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Determining Factors Influencing Early Childhood Educators' Digital Competences: The Case of Open University Undergraduate Program

Della Raymena Jovanka[1], Yufiarti Yufiarti[2], Elindra Yetti[3], Erie Siti Syarah[4]
Universitas Terbuka, Universitas Negeri Jakarta, Universitas Negeri Jakarta, Universitas Terbuka

Abstract

The digital era necessitates societal readiness to embrace technological advancements across various sectors. In education, experts and policymakers increasingly emphasize classroom technology to enhance the digital competence of early childhood educators and higher education students. This study examines the factors influencing teachers' digital competence in Indonesia, specifically focusing on demographics (age, educational background, teaching experience, prior ICT training), geography (domicile across Western, Central, and Eastern Indonesia), technological devices, socio-economics status, and self-regulated learning (SRL). Data were collected from 492 in-service early childhood education (ECE) teachers, aged 20 to over 45, through online surveys distributed via online tutorial platforms and WhatsApp. The findings indicate that access to technological devices and SRL have a direct and significant impact on teachers' digital competence. Meanwhile, demographic, geographic, and socio-economics characteristics indirectly influence digital competence through SRL. This study provides valuable implications for universities, government, and the broader public. It serves as a framework for integrating comprehensive ICT training into teacher education programs, ensuring equitable technological access across all regions, and supporting initiatives that enhance educators' resources globally.

Keywords
Demography, geographic, self-regulated learning, socio-economics, teachers' digital competence, technological devices.

[1] dla@ecampus.ut.ac.id
[2] yufiarti@unj.ac.id
[3] elindrayetti@unj.ac.id
[4] syaraherie@ecampus.ut.ac.id

Introduction

The digital transformation of education has become a prominent priority in recent years, propelled by rapid technology advancements and the necessity to meet students' needs (Fernández-Batanero et al., 2020; Vial, 2021). Consequently, teachers are required to integrate various digital learning materials, such as text, images, animations, music, and videos (Palfrey & Gasser, 2008), while also creating and managing resources for educational content (Kennewell & Beauchamp, 2003). For instance, Sweden's preschool curriculum introduces an educational approach combining care and instruction, emphasizing the critical need for educators to be digitally competent (Masoumi, 2021). Although debates exist regarding whether digitalization in preschool adequately prepares children for the information age or potentially hinders their development (Lindahl & Folkesson, 2012), it is undeniable that teachers must possess robust digital skills to navigate these complexities. This transformation has heightened expectations for teachers to continuously learn and integrate technology effectively (Cook et al., 2023).

Moreover, educational policies increasingly emphasize digital competence, defining it as a combination of skills, knowledge, attitudes, and strategies that enable individuals to use digital technology creatively, critically, meaningfully, and ethically (Hatlevik et al., 2015; Ilomäki et al., 2016). Teachers are legally and professionally expected to master Information and Communication Technology (ICT) to revolutionize the educational process.

Based on existing literature, this study addresses several specific research gaps: (1) the absence of research on how teacher's domicile factor influences digital competence. This study aims to assess whether the location of teacher residences spread throughout Indonesia, including urban, suburban, rural, or land, sea, and archipelago areas, affects the mastery of teacher's digital competence. (2) the study's respondents were in-service ECE teachers from Indonesia. (3) there is no age limit for the respondents (all active students). 4) The factors considered in this study are ownership of technological devices, duration of access to the internet, and frequency of computer and internet use in daily life. 5) Self-Regulated Learning (SRL) in this study refers to the theory proposed by Zimmerman and Schunk, including metacognition, motivation, and teacher behavior.

Specifically, this study investigated whether demographics, geographic regions, technological devices, socio-economic factors, and SRL affect the digital competence of ECE educators enrolled in an Open University undergraduate program. Measuring digital competence based on the widely validated DigCompEdu framework by the European Commission, this research aims to provide a comprehensive understanding of how these variables interact to shape teachers' technological proficiency.

Digital competence refers to teachers' ability to use and integrate technology into their teaching and daily lives. The skill is crucial as it can enhance student motivation, deepen understanding, promote active and collaborative learning, and foster lifelong learning. Using technology effectively in the classroom promotes creative thinking and student communication (Webb et al., 2005).

This study measures teachers' digital competence based on the framework DigCompEdu European Commission. This framework has been widely used to measure teachers' digital competence because several previous research results revealed that the instruments in DigCompEdu which have a high-reliability index, are global, and have various dimensions that make them up (Cabero-Almenara, 2020). Digital competencies based on the DigCompEdu European Commission framework include five areas (Editors et al., 2013): information and media literacy, digital communication and collaboration, digital content creation, responsible use, and digital problem-solving. Specifically:

1. Information and media literacy includes the ability to identify, locate, retrieve, store, organize, and analyze digital information and assess its relevance and purpose.
2. Digital communication and collaboration include communicating in a digital environment, sharing resources through tools online, connecting with others and collaborating through digital tools, interacting with, and participating in communities and networks, and cross-cultural awareness.
3. Digital content creation includes creating and editing new content (from word processing to images and videos); integrating and re-deciphering previous knowledge and content; generating creative expression, output media, and programming; and handling and applying intellectual property rights and licenses.
4. Responsible use or security, covering personal protection, data protection, digital identity protection, security measures, and safe and continuous use.

