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Latent class profiles of teacher use of digital tools in PISA 2018 data

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Abstract
This study examined teachers' digital tool use through latent class analysis (LCA) and identified predictors that separated the emergent subgroups of teachers. Data from the PISA 2018 teacher questionnaire were employed to analyze the teachers' digital tool behaviors in ICT (Information and Communications Technology) strong countries: Germany, Korea, and USA. The LCA suggested three subgroups of teachers, with similar percentages in each country: 'minimal users' (Class 1: 22–33%); 'moderate users' (Class 2: 46–60%); and 'versatile users' (Class 3; 17–21%). Cross-national similarities were also found in the profile patterns of 'minimal users' and the variables predicting the subgroup membership. The single most important factor of digital tool use across the three countries was teacher training in ICT, either during pre-service training or through in-service professional development programs. Notable cross-national differences were found, however, in the profiles of 'moderate' users and their use of specific types of digital tools. Discussion concludes with practical suggestions to enhance teacher use of digital tools.

Keywords Digital tools · Teacher training · Latent class analysis · PISA 2018

1 Introduction

While educators have long been called upon to prepare future teachers for the rapidly changing digital world (cf. Starkey, 2020), understanding teacher use of technology in the classroom is now more important than ever. This is partly because many young children are growing up as digital natives and are exposed to various types of digital devices, computer games, and social media before starting their formal schooling. Thus, if teachers use digital tools that look outdated, they may lose interest in learning at school (Ruggiero & Mong, 2015; Starkey, 2020). Furthermore, in a time of increasing concerns about potential impacts of Artificial

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Intelligence (AI) applications on the education sector, there is a growing expectation that teachers should be able to know and use a diverse range of digital tools.

In the present study, ‘digital tools for classroom use’ is defined as any electronic device or program used as a medium to produce teaching and learning materials. This is adopted from the definition provided in Ruggiero and Mong (2015) as “anything that used an additional input to produce learning materials [by electricity]” (p. 166) to make “learning easier and more engaging” and to “meet the instructional goals” (p. 169). Digital literacy is a complex concept, stemming from cognitive, socio-cultural, and philosophical perspectives (cf. Martin & Grudziecki, 2006). It has been argued that digital literacy encompasses not just technical skills but also interests, attitudes, communication, and social awareness (OECD, 2019). Further, van Braak et al. (2004) emphasize the ability to use *a wide range of varying digital tools* as an indicator of one’s overall ICT (Information and Communications Technology) competence. It is believed that those who are interested in and capable of using *various* digital tools are more likely to try new ones (e.g., Ferneding, 2003). In contrast, if a person uses only basic computer applications (e.g., Word processing), s/he may be less likely to use emerging digital tools, even if they are available. Therefore, information about teachers’ current digital tool use may suggest the ways they approach new and more advanced types of technology.

The primary aims of this study are two-fold: (a) to develop a typology of teachers, by identifying subgroups of similar teachers, with respect to their use of digital tools, through latent class analysis (LCA); and (b) to examine predictors of the likelihood of belonging to the subgroups identified in the LCA model. The current investigation focuses on ICT-strong countries—Germany, Korea, and the United States—as exemplar cases. Examination of exemplary user cases has a long history in ICT research (e.g., Hadley & Sheingold, 1993). Researchers have unequivocally claimed that ICT-related infrastructure and resources within the school (e.g., hardware, software, and infrastructure support) is one of the most (if not the most) critical factors in teacher use of technology (e.g., Tondeur et al., 2012). Therefore, by examining ICT-strong countries, this study starts with the assumption that this factor is not an overwhelming barrier to many teachers under the current investigation.

Then, the following questions arise. *When the overall ICT infrastructure and resources are not a major barrier to many teachers within the country, would their behaviors in using a range of digital tools be similar? Alternatively, would distinctive patterns of digital tool use behaviors emerge, even among teachers in the ICT-strong countries, due to within-country and cross-country variations in ICT resources and other factors? Relatedly, to what extent would the predictors linked to teacher use of digital tools show similarity across the ICT-strong countries (Germany, Korea, and the United States)?* It is hoped that the results of this study may also be useful to teacher educators in less developed countries by suggesting how their teachers may use digital tools as they gain more access to resources. Overall, this study seeks to identify teacher behaviors in ICT use and examine teacher-personal and system-level factors that may help teachers to adapt to the rapidly changing digital environment.

2 Typologies of technology-using teachers

Several studies have developed teacher typologies of ICT use. A summary description of these studies is presented in Table 1. The three early studies (Rogers, 1962; Clariana, 1992; Hadley & Sheingold, 1993) represent technology-use behavior before the widespread use of the Internet. Five subgroups of technology adopters were identified by all three studies, recognizing that some people are early adopters and innovators, while others remain as non-participatory or struggling users. Studies have also suggested that once teachers gain experience, they can become ICT integrators (i.e., there is no difference in pedagogical approaches for ICT-based and regular classroom learning) or ICT extenders (i.e., ICT-based curriculum is extended for higher-order thinking activities; cf. Clariana, 1992).

While these early studies focused on the developmental stages of teachers adopting ICT, subsequent studies (see the middle five studies in Table 1) examined teacher typologies based on psychological/behavioral dispositions such as attitudes and beliefs (Mama & Hennessy, 2013; Mukama, 2009; Thurm, 2018) or pedagogical approaches in using technology (Donnelly et al., 2011; Tondeur et al., 2008). Overall, there is some consensus in classifying teachers into three or four groups; Mukama (2009) identified three subgroups of teachers, while the other four studies identified four subgroups. Furthermore, although different labels were used, similar types of teachers were identified across these studies. There is a group identified to be passive and reluctant (Mukama, 2009), inadvertent (Donnelly et al., 2011), technology-avoiding (Mama & Hennessy, 2013), and infrequent technology-users (Thurm, 2018). On the other end of the spectrum, a group of teachers were found to be active and aspiring leaders of ICT integration in the school (Mukama, 2009), to have high levels of diverse knowledge allowing for creative use of ICT (Donnelly et al., 2011), and to use ICT to create student-centered, engagement-focused, and constructivist-oriented classroom cultures (Donnelly et al., 2011; Mama & Hennessy, 2013; Tondeur et al., 2008).

Recently, teacher typology studies have used a statistical technique known as latent class analysis (LCA) or latent profile analysis (LPA, see the four studies listed at the bottom of Table 1). Two-subgroup typologies were identified in Tondeur et al. (2017) as high/low profile groups, and in Huang et al. (2021) as competent/less competent teachers. The four-subgroup typology described by Graves and Bowers (2018) included 'assessors' and 'presenters', in addition to 'evaders' and 'dexterous' users. Further, three-subgroups identified in Tang and Bao (2021) were labelled as 'savvy', 'struggling', and 'resource-constrained'. While these studies have utilized the same or similar statistical approaches, the results reflect varied foci in the main constructs: attitudes towards ICT (Tondeur et al., 2017), instructional purposes for using ICT (Graves & Bowers, 2018), self-regulation in using ICT (Huang et al., 2021), and perceived barriers in using ICT (Tang & Bao, 2021). The present study investigates teacher typologies for the use of a diversity of digital tools, motivated by the need to understand teacher behaviors in using emerging digital platforms and to address a gap in the current literature surrounding teacher typologies based on digital tools.

Table 1 Studies of teacher typologies in ICT use

Study	Study design & sample	Variable to create typology	Teacher typology (number of groups)
Rogers (1962)	A book proposing clusters of technology adopters	Innovation adoption	Innovators; Early adopters; Early majority; Late majority; and Laggards (5 groups)
Clariana (1992)	A position paper based on U.S. teachers' use of Integrated Learning System	ICT integration	Novice non-participatory; Novice participatory; Practitioner; Integrator; and Extender (5 groups)
Hadley and Sheingold (1993)	Primary and secondary school teachers ($n=608$) in U.S.	ICT integration	Enthusiastic beginners; Supported integrators; High school naturals; Unsupported achievers; and Struggling aspirers (5 groups)
Mukama (2009)	Small-scale qualitative study of pre-service teachers in Rwanda ($n=12$)	Attitudes, skills, and behaviors	Active (agents of change in learning practice); Passive (skilled but no interest); Reluctant users (skilled but ICT is not a priority) (3 groups)
Donnelly et al. (2011)	Small-scale qualitative study of science teachers in Ireland ($n=13$)	Instructional purposes for use of digital tools	Contented traditionalist; Inadvertent user; Selective adopter; and Creative adapter (4 groups)
Mama and Hennessy (2013)	Small-scale qualitative study of primary school teachers in Cyprus ($n=11$)	Attitudes and beliefs about technology use	Constructivist-oriented purpose; Engagement-oriented purposes; Administrative-oriented, and Technology-avoiding (4 groups)
Thurm (2018)	Secondary in-service teachers in Germany ($n=160$); 'profile' was not based on cluster analysis or latent profile analysis	Beliefs about and practice in technology use	Positive beliefs & frequent users, Positive beliefs & infrequent users; Negative beliefs & infrequent users; and Negative beliefs & frequent users (4 groups)
Tondeur et al. (2008)	Primary teachers across 70 schools in Belgium ($n=574$); cluster analysis	Beliefs about pedagogical approaches	Both constructivist and traditional pedagogical approaches; Constructivist approach; Traditional approach; and Undefined (4 groups)
Tondeur et al. (2017)	Pre-service teachers from 18 teacher education institutions in Belgium ($n=688$); latent profile analysis	Attitudes towards ICT and TPACK constructs	Low ICT profile group and High ICT profile group (2 groups)

