numbers are closer to each other, 0.927 as well as 0.961. Meanwhile, CFI stands for comparative fit index, and it displays a good fit with 0.984 values.

Hypotheses testing: CFA was used to estimate the model of measurement, and SEM was employed to assess research hypotheses based on standardized structural coefficients. Tables 4 and 5 provide more information.

Table 4: Hypothesis Test Results

Hypothesis / Path	**Standardized Coefficient**	**S.E.**	**t-value**
KD -> UK	0.720***	0.063	11.809
KD -> PK	-0.008	0.190	-0.094
UK -> PK	-0.075	0.179	-0.857

Note: ***p<.001, **p<.01, *p<.05, and significant level at t-value >1.96

Table 5: Mediating Effect Test Result

Mediating Effects	Sobel's test	z-test	p(Sig.)
KD -> UK -> PK	A =0,720, B = 0,075 S.E.a = 0,063, S.E.b = 0,179	-0.4187	0.67542

H1: Digital skills positively impact E-worker productivity.

Hypothesized that digital skills have a direct and positive impact on E-worker productivity. The standardized structural coefficients revealed that digital skills have an insignificant relationship with E-worker productivity (β = -0.008, p<0.05, t-value < 1.96); hence, H1 is not supported.

H2: Digital skills positively impact work effort.

H2 stated that digital skills (KD) have a direct and positive impact on work effort (UK). The standardized structural coefficients uncovered those digital skills have significant relationship with work effort (β = 0.720, p>0.05, t-value > 1.96); hence, H2 is supported.

H3: Work effort has a positive effect on E-worker productivity

H3 stated that work effort directly and positively impacts E-worker productivity. The standardized structural coefficients unveiled that work effort has an insignificant relationship with E-worker productivity (β = -0.075, p<0.05, t-value < 1.96), thus rejecting H3.

H4: Digital skills positively impact E-worker productivity with work effort as a mediator variable.

H4 is not accepted that work effort mediated the relationship of digital skills and E-worker productivity because mediated model shows an insignificant bond between digital skills and E-worker productivity.

The mediated effect's z-score is the mediated effect divided by its standard error. To test for significance, this result was compared to a conventional normal distribution. To infer that the effect is higher than predicted, the z-score must be more than 1.96 (z-test = -0.418 and p(Sig.) = 0.675)