5. Digital problem-solving or troubleshooting capabilities include the ability to identify digital needs and resources, make informed decisions about digital tools that are most appropriate according to goals or needs, solve conceptual problems through digital means, technology used creatively, solve technical problems, update themselves and other competencies (Editors et al., 2013). The teacher's digital competence is divided into six levels (Caena & Redecker, 2019; Ghomi & Redecker, 2019; Redecker & Punie, 2017), namely newcomer (A1), Explorer (A2), Integrator (B1), Expert (B2), Leader (C1), and Pioneer (C2).

Another way to determine whether teachers have digital competence is to measure it using tools or instruments that various experts have developed. The frameworks used to measure this digital competence are NETS-T, Teachers ICT Competence Standards, DigiLit Leicester, DigCompEdu, and Common Framework for TDC. One of the instruments commonly used to measure digital competence is the DigCompEdu framework. This instrument allows teachers (1) to learn more about the DigCompEdu framework, which is about what it means to be a digitally competent educator, (2) to gain a first understanding of their strengths, and (3) to get ideas on how to improve their competencies (Ghomi & Redecker, 2019). The DigCompEdu framework is a way to assess digital teaching competencies most valued by experts (Jiménez-Hernández et al., 2020).

On the other hand, assessing teachers' digital competence by themselves has shortcomings. One of them is that students' self-assessment of digital competencies is still lacking in several areas, which include information literacy development, digital creation, digital research, and digital identity management. In addition, students' digital competencies were related to previous experience in the digital environment of everyday life. The higher the level of self-perceived digital competence of students based on the digital tasks of daily life, the more likely they are to develop high self-perceived digital competence in other digital areas related to their education (Martzoukou et al., 2020).

Demographic factors also influence teacher digital competence. Teacher, work experience, screen time, and ICT education are all factors that contribute to teachers' digital competence in the classroom and predict their level of digital competence (Guillen-Gamez et al., 2020; Røkenes & Krumsvik, 2014, 2016). The influence of demographic variables on digital competencies, such as community autonomy, does not affect the dimensions of use and attitudes.

Geographic regions or teachers' domicile can significantly impact teachers' digital competencies, especially regarding the availability of technology infrastructure and internet connectivity in certain areas. This factor can affect teachers' ability to use digital devices or technology in their teaching practices effectively. For example, if an area has limited high-speed internet access or outdated technology, teachers will find it challenging to integrate digital resources into their learning (Yang et al., 2022). In addition, exposure to technology and willingness to learn and adapt to new tools can play a role in teachers' digital competence. In terms of geographic areas, teachers living in rural areas may face challenges in developing their digital competencies due to remote living factors and limited access to technology. In addition, opportunities for professional self-development also become hampered (Guillen-Gamez et al., 2023; F D Guillén-Gámez & Mayorga-Fernández, 2022). Thus, in addition to individual experience and technological infrastructure, geographical areas or residence locations can result in a digital competency gap between teachers in urban and rural areas, thus also impacting the quality of education in each region.

Related to the influence of technological tools on teacher digital competence, teachers need to be aware of technological developments and integrate technology into their teaching practices to develop their digital competence in education. Teachers' digital competencies include information and data literacy skills, communication and collaboration, digital content creation, security, problem-solving, and other related competencies (Gümüş & Kukul, 2023). In daily ECE learning, teachers already use computers, microscopes, tablets, smartphones, scanners, and different types of software that can support that learning (Lindeman et al., 2021). Teachers can teach various knowledge and skills that students learn through digital devices. These digital activities help children learn letters, numbers, and colors. In addition, they learn digital languages, hand-eye coordination, how the internet works, and general knowledge of digital technologies (Jernes et al., 2010). In addition to individual skills, children also learn social skills such as teamwork, waiting their turn, and respecting others. Nonetheless, the main goal of teachers is to involve students in using digital resources (Abdullahi & Adebayo, 2019; Jernes et al., 2010).

Regarding knowledge of technological devices, the results showed that respondents had technological devices, mainly smartphones, laptops, digital cameras, and GPS devices. When given questions in the form of knowledge of ICT concepts, students can or fail to answer the questions. Students could answer well when given questions about the use of technological devices, except for questions about communication tools and social networks (Casillas Martín et al., 2020).

Regarding socio-economic impact on teachers' digital competence, teachers with less teaching experience may have lower levels of digital competence because they are less exposed to technology in their professional development (Mojca & Nančovska Šerbec, 2017). Teachers with low socio-economic status may have lower levels of digital competence due to limited access to technology and resources. Teachers who work in schools with more resources and support in technology integration can demonstrate better levels of digital competence (Benjamin et al., 2022; Garzón-Artacho et al., 2021). Teachers with more knowledge about ICT tend to have a greater level of digital competence. ICT training followed earlier can also affect teachers' digital competence (Mojca & Nančovska Šerbec, 2017). In addition, teachers accustomed to utilizing ICT in learning have better digital competence (Lucas et al., 2021). These factors and characteristics of teachers can affect teachers' digital competence in a variety of ways, including their desire to utilize technology in the classroom, their ability to incorporate or integrate technology in learning, and their confidence in utilizing digital tools (Loretta & Meri-Tuulia, 2021).