Table 1 (continued)

Study	Study design & sample	Variable to create typology	Teacher typology (number of groups)
Graves and Bowers (2018)	Secondary data analysis using the data collected from Fast Response Survey System ($n=2{,}764$ teachers) in U.S; latent class analysis	Instructional purposes for of using technology	Dexterous; Evaders; Assessors; and Presenters (4 groups)
Huang et al. (2021)	Pre-service teachers in the US ($n=64$); latent profile analysis	Self-regulation in using digital tools	Competent self-regulator; and Less competent self-regulator (2 groups)
Tang and Bao (2021)	Secondary data analysis about open educational resources; data from the Open University, UK ($n=367$ teachers from 72 countries); latent class analysis	Perceived barriers in using open educational resources	Savvy; Struggling, and Resource-constraint (3 groups)

3 Personal and institutional factors in teacher use of digital tools

Another line of research relevant to the current investigation is the range of studies examining factors associated with teacher use of digital tools. There has been a large number of such studies that led to several review papers on the topic (e.g., Buabeng-Andoh, 2012; Mumtaz, 2000; Røkenes & Krumsvik, 2014; Starkey, 2020; Wang et al., 2018). In summary, there is a broad recognition of two categories, teacher-personal and institutional factors, which assumes that institutional support is necessary in facilitating teachers' skills, talent, and intention to use technology (Tondeur et al., 2008).

Among the teacher-personal factors, gender (Kay, 2006; van Braak et al., 2004), teaching experience/age (Jang & Tsai, 2012; Hsu et al., 2017), and teaching subject areas (Jang & Tsai, 2012; Sezer, 2015) are often included as relevant to teachers' technology use. However, mixed results have been reported. For instance, while male teachers showed higher scores in technology integration in the classroom (Kay, 2006), researchers also claimed that gender gap in computer and technology literacy has narrowed over time and that female teachers tended to show greater improvement after ICT training (Yukselturk & Bulut, 2009).

In addition to the demographic and teaching-related variables mentioned above, a large volume of studies has focused on teachers' psychological/behavioral dispositions. Commonly studied dispositions include self-efficacy in instructional settings (Gil-Flores et al., 2017; Hammond et al., 2009; Tondeur et al., 2017), the tendency to collaborate with other teachers (Buabeng-Andoh, 2012; Gil-Flores et al., 2017; Mumtaz, 2000; Pelgrum & Voogt, 2009; Tondeur et al., 2012), and teacher commitment as time spent on teaching (Hew & Brush, 2007; Hammond et al., 2009; Vannatta & Nancy, 2004). These studies suggest that higher levels of these psychological/behavioral dispositions are positively linked to teachers' ICT competency.

Among the institutional factors, teacher training in ICT in initial education programs (Hammond et al., 2009; Tondeur et al., 2017; Wang et al., 2018) or professional development in ICT (Albion et al., 2015; Pelgrum, 2001; Tondeur et al., 2010), ICT-related school resources (Buabeng-Andoh, 2012; Gil-Flores et al., 2017; Hammond et al., 2009; Tondeur et al., 2012), and the existence of clear guidelines and policies for teacher use of ICT in school (Gil-Flores et al., 2017; Hew & Brush, 2007; Tondeur et al., 2012) have been found as important contextual variables for teachers' ICT use. For instance, the provision of school resources to support ICT use in classrooms has been unequivocally advocated in most reviewed studies. Furthermore, researchers have argued that the existence of school-level ICT policies can have positive impacts on teacher use of digital tools, because such policies can guide instructional innovation (Baylor & Ritchie, 2002), foster a collaborative culture of ICT use (Pelgrum & Voogt, 2009), specify teacher responsibilities and expectations for ICT integration, and provide directions for professional development within the school (Pelgrum, 2001; Vanderlinde et al., 2014).

4 The present study

The primary aims of the present study are (a) to identify subgroups of teachers with respect to their use of digital tools, based on latent class analysis (LCA); and (b) to examine personal and institutional factors that would predict the membership in the identified LCA model. By examining three ICT-strong countries, the study also aims (c) to document cross-national similarities/differences in teacher behaviors in digital tool use and their predictors. Among teachers' personal factors, gender, age, years of teaching, teaching subject, as well as psychological/behavioral dispositions of self-efficacy, collaboration, and commitment, were examined. Among institutional factors, teachers' initial educational program, teacher education and training in Technology and ICT, ICT-related school resources, and ICT-related school policy were included as potential predictors. The selection of these variables was motivated by the desire to include a comprehensive set of variables that have been extensively studied and found to be linked to teachers' digital tool use. Previous studies have noted that policymakers and educational leaders tend to focus on *whether* (rather than how) teachers use certain digital tools (Graves & Bowers, 2018), under the premise that teachers themselves would assess specific functions of digital tools once they are familiar with them and can determine appropriate use (Hadley & Sheingold, 1993: Mumtaz, 2000). In this context, the present study's results may provide useful insights to both policymakers and educational leaders in suggesting useful ways to allocate educational resources and improve teacher training opportunities in ICT.

5 Methods

5.1 Data & participants

The data for the present study were drawn from teacher responses to the teacher questionnaire of the PISA (Program for International Student Assessment) 2018 cycle. PISA is an international student assessment on reading, mathematics, and science, implemented every three years by the OECD (the data available in the OECD's PISA website https://www.oecd.org/pisa/data/2018database/). As part of the project, teachers were asked about digital tool use, along with their demographic background and other teaching-related practices. Among the top ten IT-strong countries (according to the Government Artificial Intelligence Readiness Index 2021 produced by Oxford Insights), Germany, Korea, US, and UK participated in the teacher questionnaire component of PISA 2018. However, the UK sample size was substantially smaller ($n = 937$) than the other three countries, and thus, data from teachers in Germany ($n = 2{,}646$), Korea ($n = 2{,}496$), and US ($n = 1{,}674$), with a total sample size of $N = 6{,}816$, were analyzed in this study.

5.2 Measures

5.2.1 Teacher use of digital tools

Teachers' digital use was measured by asking how often they used 14 different types of digital tools, ranging from word-processing to simulation/modelling (see Table 5 for a full list). The item stem of 'How often do you use the following tools in your teaching this school year?' was presented with a four-point frequency response set ('never', 'in some lessons', 'in most lessons', and 'in every or almost every lesson'). However, the participants rarely chose 'in most lessons' or 'in every or almost every lesson' for half of the items, which resulted in highly skewed distributions. Furthermore, it seems reasonable that digital tools may not be used in most or all lessons, even among regular digital users. Therefore, latent class analysis was conducted using the dichotomously scored item responses yes ('I use') versus no ('I do not use'). Individual teachers' overall digital tool use was also assessed by their scores on a single scale labelled as "TCCITUSE" (Cronbach's α=.82/.90/.84 in Germany/Korea/US). The scale was constructed from the scores of all 14 digital tool items (based on the original responses) as part of the public data construction process. The individual teachers' scores on the TCCITUSE scale were also used in this study.

5.2.2 Predictors of teacher use of digital tools

A total of 14 variables were employed as potential predictors of teacher use of digital tools. The list of these variables is presented in Table 2, along with response category, scale information (e.g., Cronbach's alpha and example items), and item number in the PISA teacher questionnaire.

5.3 Statistical analysis

5.3.1 Latent class analysis (LCA)

Latent class analysis (LCA) was conducted to identify subgroups of teachers with respect to their digital tool use. In LCA, the estimated latent classes are produced to describe the unobserved heterogeneity of observed cases (i.e., grouping of individuals) in the target population. Thus, LCA is known as a person-centered approach (Morin et al., 2016; Wang & Wang, 2020) that allows grouping of individuals based on the item response patterns. In this study, single-country-level LCA was conducted first for each of the three countries separately, followed by multiple-group LCA, where the data from all three countries fitted simultaneously with the parameters being estimated freely for each of the three countries. As mentioned above, the dichotomously scored item responses (either "yes" or "no") to the fourteen digital tools were entered into LCA. Therefore, the parameter estimates in LCA are the proportions of individuals in each subgroup of teachers

Table 2 Descriptions of the study variables

Variable		Response category	Item number in PISA 2018
Digital tool use: 14 types of digital tools (see Table 5)		No (1); Yes (2)	TC169Q01HA(R) to TC169Q14HA(R)
Demographic information			
Gender	Are you female or male?	Female (0); Male (1)	TC001Q01NA
Age	How old are you?	Open-ended	TC002Q01NA
Current teaching context			
Years in teaching	Year(s) working as a teacher in total	Open-ended	TC007Q02NA
Subject area	Reading, writing and literature	No (0); Yes (1)	TC018Q01NB
	Mathematics	No (0); Yes (1)	TC018Q02NB
	Science	No (0); Yes (1)	TC018Q03NB
	Social studies	No (0); Yes (1)	TC018Q05NB
	Arts	No (0); Yes (1)	TC018Q08NB
Psychological/behavioral disposition			
Collaboration (EXCHT)	Exchange and co-ordination for teaching; Example items: “Exchange teaching materials with colleagues”; “Attend team conferences”	4-items; Cronbach’s α = 0.73/0.84/0.79 in Germany/Korea/US	TC046Q04NA to TC046Q07NA
Self-efficacy (SEFFINS)	Teacher’s self-efficacy in instructional settings; “Implement alternative instructional strategies in my classroom”; ‘Craft good questions for my students”	4-items; Cronbach’s α = 0.68/0.82/0.78 in Germany/Korea/US	TC199Q03HA, TC199Q10HA to TC199Q12HA
Commitment as time spent	Time spent reading for your work out of your classes (per week)?	4-point frequency scale: “Less than 1 hour’; “1–3 h”; “4–6 h” and “More than 6 h’	TC175Q01HA
Initial teacher training program			
Initial program	Teacher education program	Less than 1 year (0); Longer than 1 year (1)	TC014Q01HA(R)