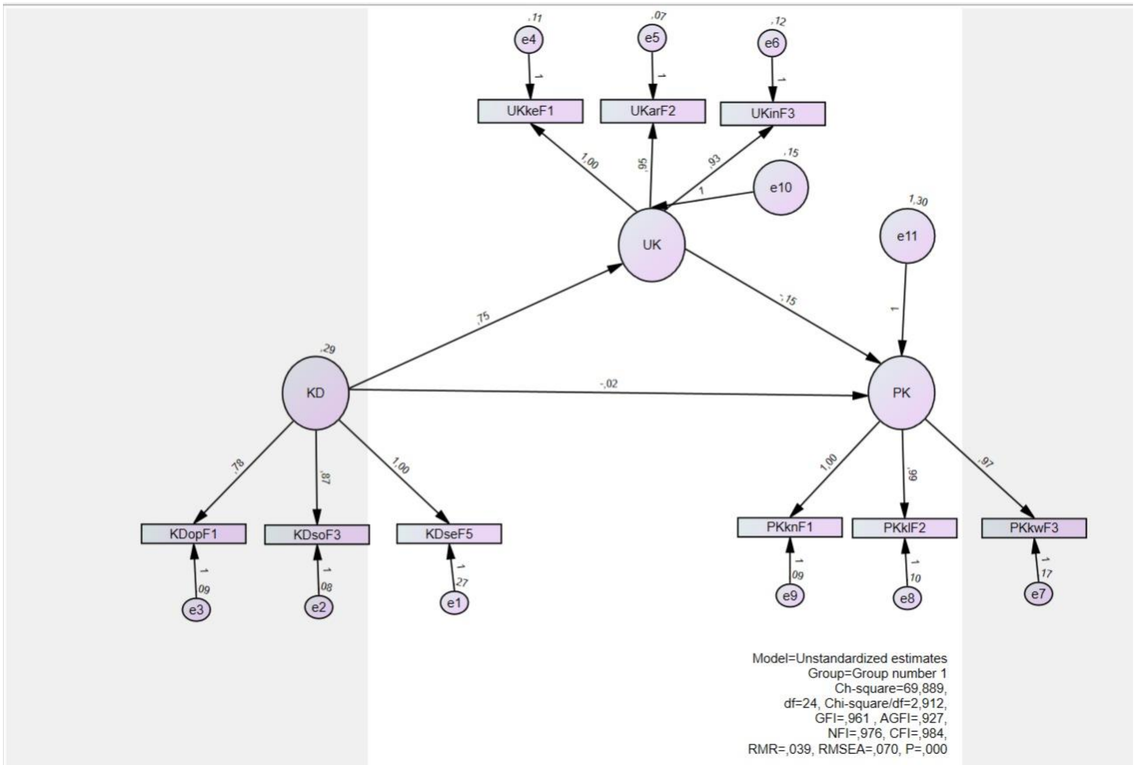

Figure 3. Theoretical Model After SEM

Discussion

The study's rationale was to scrutinize the effect of digital skills on E-worker productivity, mediated by work effort. Results showed that digital skills do not have a significant and direct relationship with E-worker productivity. This result could be because when conducting CFA and SEM, we must remove two out of five indicators of digital skills due to bad factor loadings. The indicators that have been removed are information navigation skills and creative skills. This low factor loading reflects people's prowess in digital skills, so the loss of two indicators causes it could not support the hypothesis.

It is interesting to be in the spotlight because even though workers who are older are seen as "digital immigrants" based on evidence, suggesting that persons in late teens and early twenties had a considerably better time navigating the Internet than those in their 40s, 50s, and 60s (Loges & Jung, 2001) but the sample in this study is dominated by people aged 25-34 years with a total percentage of 64.6% of respondents where more than half of the total respondents have received higher education and live in the big cities yet the result still insignificant.

It indicates that even though the demographics of the respondents stated so, most of them turned out to be not so technologically savvy, especially in terms of creative skills and information navigation skills. It is supported by a previous study that stated digital natives nevertheless because digital workplace skills are different from digital lifestyle skills gained informally, it was discovered that it lacked the abilities for successful use of technology in the workplace (Foundation, 2014).

As in this research, most respondents found to be lack creative skills and do not have appropriate skills to navigate information properly. The information navigation skill itself is about being able to find, choose, and analyze data in digital media. Those are particularly important in media providing an abundance of sources and material, such as the Internet. Meanwhile, operational are skills that are medium-related; information skills are related to content. The lack of this kind of skill may be the reason the data could not support the hypothesis.

Furthermore, it could indicate that, even though the respondents are predominantly from the younger generation, they still require additional training to improve their creative skills, as other people are not engaged in the creation of online content. According to Brake (2014), active content creators make up a small percentage of users of the Internet and own a greater socioeconomic position than the general online population. Most people lack a background that is creative and are unable to recognize that the whole creation is merely unappealing. Most people will be able to take simple images and share them on social media platforms; however, getting beyond this level of amateur production appears to be a challenging step that is particularly suited to professionals.

The fundamental reason for this challenge is that the media's very simple and intuitive usage encourages consumption rather than productive and creative use (Van Deursen & Van Dijk, 2014). Schradie (2011) supports previous arguments and claims that only because doing online does not mean being able to create content.

In addition, Van Deursen and Van Dijk (2014) also suggest that the shift to mobile devices would widen the usage gap since the ability to conduct skills related to content as well as owning input that is generated by user and creative in mobile services is much more limited and constrained by the application rathen than it is in full-featured laptops and desktops. However, many young generations are currently engrossed in their smartphones. As a result, the transition to mobile devices may exacerbate the digital skills gap between those who utilize modern laptops and desktop computers as well as others who are reliant on mobile devices with limited and preprogrammed functionalities.