Regarding ICT mastery based on socio-economic status, previous research has shown that maternal education level is positively related to students' technical ICT skills and high levels of ICT competence (Aesaert & Van Braak, 2015). Based on this, what is meant by SES is economic and social status characterized by aspects of education, income, and work of a person. Using digital tools and communication between teachers and students is above average. The level of competence does not depend on how the skill is acquired. Students have a higher level of competence in using IT professionally than teachers, while teachers have a higher level of competence in using IT to perform educational tasks (O Kuzminska, 2019; Olena Kuzminska et al., 2018). This study aims to measure the influences of demographic factors, geography, technological tools, socio-economics, and self-regulated learning on the early childhood educators' digital competence.

1. Research Design, Site and Participants

This study employed a quantitative research design utilizing an online survey methodology. The primary objective was to investigate the variables influencing the digital competence of Indonesian ECE teachers, specifically examining socio-economic status, geographic location, technological availability, demographic characteristics, and self-regulated learning (SRL).

1.1 Participants

The sample comprised 492 ECE teachers currently enrolled in the Open University's undergraduate program. Participants were drawn from 39 regional offices across Western, Central, and Eastern Indonesia, representing a diverse geographical cross-section of the country.

1.2 Data Collection and Analysis

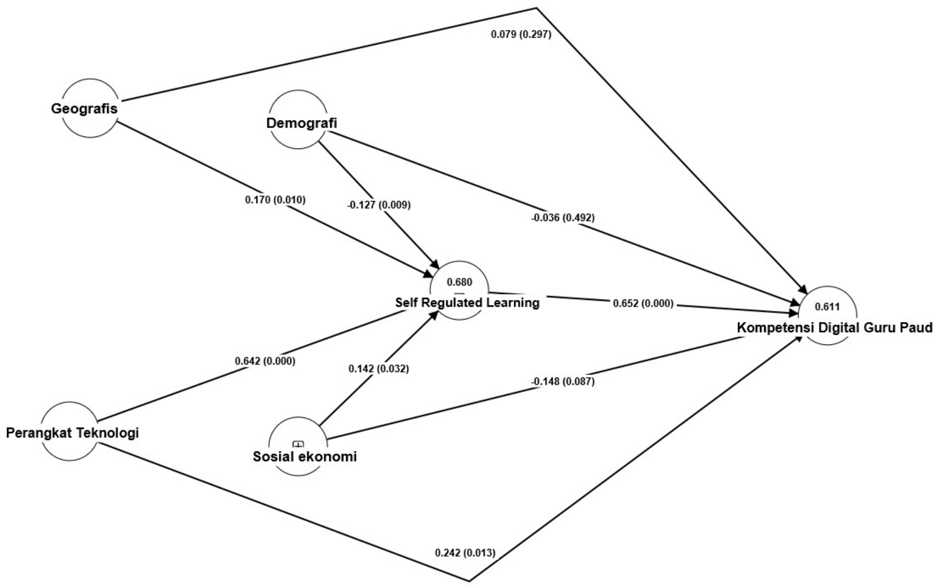
Data were collected via a structured questionnaire developed on Microsoft Forms. The survey links were distributed to students participating in webinar sessions through online tutorial platforms and WhatsApp groups. The structural relationships between variables were analyzed using Structural Equation Modeling (SEM) with Confirmatory Composite Analysis (CCA) via SmartPLS software.

1.3 Ethical Considerations

All participants were assured that their involvement was entirely voluntary and that their responses would remain strictly confidential. To protect the identities of the respondents and specific study sites, pseudonyms were utilized. This procedure served to uphold ethical standards, substituting for a formal Institutional Review Board (IRB) clearance, which is uncommon in this specific educational context.

2. Findings

Image 1: *Path Diagram*



Collinearity was assessed using the Variance Inflation Factor (VIF). It can be seen in Table 1. All VIF values were well below the threshold of 5.0, confirming the absence of multicollinearity issues within the model (table 1). The model demonstrated moderate explanatory power, with the coefficient of determination (R^2) indicating that the exogenous variables explained a substantial variation in both ECE Teachers' Digital Competence ($R^2 = 0.611$) and SRL ($R^2 = 0.680$). Effect size (f^2) analysis revealed that SRL exerted a major influence on teachers' digital competence ($f^2 = 0.350$), while the use of technological devices had a moderate effect on SRL ($f^2 = 0.187$). Demographic, geographic, and socio-economic factors demonstrated minimal direct effect sizes. Furthermore, cross-validated redundancy (Q^2) values were greater than zero for both Digital Competence ($Q^2 = 0.455$) and SRL ($Q^2 = 0.665$), confirming the model's robust predictive relevance.