Table 2 (continued)

Variable		Response category	Item number in PISA 2018
Program in Technology	Teacher education in Technology. (Included in the item set along with Reading, Mathematics, Science, etc.)	No (0); Yes (1)	TC018Q04NA
Training in ICT	Teacher education in ICT skills for teaching (Included in the item set along with teacher-parent cooperation, evaluation of results, etc.)	No (0); Yes (1)	TC045Q05NA
Professional development (PD) in ICT			
PD in ICT	Professional development ICT skills for teaching in the last 12 months	No (0); Yes (1)	TC045Q05NB
Need in ICT PD	Current need for professional development: ICT skills for teaching	4-point Likert-type scale: "No need"; "Low need"; "Moderate need"; and "High need"	TC185Q05HA
School environment			
School resources	School's instruction hindered by: A lack of educational material	4-point Likert-type scale: "Not at all", "Very little", "To some extent", and "A lot"	TC028Q05NA
School policy	Having school policy concerning the use of digital devices for teaching	No (0) Yes (1)	TC184Q01HA(R)

Note. A symbol (R) indicates that collapsed response categories were used in the analysis who reported using a particular digital tool. The final LCA model outcome is a categorical variable, namely individuals' subgroup/class membership.

LCA is an exploratory process—the number of latent classes is unknown and cannot be directly observed in the data. Thus, models with an increasing number of latent classes are compared (Wang & Wang, 2020). There is no consensus on which indices or statistical tests are the most effective in deciding the optimal model (see Morin et al., 2016). Therefore, it is a common practice to consider the model fit results from several indices (Wang & Wang, 2020). The commonly employed model fit indices are listed in Table 2. Overall, a lower value on information criteria (i.e., AIC, BIC, and SA_BIC) suggests a better fit to the data. A significant p-value in the likelihood ratio tests (i.e., VLMR_LRT, aLMR_LRT, and BLRT), using the conventional $p < .05$, indicates that the k-class model has a significant improvement in model fit compared to the (k-1)-class model, and thus the k-1 profile model should be rejected in favour of a k-profile model.

It should be noted that since these likelihood tests rely on statistical significance, the fit statistics results are heavily influenced by sample size (Marsh et al., 2009). In other words, with sufficiently large samples (such as the data of this study), the fit indices may suggest more latent classes keep being added to the model. To overcome this issue, elbow plots are often used (whereby information criterion values are plotted), which can be more effective in illustrating relative gains by an additional group. It is recommended that either the point of formation of a *first* angle (i.e., where the most substantial model fit improvement is shown) or the point after which the slope flattens (i.e., where no further substantial model fit improvement is shown) (see Morin et al., 2016) be considered as the optimal number of subgroups in the model.

Another consideration in determining the optimal number of classes is the correct class membership assignment (Wang & Wang, 2020). The lower boundary of the probability of correct class membership assignment (presented in Table 4) should be about 0.70 (Nagin, 2005). A statistic called entropy (Celeux & Soromenho, 1996) as the summary index of the membership classification accuracy is also often considered. An entropy can take a value ranging from 0.0 to 1.0. A value closer to 1 is desirable as it indicates fewer classification errors (Morin et al., 2016), while a value smaller than 0.60 is considered a poor classification result (Asparouhov & Muthén, 2014).

Finally, and perhaps most importantly, each subgroup (i.e., latent class) identified by LCA should be conceptually interpretable and theoretically meaningful, and the interpretations of each subgroup should be distinctive from another (Morin et al., 2016; Wang & Wang, 2020). Without appropriate interpretation of each subgroup, the model will not be meaningful nor useful, regardless of model fit. Furthermore, the class proportion should not be too small (e.g., fewer than 10% of the sample size) for each class to have a practically meaningful representation of the corresponding subpopulation in the target population (Wang & Wang, 2020). Mplus 8.0 (Muthén & Muthén, 2017) was used for LCA in this study.

5.3.2 Subsequent analysis to predict latent class membership

Two types of regression analysis were performed to examine teacher characteristics across the subgroups identified in the LCA model. In the first step, a total of 14 variables (see Table 2) were included in multiple regression analysis with the individuals' scale scores (on TCICTUSE) as the dependent variable representing teachers' overall digital use. The forward method was used to allow only the statistically significant variables to remain in the model, and therefore, this process reduces the number of predictor variables in the model. To select the variables that are highly statistically significant, a stringent *p*-value level of 0.001 was used as the criterion in the forward method.

In the second step, those predictor variables that remained in the multiple regression model were subjected to multinomial logistic regression to identify which predictors are associated with subgroup membership identified in the model (i.e., Class 1, Class 2, or Class 3). In this set of analyses, the dependent variable is the latent class membership, which is a multinominal (categorical) variable, and thus multinominal logistic regression was used. Odd ratios (OR) are produced as the parameter estimates of the predictor variables, which indicate the likelihood of individual teachers to be classified into one of the latent class groups. For categorical predictor variables (which were dummy-coded and indicated with '[yes]' in Tables 6 and 7), their associated odd ratios (ORs) indicate the effects for teachers who answered 'yes' (e.g., having professional development in ICT), as opposed to 'no' (e.g., not having professional development in ICT), on the likelihood of being classified into one of the latent class groups. For continuous variables, their associated odd ratios (ORs) indicate the effects of a one-unit change in the predictor variable on the likelihood of being classified into one of the latent class groups. The OR values of 1.68, 3.47, and 6.71 correspond to Cohen's *d* of 0.2 (small), 0.5 (medium), and 0.8 (large) effect sizes, respectively (see Chen et al., 2010). As most, if not all, predictors are expected to be statistically significant (because only the statistically significant variables were selected from the previous step of multiple regression), the results are discussed with respect to the variables showing an odd ratio (OR) of at least 1.68 (i.e., at least a small effect size).

6 Results

6.1 Selection of the optimal model based on latent class analysis (LCA)

Model fit results from latent class analysis (LCA) are presented in Table 3, along with elbow plots in Fig. 1 (i.e., visual representation of AIC, BIC, and djusted BIC values). Results based on Germany's data are reviewed first. It appears that there was a substantial model fit improvement in the 2-, 3-, and 4-class solutions. However, the VLMR and aLMR likelihood ratio tests indicate no statistical improvement between the 2-class and 3-class solutions, while the 3-class solution appears to be the 'first' angle (i.e., the most substantial model fit improvement). Comparing the profile patterns of the 2-class and 3-class solutions, the

Table 3 Model fit statistics: Single-group and multigroup latent class analysis (LCA)

Class	# Free parameter	Log L	AIC	BIC	Adjusted BIC	Entropy	VLMR_LRT *p*-value	aLMR_LRT *p*-value	BLRT *p*-value
Germany (*N* = 2,646)									
2	29	-17,573	35,205	35,375	35,283	0.76	< 0.001	< 0.001	< 0.001
3	44	-17,156	34,401	34,660	34,520	0.75	0.1080	0.1095	< 0.001
4	59	-16,956	34,030	34,376	34,189	0.71	0.0014	0.0015	< 0.001
5	74	-16,801	33,749	34,185	33,949	0.69	< 0.001	< 0.001	< 0.001
6	89	-16,713	33,603	34,127	33,844	0.69	0.0294	0.0308	< 0.001
Korea (*N* = 2,496)									
2	29	-17,368	34,794	34,963	34,871	0.91	< 0.001	< 0.001	< 0.001
3	44	-16,371	32,830	33,086	32,946	0.85	< 0.001	< 0.001	< 0.001
4	59	-16,101	32,320	32,664	32,476	0.81	< 0.001	< 0.001	< 0.001
5	74	-16,004	32,156	32,587	32,352	0.77	< 0.001	< 0.001	< 0.001
6	89	-15,949	32,075	32,593	32,311	0.76	0.1631	0.1657	< 0.001
USA (*N* = 1,674)									
2	29	-12,555	25,168	25,325	25,233	0.79	< 0.001	< 0.001	< 0.001
3	44	-12,181	24,450	24,688	24,548	0.80	< 0.001	< 0.001	< 0.001
4	59	-12,080	24,278	24,598	24,411	0.71	0.1809	0.1833	< 0.001
5	74	-11,988	24,125	24,526	24,291	0.70	0.0019	0.0020	< 0.001
6	89	-11,929	24,037	24,519	24,236	0.69	0.7009	0.7026	< 0.001
Multigroup solution (*N* = 6,816)									
2	89	-54,858	109,894	110,502	110,219	0.82	n/a	n/a	n/a
3	134	-53,070	106,407	107,322	106,896	0.80	n/a	n/a	n/a
4	179	-52,498	105,355	106,577	106,008	0.75	n/a	n/a	n/a
5	224	-52,155	104,758	106,287	105,575	0.72	n/a	n/a	n/a
6	269	-51,951	104,439	106,276	105,421	0.71	n/a	n/a	n/a