Another interesting point to address is that digital skills have a direct and positive impact on work effort. The more E-workers have the digital ability, the more effort they put into their work. The direction, persistence, and intensity of E-workers when doing their job influence their digital skills. Therefore, it is important for any employer to keep empowering and provide sufficient support and digital skills training for their E-workers to increase their work effort when doing their jobs.

However, in this research, it is found that work effort has an insignificant impact on E-worker productivity. The result of work effort with productivity is contradictory with the previous studies which stated that change of productivity of labor could be positively associated with the change of work effort estimates (Green, 2004), even though (Green, 2004) also argue that an improvement in productivity due only to increased labor effort is not the same as an increase in efficiency.

It can be seen that as on the level of education that 47.3% of respondents had education till bachelor's degree, whereas 37.7% belong to master's level, and the proportion of 12.9% have education till Diploma means that most respondent actually has good exposure of education. Today's graduates have the opportunity to study technology since they were young so that the period of education and learning, such as information technology and computers that have accumulated since elementary school to higher education, makes their digital skills to do work virtually better. Even though 58,40% of the respondents have been working remotely only for 1-2 years but this young generation is more than ready to do E-working without requiring special work efforts, or it can also be assumed otherwise that the respondents were people who have good digital skills, but these abilities were not used optimally to increase their productivity. In this regard, we need further research regarding this matter.

Furthermore, since participants mostly come from big cities in Indonesia, such as DKI Jakarta, Tangerang, Depok, Bekasi, Bogor, and Bandung, it can be concluded that work effort may have no direct impact on E-worker productivity because most participants are not coming from rural areas so they can be productive even without having to spend much effort because these kinds of urban people have an adequate support system to make their work easier. It is interesting to be researched in the future to determine whether a difference exists between the work effort and work productivity significantly or between residents from remote areas and residents of big cities while doing their virtual works.

Further, the study explained that the work effort's mediating roles do not play an important part in explaining digital skills and E-worker productivity because mediated model shows an insignificant bond between digital skills and E-worker productivity. It may be argued that if management could get people to put in more effort, technical progress and digital skills would have a stronger influence on productivity. However, the effects were insignificant. The findings also contradict with the previous study, which stated that high-effort workers' productivity tends to rise in companies that prepare to work with increasingly effort-intensive technology; therefore, it is also important to always provide proper technologies to support E-workers so they can provide their best work effort while doing their job from anywhere (Green, 2004).

Limitation and Future Research

The study's major limitation is that the author only had limited time to analyze the results, and the sample size was not too big. Future research may increase the sample size to obtain more precise results. Also, the demographic characteristics were not employed in the study to determine the impact of digital skills on E-worker productivity.

As a result, these factors might be used in future studies to investigate the links. In the future, the analysis can be carried out by age group or region so it can be seen whether the area of residence affects E-workers' digital skills and productivity. It can also be investigated further whether the duration of implementation or the E-working experience also impacts the productivity of virtual workers. A comparison study in future research between different job scopes or different industries could also be made to access the impact of digital skills and productivity of E-workers.

4. CONCLUSION

The goodness of fit's chi-square is 2.912, CMIN of 69.889, with degrees of freedom of 24, according to the results of the given theoretical model. This first statistic provides information about the fit of data with the model. Then, the Goodness of Fit Index (GFI) score is 0.961 with 0.070 in RMSEA and 0.039 in RMR. The NFI value is 0.976 with an AGFI score of 0.927 and a CFA score of 0.984, which satisfy the criterion values.

Due to poor factor loadings, two of the five digital skills indicators (information navigation skills and creative skills) must be excluded, affecting the theoretical model after SEM results and portraying people's prowess in digital skills. Digital skills have been demonstrated to have no substantial and direct association with E-worker productivity. Digital skills, on the other hand, were discovered to affect the direction, persistence, and intensity of work effort directly and positively. As a result, it is critical for any business to continue empowering and providing necessary assistance and digital skills training for their E-workers to boost their work effort.

This study also discovered that work effort has no effect on E-worker productivity and that the mediated model indicates no link between digital skills and E-worker productivity, which contradicts earlier research. Enlarging the sample size and employing demographic characteristics to investigate the relationships and probable effects should be considered in the future to produce more precise results.

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