Image 2: Confirmatory Composite Analysis (CCA) Structural Model

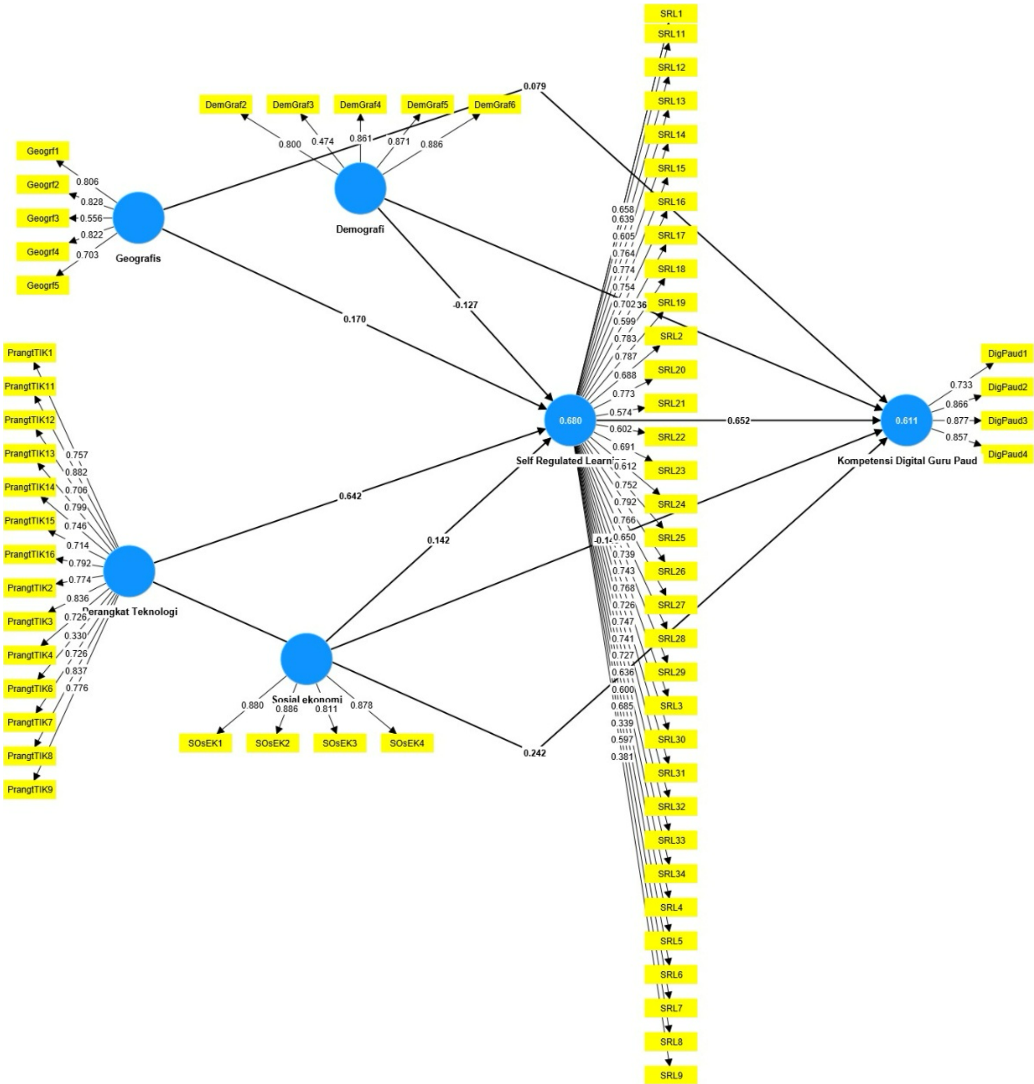


Table 1:

Collinerity Statistics using Varians Inflation Factor (VIF)

Variables	VIF		VIF		VIF
DemGraf2	1,927	TechDev8	4,687	SRL27	3,827
DemGraf3	1,202	TechDev9	3,383	SRL28	3,397
DemGraf4	2,343	SOsEc1	2,472	SRL29	3,719
DemGraf5	2,937	SOsEc2	2,554	SRL3	3,884
DemGraf6	3,126	SOsEc3	1,952	SRL30	4,280
DigComp1	1,572	SOsEc4	1,425	SRL31	4,985
DigComp2	2,321	SRL1	1,823	SRL32	4,350
DigComp3	2,660	SRL10	1,431	SRL33	3,473
DigComp4	2,248	SRL11	1,343	SRL34	4,245
Geogrf1	2,276	SRL12	1,656	SRL4	3,292
Geogrf2	2,376	SRL13	2,435	SRL5	2,218

Variables	VIF		VIF		VIF
Geogrf3	1,276	SRL14	2,176	SRL6	3,487
Geogrf4	1,937	SRL15	2,552	SRL7	2,754
Geogrf5	1,552	SRL16	1,725	SRL8	3,269
TechDev1	2,372	SRL17	2,592	SRL9	2,579
TechDev11	4,825	SRL18	3,179		
TechDev12	2,388	SRL19	3,816		
TechDev13	3,735	SRL2	1,578		
TechDev14	3,681	SRL20	2,267		
TechDev15	2,503	SRL21	1,329		
TechDev16	2,994	SRL22	2,549		
TechDev2	3,019	SRL23	4,649		
TechDev3	4,809	SRL24	4,486		
TechDev	2,114	SRL25	3,960		
TechDev6	1,287	SRL26	4,261		
TechDev7	2,546	SRL27	3,035		