Notes. Akaike information criteria (AIC; Akaike, 1983); Bayesian information criteria (BIC; Schwarz, 1978); and sample-size adjusted BIC (Sclove, 1987); Vuong-Lo-Mendell-Rubin Likelihood ratio test (VLMR_LRT; Lo et al., 2001); adjusted Lo-Mendell-Rubin Likelihood ratio test (aLMR_LRT); and Bootstrapped Likelihood ratio test (BLRT; McLachlan, 1987)

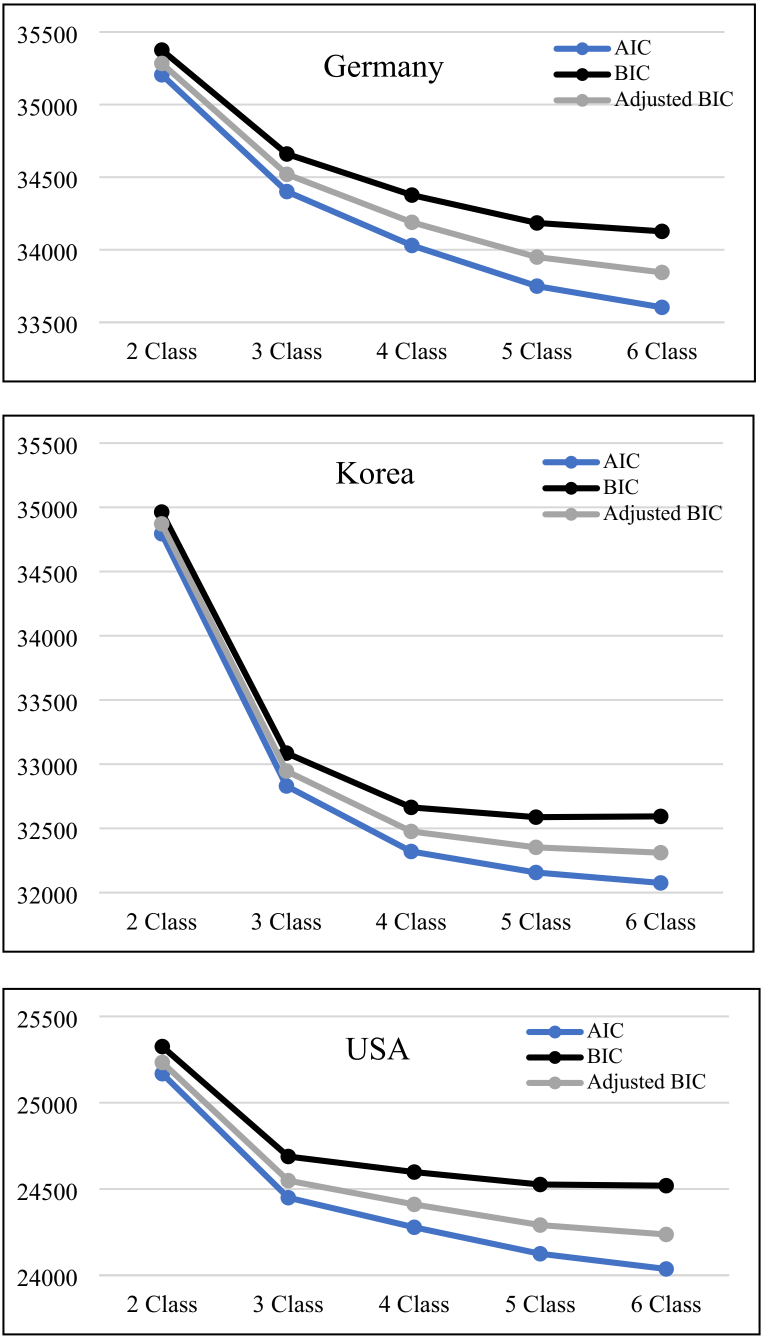


Fig. 1 Elbow Plots from latent class analysis (LCA): Germany, Korea, and USA

additional 'middle-group' in the 3-class solution appeared to have a distinctive profile pattern (see the next section for subgroup interpretation). The subgroup membership sizes were reasonably distributed (i.e., all greater than 10%): 22% of Class 1; 60% of Class 2; and 18% of Class 3. The entropy values were virtually the same between the 2- and 3-class solutions (0.76 vs. 0.75; see Table 3), while they decreased in the models containing 4 or more. Furthermore, the 3-class solution showed the classification results of greater than 80% accuracy in all three classes (Table 4). Given these multiple considerations, it was concluded that the 3-class solution may be an optimal LCA model for the German data.

For the Korean data, the model fit was successively better with a greater number of classes, as expected. However, there was a clear indication that the 3-class solution shows the first angle (i.e., the most substantial model fit improvement), and the model fit was not improving substantially from the models with 4-classes or more (see the elbow plots in Fig. 1). As was the case with the German data, the membership size distribution was good: 33% of Class 1; 46% of Class 2; and 21% of Class 3, with each showing a distinctive profile pattern (see the next section for subgroup interpretation). Furthermore, the 3-class solution showed a sufficiently high entropy value (0.85; see Table 3) and greater than 90% classification accuracy probabilities (see Table 4). Given these considerations, the 3-class solution was selected as the optimal LCA model for the Korean data.

For the US data, the most substantial model improvement was clearly demonstrated in the 3-class solution (see Table 3; Fig. 1). For instance, the VLMR and aLMR likelihood ratio tests showed a statistically significantly better fit improvement in the 3-class solution compared to the 2-class solution, with no further improvement in the 4-class solution. As was the case in the German and Korean data, each of the three subgroups showed distinctive profile patterns (see the next section for subgroup interpretation). The 3-class solution also showed a high entropy value (0.80; see Table 3), higher than 85% classification accuracy probabilities (see Table 4), and a good distribution of the membership sizes: 26% of Class 1, 58% of Class 2, and 17% of Class 3. Given these multiple considerations, the 3-class solution was selected as the optimal LCA model for the US data as well.

Multigroup LCA was conducted to examine whether there is an overarching LCA model across all three countries simultaneously. The model fit was evaluated by the information criteria values because the likelihood ratio tests for multigroup LCA have not been developed as yet (Muthén & Muthén, 2017). The 3-class solution showed the most substantial model fit improvement with an entropy of 0.80. It is not surprising that the multigroup LCA results also suggests a 3-class solution as the most optimal solution, given the 3-class solution suggested by the single country-level LCA results for each of the three countries.

6.2 Interpretation of subgroups of teachers

The digital use profiles of each of the subgroup teachers are visually displayed in Fig. 2. A line represents the proportions of teachers in each subgroup, and those numbers are also presented in Table 5. Although each line has a different 'shape',

Table 4 Membership percentages (in brackets) and classification probabilities for the most likely latent class membership (column) by latent class (row)

	Germany			Korea			USA		
	Class 1 (22%)	Class 2 (60%)	Class 3 (18%)	Class 1 (33%)	Class 2 (46%)	Class 3 (21%)	Class 1 (26%)	Class 2 (58%)	Class 3 (17%)
Class 1 “Minimal Users”	**0.82**	0.18	0.00	**0.92**	0.08	0.00	**0.86**	0.14	0.00
Class 2 “Moderate Users”	0.03	**0.93**	0.04	0.06	**0.92**	0.02	0.05	**0.93**	0.02
Class 3 “Versatile Users”	0.00	0.17	**0.83**	0.00	0.03	**0.97**	0.00	0.10	**0.90**

Notes. Percentage of correct classification is indicated in bold for emphasis the profile level was the most distinctive feature that separated the within-country subgroups of teachers. That is, the profile of Class 1 was characterised by the lowest level of using all 14 digital tools. The profile of Class 3 was characterized by the highest level of using all 14 digital tools. Digital tool use of teachers in Class 2 are in between teachers in Classes 1 and 3. Therefore, there is no cross-over line in the three-subgroup profile pattern. This led to the subgroup interpretations of Class 1 as '*minimal users*'; Class 2 as '*moderate users*'; and Class 3 '*versatile users*' as the within-country teacher classification in all three countries. Although all three countries showed a pattern of three subgroups, differences in country-specific profile patterns were also noted.

Germany data Class 1 ('*minimal users*') consisted of 51% of teachers who used websites and 48% using word processing programs. These teachers rarely used the other 12 digital tools (see Table 5). Class 2 ('*moderate users*'), however, showed much higher percentages of teachers using digital tools including 93%, 91%, and 62% using word processing programs, websites, and practice software, respectively. However, only these three digital tools were commonly used by this subgroup. More active and varied use of digital tools was shown by Class 3 ('*versatile users*'), but data monitoring (33%), social media (28%) and E-portfolios (26%) were not commonly used even among teachers in Class 3 (see Table 5).

Korea data Similar to the German teachers, Class 1 ('*minimal users*') of Korean teachers showed little engagement with digital tools beyond word processing programs (65%; see Table 5). Compared to Class 1, Class 2 ('*moderate users*') showed greater use of a diverse range of digital tools, with six out of 14 tools being commonly used. Class 2's digital tool use pattern was similar to that of Class 1 on more advanced types of digital tools such as data monitoring, E-portfolios, simulations, and concept maps (i.e., not used much), but it was similar to Class 3 on the other tools such as word processing, practice software, websites, email/blogs, multi-media and spreadsheets (see Table 5; Fig. 2).

Unlike Class 3 teachers in Germany, the majority Class 3 ('*versatile users*') teachers in Korea showed highly active use of all 14 tools—all tools were used by more than 84% and 12 tools were used by more than 90% of the teachers within this group. Digital tools requiring advanced skills, such as data monitoring (96%) and simulation/modelling (91%), were also commonly used by this group. Furthermore, E-portfolios, concept maps, and social media (92%, 88%, and 85%) were much more commonly used, compared to Class 3 of German teachers (see Table 5).

US data The profile patterns of the US teachers were similar to those of the Korean teachers. Class 1 ('*minimal users*') showed engagement with word processing programs (65%), similar to Korean Class 1 teachers (see Table 5). Class 2 ('*moderate users*') showed eight out of 14 tools being used. As can be seen in Fig. 2, the line representing Class 2 is placed in between the two other lines representing Class 1 and Class 3, showing the overall moderate use of most of the digital tools (see Fig. 2).

Fig. 2 Profiles of latent class subgroups of teachers with respect to digital tool use: Germany, Korea, and USA ▶

Like Korean teachers in Class 3, Class 3 ('*versatile users*') in the US showed widespread use of all 14 tools. Impressively, 100% of Class 3 teachers reported to have used interactive tools. There was also widespread use of multimedia (97%), simulation/modelling (97%), digital games (96%), email/blogs (95%), and spreadsheets (95%). However, concept maps (70%), E-portfolios (64%), and social media (53%) were less commonly used, compared to Class 3 teachers in Korea.

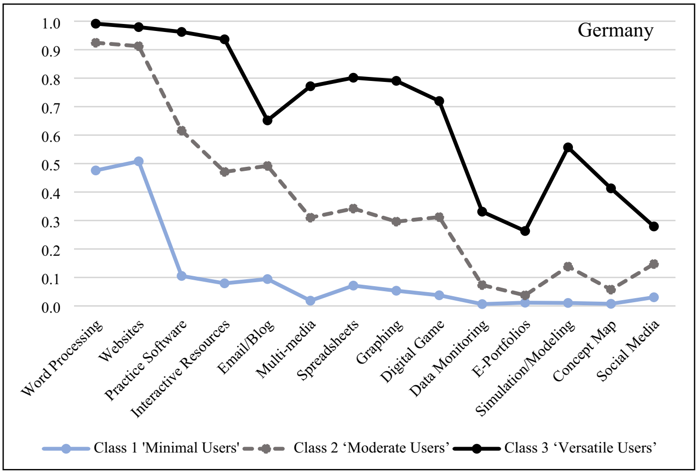
6.3 Variable of importance

As shown in the previous section, there were some cross-national differences in the profile pattern, which can be also manifested in the analysis of 'variable of importance'. The variable importance was calculated as the sum of the differences in the proportions of teachers in each subgroup. For instance, the percentages of German teachers using word processing programs were converted to a variable of importance value 1.02 ([0.99 of Class 3 − 0.93 of Class 2 = 0.06] + [0.93 of Class 2 − 0.48 of Class 1 = 0.45] + [0.99 of Class 3 − 0.48 of Class 1 = 0.51]). Such numbers were calculated for all 14 digital tools and are listed in Fig. 3 in descending order. Thus, those listed on top had higher 'variable of importance' values, suggesting greater contributions in differentiating three subgroups of teachers.

As can be seen in Fig. 3, practice software and interactive tools contributed the most in differentiating the three subgroups of German teachers. Specifically, there were 11% and 8% of Class 1 teachers using these two tools, respectively. The corresponding percentages were 62% and 46% in Class 2 and 96% and 94% in Class 3 (see Table 3). Therefore, information about teacher use of these two tools can sufficiently determine types of teachers with respect to their digital tool use in Germany. On the other hand, social media, E-portfolios, data monitoring, and concept maps ranked the lowest and did not determine subgroup membership, as the majority of teachers across all subgroups in Germany reported not using these tools (also see Table 5).

For Korean teachers, the digital tools that ranked high were data monitoring, interactive tools, E-portfolios, and simulation/modelling techniques, suggesting that these four digital tools may be sufficient in distinguishing the three subgroups of teachers. For example, the use of data monitoring was a clear indicator of the subgroups, evidenced by 2% of teachers in Class 1; 19% of teachers in Class 2; and 96% of teachers in Class 3 (see Table 5). On the other hand, word processing programs, practice software, and websites ranked the lowest in the variable importance, because they were used by most teachers in Korea, and therefore these tools would not be useful indicators for differentiating Korean teachers with respect to digital tool use.

The 'variable of importance' of US teachers was similar to that of Korean teachers. Digital tools that were ranked high were simulation/modelling, interactive tools, data monitoring, and multi-media (see Fig. 3). Word processing programs, websites, practice software, and digital games ranked low because they were used by


Germany
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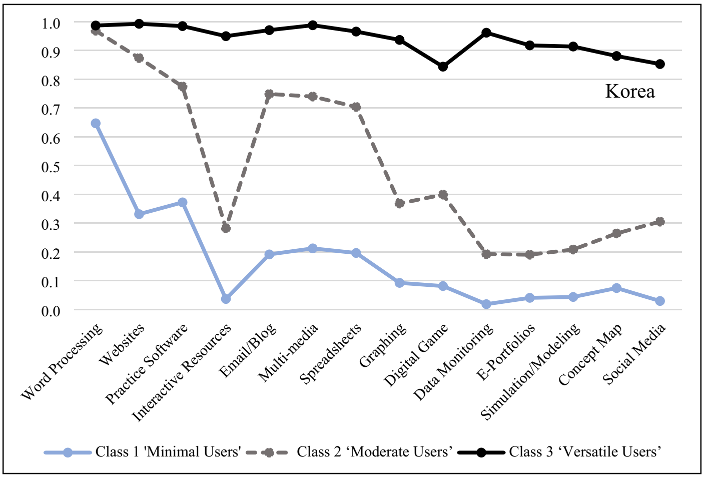
Word Processing
Websites
Practice Software
Interactive Resources
Email/Blog
Multi-media
Spreadsheets
Graphing
Digital Game
Data Monitoring
E-Portfolios
Simulation/Modeling
Concept Map
Social Media
Class 1 'Minimal Users'
Class 2 ‘Moderate Users’
Class 3 ‘Versatile Users’


Korea
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Websites
Practice Software
Interactive Resources
Email/Blog
Multi-media
Spreadsheets
Graphing
Digital Game
Data Monitoring
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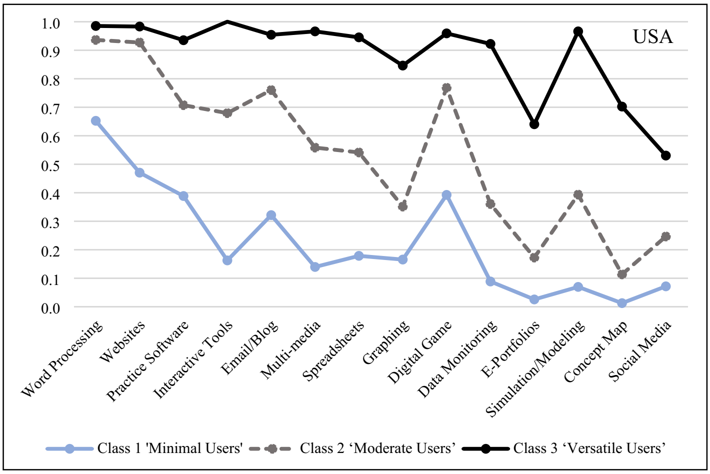
USA
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Word Processing
Websites
Practice Software
Interactive Tools
Email/Blog
Multi-media
Spreadsheets
Graphing
Digital Game
Data Monitoring
E-Portfolios
Simulation/Modeling
Concept Map
Social Media
Class 1 'Minimal Users'
Class 2 ‘Moderate Users’
Class 3 ‘Versatile Users’

Table 5 Proportions of teachers in each of the latent classes

Digital Tool	Germany				Korea				USA			
	Class 1	Class 2	Class 3	Total	Class 1	Class 2	Class 3	Total	Class 1	Class 2	Class 3	Total
Word Processing	0.48	**0.93**	**0.99**	**0.80**	**0.65**	**0.97**	**0.99**	**0.87**	**0.65**	**0.94**	**0.99**	**0.86**
Websites	**0.51**	**0.91**	**0.98**	**0.80**	0.33	**0.87**	**0.99**	**0.73**	0.47	**0.93**	**0.98**	**0.79**
Practice Software	0.11	**0.62**	**0.96**	**0.56**	0.37	**0.78**	**0.99**	**0.71**	0.39	**0.71**	**0.94**	**0.68**
Interactive Tools	0.08	0.47	**0.94**	0.50	0.04	0.28	**0.95**	0.42	0.16	**0.68**	**1.00**	**0.61**
Email/Blog	0.09	0.49	**0.65**	0.41	0.19	**0.75**	**0.97**	**0.64**	0.32	**0.76**	**0.95**	**0.68**
Multi-media	0.02	0.31	**0.77**	0.37	0.21	**0.74**	**0.99**	**0.65**	0.14	**0.56**	**0.97**	**0.56**
Spreadsheets	0.07	0.34	**0.80**	0.40	0.2	**0.70**	**0.97**	**0.62**	0.18	**0.54**	**0.95**	**0.56**
Graphing	0.05	0.3	**0.79**	0.38	0.09	0.37	**0.94**	0.47	0.17	0.35	**0.85**	0.46
Digital Game	0.04	0.31	**0.72**	0.36	0.08	0.40	**0.84**	0.44	0.39	**0.77**	**0.96**	**0.71**
Data Monitoring	0.01	0.07	0.33	0.14	0.02	0.19	**0.96**	0.39	0.09	0.36	**0.92**	0.46
E-Portfolios	0.01	0.04	0.26	0.10	0.04	0.19	**0.92**	0.38	0.03	0.17	**0.64**	0.28
Simulation/Modelling	0.01	0.14	**0.56**	0.24	0.04	0.21	**0.91**	0.39	0.07	0.39	**0.97**	0.48
Concept Map	0.01	0.06	0.41	0.16	0.07	0.26	**0.88**	0.40	0.01	0.11	**0.70**	0.27
Social Media	0.03	0.15	0.28	0.15	0.03	0.31	**0.85**	0.40	0.07	0.25	**0.53**	0.28
Average	0.11	0.37	**0.67**	0.38	0.17	0.5	0.94	**0.54**	0.22	0.54	0.88	**0.55**