2.1 Coefficient of Determination (R^2)

The Coefficient of Determination (R2) is a way to assess how many endogenous constructs can be described by exogenous constructs. The value of the coefficient of determination (R2) is expected to be between 0 and 1. If the R2 values of 0.75, 0.50, and 0.25 indicate that the model is strong, moderate, and weak (Sarstedt et al., 2020). Chin gave criteria R2 values of 0.67; 0.33; and 0.19 partly strong, moderate, and weak (Chin, 1998) Based on the understanding of the coefficient of determination (R^2) described by (Sarstedt et al., 2020) and (Chin, 1998), R^2 is a measure that shows how well endogenous constructs are described by exogenous constructs in the model. An R^2 value close to 1 indicates a better explanation. Sarstedt et al. (2020) classified R^2 values of 0.75 as strong, 0.50 as moderate, and 0.25 as weak, while Chin gave R^2 value criteria of 0.67 for the strongest, 0.33 for moderate, and 0.19 for weak (Sarstedt et al., 2020).

In this study, the results of measurements using coefficient determination (R^2) for the variables Digital Competency of ECE Teachers and Self-Regulated Learning showed R^2 values of 0.611 and 0.680, and Adjusted R-square values of 0.607 and 0.677, respectively. This suggests that the model has moderate power in explaining such variables based on the criteria provided by Chin and Sarstedt et al. That is, both endogenous constructs—ECE Teacher Digital Competence and Self-Regulated

Learning—can be significantly explained by exogenous constructs in the model, with Self-Regulated Learning showing a slightly better explanation than ECE Teacher Digital Competence. This classification indicates that this model is quite effective in explaining the variance of the endogenous variable under study.

Table 2: *R-Square*

	R-square	**Adjusted R-square**
Digital Competence of ECE Teachers	0,611	0,607
Self-Regulated Learning	0,680	0,677

a) f2 Effect Size (in-sample prediction)

The second measure of the predictive ability of a structural model is the effect measure, which provides an estimate of the predictive ability of any independent construction in the model. To calculate this value, each predictor construct is systematically removed from the model (Smart PLS does this automatically) and a new R2 is calculated without the predictor. Furthermore R2 with predictors in the model is compared with R2 without predictors in the model, and the difference between the two R2 values indicates whether the omitted construct is a meaningful predictor of the dependent construct (J. Hair et al., 2017). The effect size referred to as f2 is rated small, medium, and large. Values above 0.02 and up to 0.15 small category; values of 0.15 to 0.35 in the medium category; and values of 0.35 and above are categories with large effects (Cohen, 1988). Effect size is also considered a predictive metric in Table 3 below.

Tabel 1: *f-Square*

Variables	**Digital Competence of ECE Teachers**	**Technological Devices**	**Self-Regulated Learning**
Demographics	0,001		0,018
Geographic	0,003		0,020
Digital Competence of ECE Teachers			
Technological Devices	0,018		0,187
Self-Regulated Learning	0,350		
Socio-economic	0,011		0,013

Based on the effect size criteria provided by Cohen (1988), data analysis showed that Self-Regulated Learning has a major influence (f^2=0.350) on the Digital

Competency of ECE Teachers, indicating that the ability to regulate self-learning significantly increases the digital competence of teachers. On the other hand, Technology Devices showed a moderate effect (f^2=0.187) on Self-Regulated Learning, indicating that technology use contributes to students' ability to organize their learning. Demographics and Geographies, with f^2 values of 0.018 and 0.020 on Technology Device respectively, and small f^2 values on ECE Teachers' Digital Competency (0.001 and 0.003), showed minimal influence on digital competence and technology use. Socioeconomics also showed very small effects (f^2=0.011 and 0.013) on the Digital Competence of ECE Teachers and Technology Device, reaffirming that these factors had minimal contribution to exogenous variables in the model studied. This analysis underscores the importance of Self-Regulated Learning in ECE teacher education and the moderate role of technology in supporting the process, while demographic, geographical, and socio-economic factors are less influential (Cohen, 1988; J. Hair et al., 2017).

2.2 Cross-Validated Redundancy (Q2)

Cross-validated redundancy (Q2) or Q-square test is used to assess predictive relevance. The value of Q2>0 indicates that the model has an accurate predictive relevance to certain constructs while the value of Q2<0 indicates that the model lacks predictive relevance (Sarstedt et al., 2017). When interpreting Q2, a value greater than zero means that the predictive is relevant. While a value below 0 indicates a lack of predictive relevance. In addition, Q2 values greater than 0.25 and 0.50 represent medium and large predictive rates of the PLS-SEM model. The results of measurements using Cross-validated redundancy (Q2) in this study can be seen in table 4.4. The data in the table above shows the value of Q2>0, that the model has an accurate predictive relevance to the construct.

Tabel 2: *Q^2 Square*

Variables	Q^2prediction	RMSE	MAE
Digital Competence of ECE Teachers	0,455	0,741	0,554
Self-Regulated Learning	0,665	0,582	0,442

b) Structural Model Path Coefficients and Hypothesis Testing

Hypothesis testing in this study was conducted through R square (R2) and T/P Value. The statistical test T/P Value shows how far the influence of one explanatory or exogenous (independent) variable individually in explaining the variation of the endogenous variable (dependent). The T/P Value statistical test is also used to determine the presence or absence of the influence of each independent variable individually on endogenous variables tested at a significance level of 0.05 (J. F. Hair et al., 2019). This can be seen by comparing the table t value with the statistical t value.