Note. The proportions greater than 0.50 are in bold for emphasis

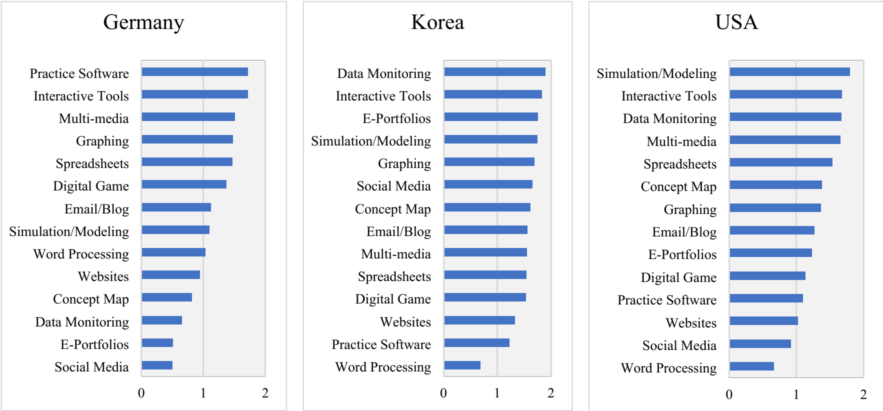

Fig. 3 Variable importance in determining the latent class groups: Germany, Korea, and USA

most teachers, while social media ranked low because it was not used much by most of the teachers in the US.

6.4 Cross-national comparison in the overall use of digital tools

The overall digital tool use of teachers across the three countries was examined in the scale scores on “TCCITUSE” (i.e., the scale consisting of all 14 digital tool items; see Fig. 4). The overall digital tool use of the total group was similar between the Korean (a scale score of −0.10) and US teachers (0.13), while it was relatively lower among the German teachers (-0.53). This pattern was displayed across all three subgroups, with the highest and lowest scale score differences being 0.93 in Class 1 between Germany and US; 0.69 in Class 2 between Germany and US; and 0.65 in Class 3 between Germany and Korea.

Korea and US data revealed similar overall scores across all three subgroups. However, digital tool use in these two countries differed most in their respective preferred digital tools among Class 2 teachers (see Table 5). Class 2 US teachers showed preferences for using interactive tools (68% vs. 28% of Korea), digital games (77% vs. 40% of Korea), data monitoring (36% vs. 19% of Korea), and simulation/modelling (39% vs. 21% of Korea), while Class 2 Korean teachers showed more widespread use in multimedia (74% vs. 56% of US) and spreadsheets (70% vs. 54% of US). Overall, it appears that more advanced types of digital tools such as data monitoring and simulation/modelling were more commonly used by US teachers than Korean teachers.

6.5 Predictors of teacher use of digital tools

To predict teachers’ use of digital tools (i.e., scale scores on TCICTUSE as the dependent variable), a total of 14 potential predictors were entered into the initial

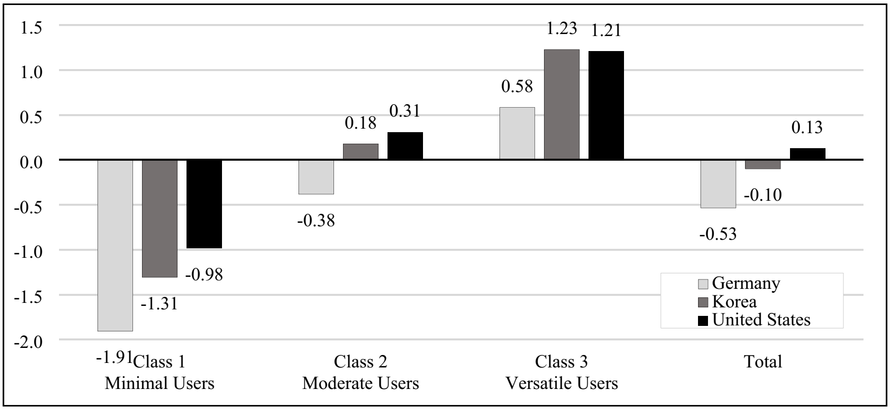

Fig. 4 Teachers' overall digital tool use: Germany, Korea, and USA

step of multiple regression analysis using the forward method. The variables that remained (i.e., statistically significant) are shown in Table 6. Subsequently, those variables were used to predict teachers' subgroup membership via multinominal logistic regression; the results are shown in Table 7. The coefficient under Exp(B) are odd ratios (ORs); that is, the likelihood of teachers being classified into the second listed subgroup, relative to the first listed subgroup (see the subheadings inside Table 7). In this section, the variables showing an OR greater than 1.68 (Cohen's d effect size of 0.2) are discussed.

Among the German teachers (Table 7), only one variable—whether teachers had professional development in ICT [OR = 1.87, $\chi^2(1) = 17.76$, $p < .001$; see the left-hand size column]—showed an OR greater than 1.68 in predicting teachers to be classified to Class 2 ('moderate users') as opposed to Class 1 ('minimal users'). This means that for teachers who had professional development in ICT, the odds of being classified to Class 2 (as opposed to Class 1) are nearly twice (1.87) that of those who did not have professional development in ICT. Similarly, there was only one variable—whether teachers had Technology in the initial teacher education program [OR = 1.87, $\chi^2(1) = 15.13$, $p < .001$; see the middle column]—showing an OR greater than 1.68 in predicting teachers to be classified to Class 3 ('versatile users') as opposed to Class 2 ('moderate users'). However, between teachers in Class 3 ('versatile users') and Class 1 ('minimal users'), six variables showed greater than 1.68 OR. Among them, the largest OR was shown in the variable measuring whether teachers had professional development in ICT [OR = 2.43, $\chi^2(1) = 24.97$, $p < .001$; see the right-hand size column]. The odds of being classified into Class 3 (as opposed to Class 1) are 2.43 times higher for those who had professional development in ICT, compared to those who did not have such opportunity. This was followed by being a science teacher [OR = 2.30, $\chi^2(1) = 19.72$, $p < .001$], having Technology in the initial teacher education program [OR = 2.11, $\chi^2(1) = 11.20$, $p = .001$], having ICT training in the initial teacher education program [OR = 2.10, $\chi^2(1) = 26.54$, $p < .001$], working in a school with an ICT policy [OR = 1.92, $\chi^2(1) = 20.63$, $p < .001$], and being more collaborative in the school environment [OR = 1.91, $\chi^2(1) = 46.67$, $p < .001$].

Table 6 Multiple linear regression results using forward method: Germany, Korea, and USA

Germany ($R^2 = 0.15$)	B	s.e.	Beta	*t*-value	Sig.
Gender [male]	0.27	0.04	0.14	7.13	< 0.001
Age	-0.01	0.00	-0.13	-6.58	< 0.001
Teaching Science [yes]	0.24	0.05	0.10	5.05	< 0.001
Teacher education in Technology [yes]	0.27	0.06	0.09	4.57	< 0.001
Teacher education in ICT [yes]	0.15	0.04	0.08	3.88	< 0.001
PD in ICT [yes]	0.27	0.04	0.12	6.17	< 0.001
Current need for PD in ICT	-0.07	0.02	-0.07	-3.67	< 0.001
Time spent out of your classes	0.13	0.02	0.12	6.17	< 0.001
Exchange and Collaboration	0.13	0.02	0.10	5.30	< 0.001
School policy [yes]	0.19	0.04	0.10	5.21	< 0.001
Lack of educational resources	-0.07	0.02	-0.07	-3.50	< 0.001
Korea ($R^2 = 0.17$)	B	s.e.	Beta	*t*-value	Sig.
Teaching Mathematics [yes]	-0.39	0.06	-0.12	-6.50	< 0.001
Teaching Science [yes]	0.24	0.06	0.07	3.88	< 0.001
Teacher education in Technology [yes]	0.28	0.07	0.08	3.99	< 0.001
Teacher education in ICT [yes]	0.27	0.05	0.11	5.98	< 0.001
Self-efficacy in instruction	0.20	0.02	0.18	8.96	< 0.001
Exchange and Collaboration	0.20	0.03	0.14	6.94	< 0.001
School policy [yes]	0.39	0.05	0.17	8.73	< 0.001
Lack of Educational resources	0.14	0.03	0.10	5.17	< 0.001
USA ($R^2 = 0.11$)	B	s.e.	Beta	*t*-value	Sig.
Teacher education in Technology [yes]	0.27	0.05	0.14	6.05	< 0.001
PD in ICT [yes]	0.19	0.04	0.10	4.27	< 0.001
Time spent out of your classes	0.17	0.02	0.17	6.99	< 0.001
Self-efficacy in instruction	0.10	0.02	0.11	4.39	< 0.001
Exchange and Collaboration	0.09	0.02	0.11	4.34	< 0.001

Notes. s.e. = standard error of the coefficient; B = unstandardized coefficient; Beta = standardised coefficient

Among the Korean teachers (Table 7), two variables—being a science teacher [OR = 1.78, $\chi^2(1) = 17.23$, $p < .001$] and working in a school with an ICT policy [OR = 1.73, $\chi^2(1) = 29.56$, $p < .001$]—predicted teachers to be more likely to be classified into Class 2 rather than Class 1 (see the left-hand size columns). Similarly, working in a school with an ICT policy [OR = 1.79, $\chi^2(1) = 27.86$, $p < .001$] and having Technology in the initial teacher education program [OR = 1.68, $\chi^2(1) = 10.74$, $p = .001$] predicted teachers to be more likely to be classified in Class 3 rather than Class 2 (see the middle columns). Furthermore, three variables—working in a school with an ICT policy [OR = 3.09, $\chi^2(1) = 83.73$, $p < .001$], having Technology in the initial teacher education program [OR = 1.97, $\chi^2(1) = 13.23$, $p < .001$], and having ICT in the initial teacher education program [OR = 1.79, $\chi^2(1) = 20.92$, $p < .001$]—predicted teachers to be classified to Class

Table 7 Multinominal logistic regression results to predict the latent class membership: Germany, Korea, and USA

Germany	Class 1 vs. Class 2 Moderate Users					Class 2 vs. Class 3 Versatile Users					Class 1 vs. Class 3 Versatile Users				
	B	s.e.	Exp(B)	Wald	Sig.	B	s.e.	Exp(B)	Wald	Sig.	B	s.e.	Exp(B)	Wald	Sig.
Gender [male]	-0.36	0.11	0.70	10.05	0.002	-0.73	0.12	0.48	40.03	< 0.001	-1.09	0.14	0.34	56.43	< 0.001
Age	-0.02	0.00	0.98	10.81	0.001	0.001	0.01	1.00	0.07	0.793	-0.01	0.01	0.99	5.06	0.024
Teaching Science [yes]	0.48	0.16	1.62	9.26	0.002	0.35	0.14	1.42	6.75	0.009	0.83	0.19	2.30	19.72	< 0.001
Teacher education in Technology [yes]	0.12	0.20	1.13	0.40	0.529	0.62	0.16	1.87	15.13	< 0.001	0.75	0.22	2.11	11.20	0.001
Teacher education in ICT [yes]	0.23	0.11	1.26	4.62	0.032	0.51	0.12	1.66	18.57	< 0.001	0.74	0.14	2.10	26.54	< 0.001
PD in ICT [yes]	0.62	0.15	1.87	17.76	< 0.001	0.26	0.13	1.30	4.27	0.039	0.89	0.18	2.43	24.97	< 0.001
Current need for PD in ICT	-0.05	0.05	0.95	0.78	0.376	-0.26	0.06	0.77	19.68	< 0.001	-0.31	0.07	0.73	18.63	< 0.001
Time spent out of your classes	0.09	0.06	1.10	2.37	0.123	0.25	0.06	1.28	15.38	< 0.001	0.34	0.08	1.41	18.94	< 0.001
Exchange and Collaboration	0.32	0.08	1.37	17.44	< 0.001	0.33	0.07	1.39	20.95	< 0.001	0.65	0.09	1.91	46.67	< 0.001
School policy [yes]	0.33	0.10	1.39	10.07	0.002	0.32	0.12	1.38	7.13	0.008	0.65	0.14	1.92	20.63	< 0.001
Lack of educational resources	-0.02	0.05	0.98	0.15	0.698	-0.10	0.06	0.91	2.67	0.102	-0.12	0.07	0.89	2.65	0.103
Korea	Class 1 vs. Class 2 Moderate Users					Class 2 vs. Class 3 Versatile Users					Class 1 vs. Class 3 Versatile Users				
	B	s.e.	Exp(B)	Wald	Sig.	B	s.e.	Exp(B)	Wald	Sig.	B	s.e.	Exp(B)	Wald	Sig.
Teaching Mathematics [yes]	-0.72	0.13	0.49	31.13	< 0.001	0.02	0.16	1.02	0.02	0.888	-0.70	0.17	0.50	17.23	< 0.001
Teaching Science [yes]	0.57	0.14	1.78	17.23	< 0.001	-0.27	0.15	0.77	3.02	0.082	0.31	0.18	1.36	3.01	0.083
Teacher education in Technology [yes]	0.16	0.17	1.17	0.95	0.331	0.52	0.16	1.68	10.74	0.001	0.68	0.19	1.97	13.23	< 0.001
Teacher education in ICT [yes]	0.44	0.10	1.55	20.05	< 0.001	0.14	0.12	1.15	1.45	0.228	0.58	0.13	1.79	20.92	< 0.001
Self-efficacy in instruction	0.23	0.05	1.26	22.13	< 0.001	0.18	0.06	1.20	10.20	0.001	0.41	0.06	1.51	43.53	< 0.001
Exchange and Collaboration	0.32	0.07	1.38	23.00	< 0.001	0.05	0.07	1.05	0.44	0.508	0.37	0.08	1.45	20.09	< 0.001
School policy [yes]	0.55	0.10	1.73	29.56	< 0.001	0.58	0.11	1.79	27.86	< 0.001	1.13	0.12	3.09	83.73	< 0.001
Lack of Educational resources	0.09	0.06	1.09	2.09	0.148	0.20	0.07	1.22	8.89	0.003	0.28	0.07	1.33	14.78	< 0.001

Table 7 (continued)

USA	Class 1 vs. Class 2 Moderate Users					Class 2 vs. Class 3 Versatile Users					Class 1 vs. Class 3 Versatile Users				
	B	s.e.	Exp(B)	Wald	Sig.	B	s.e.	Exp(B)	Wald	Sig.	B	s.e.	Exp(B)	Wald	Sig.
Teacher education in Technology [yes]	0.39	0.13	1.48	9.61	0.002	0.45	0.14	1.57	10.66	0.001	0.84	0.16	2.32	26.13	< 0.001
PD in ICT [yes]	0.32	0.12	1.38	6.89	0.009	0.31	0.14	1.36	4.75	0.029	0.62	0.16	1.87	14.59	< 0.001
Time spent out of your classes	0.34	0.07	1.41	23.18	< 0.001	0.28	0.07	1.33	14.83	< 0.001	0.62	0.09	1.87	47.63	< 0.001
Self-efficacy in instruction	0.17	0.06	1.18	7.94	0.005	0.09	0.07	1.10	1.66	0.197	0.26	0.08	1.30	10.07	0.002
Exchange and Collaboration	0.09	0.06	1.09	2.38	0.123	0.14	0.07	1.15	4.54	0.033	0.23	0.08	1.26	8.83	0.003

Notes. s.e. = standard error of the coefficient; Exp(B) reflect the effects of the predictors on the likelihood of the membership into the second listed class relative to the first listed class; [yes] indicates that the reference category of the variable was the teacher response of ‘no’; the intercepts are not included in the table; $< 0.001 = p < .001$

3 rather than Class 1 (see the right-hand columns). Therefore, teachers who work in a school with an ICT-related policy were more than three times [OR = 3.09] likely to be classified as a versatile digital user (Class 3) than a minimal digital user (Class 1), compared to teachers who do not have ICT-related policy in their school.

Among the US teachers (Table 7), no variable showed an OR greater than 1.68 in predicting Class 1 versus Class 2 (see the left-hand size columns) or predicting Class 2 versus Class 3 (see the middle columns). Having Technology in the initial teacher education program [OR = 2.32, $\chi^2(1) = 26.13$, $p < .001$] showed an OR greater than 1.68 in separating Class 3 from Class 1, along with two additional variables—having professional development in ICT [OR = 1.87, $\chi^2(1) = 14.60$, $p < .001$] and teachers' time spent in reading for work out of class time [OR = 1.87, $\chi^2(1) = 47.64$, $p < .001$] (see the right-hand columns).

Overall, the regression analysis results clearly demonstrate the importance of teacher training in Technology or ICT, either during pre-service initial teacher training programs or in-service professional development, for teachers to be able to use a wider range of digital tools. Specifically, pre-service training was a strong predictor of being a 'versatile' digital user (Class 3) in all three countries. Professional training was also a strong predictor of being a 'versatile' digital user (Class 3) in Germany and US. In addition, country-unique predictors were being a science teacher (Germany, Korea), having an ICT-related school policy (Germany, Korea), teacher collaboration (Germany), and teacher commitment as time spent out of class time (US).

7 Discussion

The present study examined a typology of teachers with respect to the use of digital tools and identified a set of predictor variables that are associated with different subgroups of teachers. While previous studies have examined types of digital tools that teachers tend to use (e.g., Ruggiero & Mong, 2015; Vannatta & Nancy, 2004), the present study aimed to provide more nuanced and detailed information about subgroups of teachers to reflect the underlying heterogeneity in the target population. Most of the previous studies on teacher typologies of ICT use classify teachers based on attitudes, beliefs or pedagogical approaches; this study focused on teacher behaviors in digital tool use. By examining teachers in three countries, this study also aimed to produce more generalizable findings than previous studies conducted in a single country setting. The importanceof this study further lies in the current context where educators worldwide continue to explore innovative ways to engage students in learning, develop optimal strategies to appropriately allocate ICT resources, and prepare the teaching workforce to deal with the potential impacts of AI-powered programs on the educational sector. Therefore, it is timely to gain a better understanding of the current status of teachers' digital use, potential challenges, and system-level support necessary for teachers to be able to navigate the increasingly complex world of digital environments.