2.3 Direct Influence

Based on Figure 4.2, about the display *of the output* of the partial influence measurement model of each research variable, namely Demography (X1), Geography (X2), Technological Devices (X3), Socio-Economic (X4), Self-Regulated Learning (Z) and Digital Competence of ECE Teachers (Y).

Table 3:

Summary of Hypothesis Testing Results for Directly Influenced Factors

Hipotesis	Path	Path coefficient (β)	t value	p value	Results
H1	ECE Demographics → ECE Teachers' Digital Competence	-0,036	0,687	0,492	Rejected
H2	Demographics → Self-Regulated Learning	-0,127	2,596	0,009	Accepted
H3	Geographic → ECE Teachers' Digital Competence	0,079	1,044	0,297	Rejected
H4	Geographics→ Self-Regulated Learning	0,170	2,577	0,010	Accepted
H5	Technology Devices → ECE Teachers' Digital Competence	0,242	2,492	0,013	Accepted
H6	Technology Devices → Self-Regulated Learning	0,642	7,949	0,000	Accepted
H7	Self-Regulated Learning → ECE Teachers' Digital Competence	0,652	10,594	0,000	Accepted
H8	Socio-economic → ECE Teachers' Digital Competence	-0,148	1,710	0,087	Rejected
H9	Socio-economic →Self-Regulated Learning	0,142	2,145	0,032	Accepted

Table 5 shows the results of the analysis of the relationship between demographic, geographic, technological, socio-economic, and Self-Regulated Learning (SRL) variables on the Digital Competence of ECE Teachers. This analysis uses the path coefficient (β), t-value, and p-value to determine the acceptance or rejection of the hypothesis. From the data, we can see that some relationships between variables are accepted based on significant p values ($p < 0.05$), while others are rejected. Several relationships between variables are accepted and show significant influence, the rejection of certain hypotheses highlights the complexity of factors affecting digital competence and SRL. This demonstrates the importance of considering a range of factors, including personal and professional initiatives, in the development of digital competence and SRL capabilities among ECE teachers.

1. The influence of demographics on the digital competence of ECE teachers

H1 (Demographics → Digital Competencies of ECE Teachers): **Rejected** because p value = 0.492. This suggests that there is no significant relationship between teacher demographics and their digital competence. This could be because digital competence is more influenced by other factors such as training and experience than demographics.

2. The influence of demographics on Self-Regulated Learning

H2 (Demographics → Self-Regulated Learning): **Accepted** with $\beta = -0.127$, t value = 2.596, and p value = 0.009. This suggests that there is a significant negative relationship between demographics and SRL. That is, demographic factors have a negative influence on the SRL ability of ECE teachers. This could be due to differences in age, gender, or educational background that affect the way teachers organize their own learning.

3. Geographical influence on ECE teachers' digital competence

H3 (Geographic → Digital Competency of ECE Teachers): **Rejected** with p value = 0.297, indicating that geographic location does not significantly affect teachers' digital competence. This means that although geography affects SRL, its influence on digital competence may be more complex and influenced by other factors.

4. Geographical Influence on Self-Regulated Learning

H4 (Geographic → Self-Regulated Learning): **Accepted** with $\beta = 0.170$, t value = 2.577, and p value = 0.010. This suggests that geographic location has a positive influence on SRL. Teachers in certain locations may have better access to resources or support communities that facilitate SRL development.

5. The effect of technological devices on the digital competence of ECE teachers

H5 (ECE Teacher Digital Competency → Technology Device): **Accepted** with $\beta = 0.242$, t value = 2.492, and p value = 0.013. This shows that access and use of technological devices contribute positively to teachers' digital competence, affirming the importance of technology in the development of digital skills.

6. The effect of technological devices on the digital competence of ECE teachers

H6 (ECE Teacher Digital Competency → Technology Device): **Accepted** with $\beta = 0.242$, t value = 2.492, and p value = 0.013. This shows that access and use of technological devices contribute positively to teachers' digital competence, affirming the importance of technology in the development of digital skills.

7. Socio-economic influences on ECE teachers' digital competence

H7 (Socio-economic → Digital Competency of ECE Teachers): **Rejected** with p value = 0.087, indicating that there is no significant relationship between socio-economic status and digital competence. This challenges the assumption that direct economic resources contribute to digital competence, suggesting that other factors such as access to training may be more important.

8. Socio-economic Influence on Self-Regulated Learning

H8 (Socio-economic → Self-Regulated Learning): **Accepted** with $\beta = 0.142$, t value = 2.145, and p value = 0.032. This suggests that socio-economic status positively affects SRL, which may reflect how economic resources affect individuals' ability to organize their learning.