7.1 Three subgroups of teachers in all three countries

This study found several cross-national similarities, namely, the number of subgroups of teachers, percentages of members in each subgroup, profile patterns (especially Class 1), and predictors of digital tool use. Furthermore, similarities were also found between Korea and the US in the overall levels of digital tool use and the 'variable of importance'. Overall, there were more similarities than differences in teacher use of digital tools across the three countries.

The three subgroups of teachers identified in each of the three countries indicate the within-country teacher variation of digital tool use among teachers in IT-strong countries. The majority of teachers belong to the 'middle' group (Class 2), while much smaller numbers of teachers belong to the 'versatile' group (Class 3), and about a quarter of teachers belong to the 'minimal' users group (Class 1). Although some individual differences were expected, it is surprising how many Class 1 teachers and how few Class 3 teachers were identified in all three countries.

Characteristics of Class 1 ('minimal users') identified in this study are similar to the groups described as 'laggards' (Rogers, 1962), 'non-participatory' (Clariana, 1992), 'passive' and 'reluctant' (Mukama, 2009), 'technology-avoiding' (Mama & Hennessy, 2013), 'infrequent users' (Thurm, 2018), 'low ICT profile' (Tondeur et al., 2017), 'evaders' (Graves & Bowers, 2018), and 'struggling' (Tang & Bao, 2021). Unfortunately, they appeared reluctant to try not only advanced types of digital tools such as multimedia or graphics tools, but also 'basic' tools such as email or websites.

On the other hand, teachers in Class 3 ('versatile users') showed digital engagement across all 14 types of digital tools (with some exceptions in Germany). The use of advanced types of tools such as simulation/modelling and data monitoring would require teachers to commit their time to learning the programs and applying higher-level thinking skills to their own pedagogical settings. Therefore, this group of teachers can also be described as 'advanced' and 'committed' digital users who are familiar with functionalities of varied tools and are likely to learn emerging digital tools once available. Previous studies have also noted this type of teachers as 'extenders' (Clariana, 1992), 'active' (Mukama, 2009), 'frequent users' (Thurm, 2018), 'high ICT profile' (Tondeur et al., 2017), 'dexterous' (Graves & Bowers, 2018), and 'savvy' (Tang & Bao, 2021). For instance, 'dexterous' teachers in Graves and Bowers (2018) were characterized as "flexible and wide-ranging users who integrate technology for different modes and purposes" and "comfortable with any type of technology and ready to learn more" (p. 23). 'Dexterous' teachers also tended to adopt student-centered approaches toward technology, such as conducting student-led research, developing multimedia content, and creating art and webcasts. Similarly, Mukama's (2009) 'active' teachers were described as using varied tools successfully and creatively, committed to learning new tools, and playing a central role in guiding the school's effort in incorporating ICT into teaching and learning.

While it is important to recognize 'minimal' (Class 1) and 'versatile' (Class 3) users, 'moderate' (Class 2) users represent a 'typical' teacher within the country. In the past, it was recognized that ICT integration at school may happen in four stages (Anderson et al., 2002): emerging (amassing infrastructure and computer equipment), application (applying technology to replace existing pedagogical approaches), integration/infusion (exploring new ways of using ICT and developing innovative pedagogies), and finally, transformation (ICT permeates the whole school system and transforms teaching, physical settings, and the learning process). However, in the current ICT environment, especially with the advancement of AI-powered programs, teachers may face the challenges of dealing with transformative types of ICT. In this sense, the roles of the majority of teachers—the 'average-moderate' group (Class 2)—will be crucial in responding to the potentially (at least initially) disruptive effect of technology on classroom teaching and learning.

7.2 Importance of training for teacher use of digital tools

The present study found that the strongest and most consistent predictors of teachers' digital tool use was whether teachers had Technology as a subject domain (as opposed to reading or social sciences) or ICT-related training during their initial teacher education program. This finding may seem expected, given that numerous studies emphasizing the importance of teacher training (e.g., Albion et al., 2015; Buabeng-Andoh, 2012; Tondeur et al., 2017). However, this strong and consistent result across the three countries was not entirely expected given that (a) there were as many as 14 potential predictor variables in the first step of multiple regression analysis, which were selected from the existing literature, all due to their 'known' relationship to teacher use of digital tools; (b) the sets of variables that remained in the multiple regression models varied across the three countries; as a result, (c) different sets of predictors were entered into multinominal regression that was used to predict subgroups of teachers. Therefore, these multiple steps employed suggest that the same or similar variables would not emerge as strong predictors of the subgroups of teachers, but it did across the three countries.

Perhaps those who chose Technology as a subject domain in their initial teacher education program may be considered 'naturals', identified in Hadley and Sheingold (1993) as having strong aptitude in understanding analytic, quantitative, and information-gathering functions. The finding that is even more encouraging is that teachers' professional development in ICT was also a strong and consistent predictor in differentiating subgroups of teachers in Germany and US. This suggests that professional development can be effective for those who have not had the chance to be involved in ICT training during their initial teacher training stage.

7.3 Practical implications

Several practical implications can be drawn from this study. First, this study's results demonstrated that only a minority of teachers are innovative and versatile users of technology, even in IT-strong countries. Furthermore, not a small percentage of teachers (Class 1) remain inactive ICT users in all three countries. Most teachers (Class 2) continue to use basic (e.g., word processing) and typical (e.g., email and practice software) tools.

Second, digital learning support may need to be developed for each group. Teachers in Class 1 may be hesitant to learn or anxious about new technology in general. Therefore, provision of digital learning support in a comfortable environment, such as mentoring programs or professional development activities organized within the school, may be a useful strategy. On the other hand, teachers in Class 3 would likely welcome the opportunity to learn about a greater range of digital tools arising from the most recent, innovative, and advanced technology. They can also serve as ICT mentors to other teachers, guide in-school policies, and lead professional development within the school.

Third, cross-national differences were most notable in the profile pattern of Class 2 ('moderate users'). Therefore, country-specific strategies in ICT use may be developed for this group. For instance, Class 2 teachers in Germany had a profile that was close to Class 1 teachers. Therefore, strategies to improve varied use of digital tools in Germany may involve teachers in both Class 1 and Class 2 collectively and provide them with the opportunity to learn about the potential benefits of using a diverse range of tools in various pedagogical settings (e.g., independent student projects, peer-collaborative work). On the other hand, Korea's Class 2 teachers' tool use pattern resembled that of Class 3 teachers in using common digital tools, while they resembled that of Class 1 teachers in using more advanced digital tools. Therefore, ICT interventions for Class 2 teachers in Korea can be targeted towards more advanced tools (e.g., data monitoring, simulation/modelling). US's Class 2 teachers did not resemble either Class 1 or Class 3 within the country. Their targeted professional development in ICT can be centered on specific and less commonly used tools (e.g., E-portfolios and concept maps).

Fourth, the analyses of teachers in the three countries unequivocally suggested the importance of training in the form of initial teacher training or in professional development. As such, a mandatory requirement for ICT training during initial teacher training or the creation of formal teacher support networks within schools may be useful to encourage teachers to explore the various types of digital tools for teaching.

Fifth, results from the 'variable of importance' analyses indicate that teachers' overall ICT use can be predicted by their tendency to use just a handful of digital tools. Therefore, school leaders should learn about a few digital tools that can be used as 'markers' of ICT use within their school and organize professional development programs around those markers. Specific settings and conditions of each local school will also need to be considered as ICT environment can pose a different set of challenges in each school.

Finally, it is often the case that school leaders determine the allocation of school budget for ICT tools and support, guide the overall direction for development of interventions that would address the needs of their own teachers, and find ways to best utilize their resources to maximize student learning outcomes. In this sense, national policies and guidelines for teacher use of ICT must respond to the voices of school leaders and educational practitioners.

7.4 Limitations and future research directions

Limitations of this study need to be acknowledged in order to guide directions for future studies. First, while this study focused on presenting big picture views, country-specific characteristics and local school-level issues within the country were not considered. Therefore, factors like the principal's vision, school norms and culture, and country-specific teacher characteristics may need to be incorporated into future studies. Second, the data used in this paper were drawn from teacher responses, which cannot be considered representative of all teachers within the country. Third and on a related point, since the data were drawn from teacher responses collected in the teacher questionnaire, other potential outcome variables such as student achievement were not linked to the variables of this study.

Fourth, this study did not differentiate teacher use of ICT in subject-specific contexts, and future studies may shed light on how ICT use practices are influenced by different subject areas. Fifth, as this study focused on IT-strong countries, the findings may have limited relevance to other countries with insufficient IT infrastructure. For these countries, ICT resources may show a stronger relationship to teacher groups than what was demonstrated in this study. Finally, while this study clearly indicated the importance of teacher training in ICT, it did not examine specific ICT training strategies. Teacher training in ICT can range from understanding design goals, design of pedagogical practice, co-design experiences, rubric development, assessment and revision of ICT lessons/activities, to evaluation of student learning outcomes (Koh et al., 2017). Teachers' willingness to learn and adopt various aspects of technological and pedagogical approaches will also be crucial for successful implementations of ICT training.

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Declarations

Conflict of interest There is no conflict of interest.

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