9. The effect of Self-Regulated Learning on ECE teachers' digital competence

The H9 hypothesis is accepted with a path coefficient (β) of 0.652, a t value of 10.594, and a p value of less than 0.001, showing a significant relationship between Self-Regulated Learning (SRL) and digital competence of ECE teachers. This hypothesis asserts that teachers' ability to effectively organize their own learning contributes significantly to the development of their digital competencies. In this case capacity development through reflection, the application of effective learning strategies, and intrinsic motivation and clear learning objectives, all of which are crucial factors in understanding how SRL impacts the improvement of ECE teachers' digital competence.

This research is in line with research conducted by O'Donoghue & van der Werff (2022) to perform mediation analysis, which is an extension of simple linear regression that adds one or more variables to the regression equation. Mediation variables describe the way in which interventions obtain results. In short, a mediating variable is defined as "the mechanism by which X [independent variable] affects Y [dependent variable]" (Hayes, 2013). In mediation analysis, researchers assume that the independent variable (X) affects the mediator (M), further affecting the dependent variable (Y). In other words, it is assumed that the relationship between independent and dependent variables is indirect. Such mediation is ensured if: (1) the indirect influence is significant, and (2) the result of the indirect influence of *Confidence Intervals* (CI) does not show a zero value. In other words, the results between the lower bound and the upper bound at (CI) are not directly all positive or negative effects (Hayes, 2009). Using a bootstrap routine with five thousand subsamples, indirect effect significance testing was performed. The results of the mediator factor are shown in the following table 6.

Table 4: *Summary of the Indirect Influence Hypothesis*

HYPO-THESIS	PATH	PATH COEFFICIENT (B)	T VALUE	P VALUE	RESULTS
H11	Demographics → Self-Regulated Learning → ECE Teachers' Digital Competence	-0,083	2,632	0,009	Accepted
H12	Geographic → Self-Regulated Learning → ECE Teachers' Digital Competence	0,111	2,445	0,015	Accepted
H13	Technology Devices → Self-Regulated Learning → ECE Teachers' Digital Competence	0,419	6,944	0,000	Accepted
H14	Socio-economics → Self-Regulated Learning → ECE Teachers' Digital Competence	0,092	2,025	0,043	Accepted

2.4 Fit Model

Fit model determines how well the *model performs* with the sample data and indicates which *models* have a good fit in the use of SEM and it can be described in table 7.

Tabel 5: *Fit summary*

	Saturated Model	Model Approximation
SRMR	0,088	0,088
d_ULS	17,002	17,002
d_G	8,480	8,480
Chi-square	18068,292	18068,292
NFI	0,520	0,520

Table 7 provides a summary of fit which can be explained as follows.

1. Standardized Root Mean Square (SRMR)

SRMR is the difference between the model's implied correlation matrix and the observed correlation, allowing us to assess the average magnitude of the difference between observed and expected correlations as an absolute measure of the fit criterion (model). Values less than 0.10 or 0.08 (in more conservative versions, see Hu and

Bentler, 1999) are considered suitable. SRMR was introduced as a measure of goodness of fit in PLS-SEM with the aim of avoiding errors (Henseler et al., 2015). The SRMR value in this study is 0.08 which means this model is fit.

2. Exact fit criteria d_ULS and d_G

A model is suitable if the difference between the correlation matrix implied by the model and the empirical correlation matrix is so small that it can be purely attributed to sampling error. Therefore, the difference between the correlation matrix implied by the model and the empirical correlation matrix should be insignificant ($p>0.05$). Conversely, if the difference is significant ($p<0.05$), the model fit has not yet formed. From the data above the model, both D_ULS and D_G values above 0.05, which is 0.429. This fact gives meaning that the model is suitable, and fit is already formed.

3. Normed Fit Index (NFI) or Bentler and Bonett Index

NFI is defined as 1 minus the Chi² value of the proposed model divided by the Chi² value of the zero model. As a result, NFI returns a value between 0 and 1. The closer NFI is to 1, the better the match. NFI values above 0.9 usually represent an acceptable match. (Lohmöller, 1989) provides detailed information on the calculation of NFI of the PLS path model. From the data obtained in this research, based on the fit model where the NFI value is 0.824 close to 0.9 is getting closer to one. This data means that model matches are acceptable.

3. Discussion

The findings indicate that the teachers' digital competence is predominantly driven by self-regulated learning (SRL) and access to technological devices. While direct access to digital tools provides the necessary foundation for technological integration, demographic, geographic, and socio-economic factors were found to influence digital competence exclusively through indirect pathways, specifically by shaping SRL. Notably, this study found no significant direct correlation between demographic characteristics (e.g., age, gender) or geographic domicile and teachers' digital competence, align with prior research conducted by Kuzminska et.al, (Olena Kuzminska et al., 2018). This contradicts prior research asserting that younger or less experienced teachers inherently possess higher digital competence. Instead, these findings align with studies emphasizing that continuous training, teaching experience, and proactive learning behaviors are far more critical than age-based assumptions.

Despite potentially feeling less intially proficient, older educators frequently recognize the pedagogical value of technology, which mitigates any assumed negative correlation between age and ICT skills (Siddiq et al., 2016). On the other hand, this study opposes a research finding that showed younger teachers generally have a higher level of digital competence than older teachers and teachers with less teaching experience have a higher level of digital competence (Cabero &; Barroso, 2016; Yang et al., 2022).

This study also opposes the results of previous studies that highlighted demographic factors as significant influences on digital competence. For example: prior studies emphasized demographic and professional characteristics as important (Francisco D. Guillén-Gámez et al., 2020; Krumsvik, 2014; Krumsvik et al., 2016). Other research indicated gender differences, with male teachers have higher ICT knowledge due to more extensive training (Cabezas González et al., 2020; Cuhadar, 2018). In contrast, a research showed that girls had better technical ICT skills and a high level of ICT competence than boys (Aesaert &; Van Braak, 2015).

It is important to acknowledge a limitation within the demographic findings: the severe gender imbalance within the study sample (7 males versus 485 females) precluded a robust, comparative analysis of gender-based differences, which remains an area for future exploration. Ultimately, this research underscores that external factors like geographical remoteness or socio-economic constraints do not strictly dictate technological proficiency; rather, an educator's internal drive and ability to self-regulate their learning are the true catalysts for digital competence.

4. Conclusion

The current study explored the primary drivers of digital competence among in-service early childhood educators undertaking distance undergraduate degrees at the Open University. The most striking takeaway is the central role of Self-Regulated Learning (SRL). SRL non only acts as the strongest predictor of digital capability but also functions as a vital mediating mechanism for all other variables examined. This highlights how an educator's ability to autonomously manage, motivate, and reflect on their learning journey is essential for thriving in a technology-driven educational landscape. Given that the Open University relies on a distance learning model, it naturally demands a high degree of student independence. Within this setting, the core elements of SRL – specifically intrinsic motivation, metacognition, and proactive behaviors drwan from Zimmerman's social cognitive model – serve as the main engines allowing teachers to adapt to continuous technological shifts (Zimmerman & Schunk, 2008).

Additionally, physical access to technological devices directly boosts digital competence, confirming that owning items like laptops or smartphones remains a foundational requirement. Yet, simply possessing a device is merely the starting point. When paired with robust SRL, teachers gain the necessary motivational and cognitive drive to leverage technology for genuine professional growth, moving past passive information consumption.

A major theoretical contribution of this work is clarifying how comprehensively SRL mediates external factors. Interestingly, an educator's demographic background, physical location across the Indonesian archipelago, or economic status showed no significant direct impact on their digital skills. Instead, these elements create an environmental backdrop that shapes how an individual develops self-regulatory habits. This dynamic exemplifies Bandura's Social Cognitive Theory (SCT) (Bandura, 1986), demonstrating that personal agency can effectively overcome environmental hurdles. For example, teachers stationed in remote regions might cultivate stronger SRL as a coping mechanism to troubleshoot issues and acquire knowledge independently. Ultimately, in a connectivist learning environment, internal learning capacities often outweigh static external constraints.

These findings contribute to a nuance dialogue within existing literature. While the results align with studies emphasizing the criticality of autonomous learning for technology adoption, the absence of a significant direct influence of demographics and geographic contrasts with research by scholars such as Cabero and Barroso (2016) and Yang et al. (2022). This divergence is attributable to the distinct characteristics of the study's sample. The distance learning model of the Open University may inherently select for and cultivate individuals with a higher propensity for SRL. This educational context also promotes behaviors consistent with Connectivism (Siemens, 2004), a learning theory for the digital age, where competence is constructed through creating and navigating information networks. As high SRL is integral to successful connectivist learning, it is plausible that in this specific context, an individual's internal learning capacity predominates over external, static factors.

5. Implications of the Study

These findings offer several practical and strategic takeaways. For higher education institutions responsible for teacher training, the curriculum needs to evolve beyond simply transmitting basic software operations. Program should purposefully foster SRL capabilities through targeted pedagogical approaches, such as reflective journaling, project-based learning, and building online communities that encourage peer-to-peer support. At the macro level, policymakers, including the Ministry of Research, Technology, and Higher Education, should consider shifting their strategic focus. While distributing hardware remains helpful, a more sustainable, long-term strategy involves investing in programs that teach educators the fundamental skills of “learning to learn”. Embedding SRL development modules into national teacher certification programs would be a robust step towards building a resilient teaching workforce. Finally, for the teacher themselves, the message is highly encouraging: digital competence is not a fixed, predetermined trait limited by one’s geographical or economic background. Rather, it is a fluid skill set than can be actively mastered through conscious self-regulation, motivation, and strategic initiative.

6. Limitations and Future Research Directions

Despite its contributions, this investigation has certain limitations that must be acknowledged. First, the data relies heavily on self-reporting, which inherently introduces the potential for social desirability bias. Second, the cross-sectional nature of the survey only captures a specific snapshot in time, preventing the observation of how these competencies evolve developmentally. Lastly, most female participants in the sample made it impossible to conduct a rigorous analysis of gender-based differences. Moving forward, researchers should consider adopting longitudinal designs to observe how SRL and digital competence co-evolve throughout an educator’s career. Qualitative methods, such as in-depth interviews or observational studies, would also be highly valuable for uncovering the spesific, day-to-day strategies teacher use to navigate digital environments. Furthermore, designing experimental studies to evaluate specific classroom interventions aimed at boosting SRL could provide concrete, empirical evidence on the most effective ways to elevate educator’s overall digital proficiency.

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