



Applying Unsupervised Possibilistic Fuzzy C-Means to Cluster Teachers' Online Practices

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Abstract: This research examines the digital literacy skills of teachers in Finnish education using a dataset of 4,988 teachers from 2017 to 2019. The dataset includes variables such as gender, age, level of urbanization, self-efficacy, professional development, digital engagement, and information skills. Teachers were categorized based on their digital competence. The study uses Unsupervised C-Medians (UPFCM) clustering to analyze teachers' online experiences and identify distinct groups. Descriptive statistics and correlation analyses reveal relationships between key variables, suggesting that self-efficacy, teaching relevance, and digital engagement significantly influence teachers' digital literacy. The results indicate different digital competence profiles, providing insights into professional development needs. The study highlights the importance of personalized learning programs to enhance digital competence and bridge skill gaps. Using an advanced clustering approach, this study contributes to understanding teachers' digital skills. Provides a foundation for data-driven educational advancements aimed at increasing digital literacy in the teaching profession.

Keywords: competencies; digital profiles; fuzzy clustering; self-efficacy; UPFCM

Recommended citation: Begimbetova, G. A., Retnawati, H., Triyono, M. B., Haryanto., Kassymova, G. K., & Suyanto, S. (2025). Applying Unsupervised Possibilistic Fuzzy C-Means to Cluster Teachers' Online Practices. *Journal of Innovation in Educational and Cultural Research*, 6(3), 558-566.

INTRODUCTION

Teachers' digital activities have interested many researchers, and related literature depicts the frontiers that were broken the most. For instance, [Hatlevik et al. \(2018\)](#) have found the relationship between teachers' self-efficacy and digital skills interesting. These authors used a model with 15 items loading on the latent variable of digital competence; although the model revealed a robust fit, no classification of teachers according to their digital competence or activities was made. In the same perspective, [Siddiq and Scherer \(2016\)](#) focused on students' digital skills and computer self-efficacy, categorizing the data and emphasizing the crucial role of computer self-efficacy. However, the researchers did not categorize their subjects' digital skills levels. What is more, [Kahveci \(2021\)](#) dug into the connection between language teachers' digital literacy and their self-efficacy, but stratifying a related pool of big data accurately would be challenging if someone follows [Kahveci's](#) research footsteps.

The studies above epistemologically helped the world of interested scientists to grasp the multi-faceted teachers' digital profiles. However, researching teachers' self-efficacy in the context of their digital activities or practices extends beyond the classroom walls. [Rabaglietti et al. \(2021\)](#) explored the impact of teachers' self-efficacy on distance learning during the COVID-19 pandemic, while [Hatlevik and Hatlevik \(2018\)](#) investigated the relationship between teachers' ICT self-efficacy, collegial collaboration, and ICT use for educational purposes. Both of these studies also covered no big pools of data about why teachers should be online. Even in [Akkaya and Kapidere's \(2021\)](#) study, the aspect of digital games utilization in predicting teachers' digital self-efficacy is still based on small-size primary data, which ensures the manageability of those data in canonical perspectives.

[Rodriguez et al. \(2020\)](#) examined the importance of interactive and dialogic learning in improving teachers' attitudes toward digital skills. The study found that participation in dialogic professional development programs positively impacted teachers' perceptions of digital skills. It demonstrates the effectiveness of in-service training programs in improving teachers' digital skills. [Hafour's \(2022\)](#) study on the impact of Mobile-Assisted Language Learning (MALL) instruction on EFL teachers found that in-service training plays a crucial role in shaping teachers' understanding and experience of digital tools. A systematic review by [Fernández-Batanero \(2022\)](#) further emphasizes the need for comprehensive digital competencies in teachers' professional development and highlights the important role of in-service training programs in developing competencies. Research has shown that in-service training programs play a significant role in developing teachers' digital

competencies. For example, [Rodríguez et al. \(2020\)](#) found that participation in dialogic professional development programs positively influenced teachers' perceptions of the usefulness of digital skills. [Hafour \(2022\)](#) demonstrated the transformative potential of targeted professional development programs in shaping teachers' understanding and practice of digital tools. A systematic review by [Fernández-Batanero \(2022\)](#) highlighted the need for comprehensive digital competencies in teachers' professional development and highlighted the important role of professional development programs in developing these competencies.

These findings highlight the importance of interactive and dialogic learning in improving teachers' attitudes towards digital skills. In addition, studies have found that digital engagement, which reflects the frequency of teachers' use of digital technologies, can influence the level of digital skills acquisition. [Saikkonen and Karakainen \(2021\)](#) observed a correlation between digital engagement and teachers' digital skills acquisition by age, suggesting that increased digital engagement may have an unequal impact on society. Therefore, in-service training programs can help teachers improve their digital skills and bridge the digital competence gap. [Mohamadi \(2019\)](#) examined the impact of online summative and formative assessments on Iranian English language teaching competencies as foreign language teachers. The research involved 30 participants and used three different assessment interventions: online summative assessments, online portfolio writing formative assessments, and online collaborative discussion formative assessments. The results showed that all three assessment activities contributed to increasing teacher competence, with online collaborative discussion having the most significant impact on formative assessment. The study highlights the importance of incorporating formative and summative assessments in assessing and increasing teacher competence.

[Buchholtz et al. \(2018\)](#) examined integrating formative and summative assessments in mathematics teacher education. The study focuses specifically on the role of summative measures in assessing subject matter skills and provides insights into assessment practices. Recognizing the dual functionality of formative and summative assessments, [Black \(2013\)](#) argues that the study contributes to a better understanding of how assessment methods can be used to assess and improve teacher competence. [Reinders, Lanz, Ruder, Stanford, et al. \(2020\)](#) examine the use of rubrics to assess critical thinking and information processing in undergraduate STEM courses. The study focuses on providing summative feedback, particularly assessing critical thinking skills. The study contributes to a broader debate about the role of assessment in shaping educational outcomes, emphasizing the importance of summative measures, mainly through rubrics and descriptors, for assessing and improving students' higher-order cognitive skills. Unsupervised Possibilistic Fuzzy C Means (UPFCM) is a fully unsupervised PCM algorithm that can automatically find many clusters [Yang and Wu \(2006\)](#). It is free of parameter selection and initializations without a given number of clusters. UPFCM can assist in clustering big data about teachers' digital literacy skills.

None of the research reviewed covered big data or the use of artificial intelligence on teachers' digital literacy skills and self-efficacy. There are indicators that big data, word mining, and decision-making based on evidence gathered through artificial intelligence or machine learning are all topics on the rise. In this perspective, researchers seek to apply Unsupervised Possibilistic Fuzzy C-Means (UPFCM) to decide or gather evidence related to clusters of teachers based on their digital literacy skills and/or reason for surfing the internet. This is expected to pave the way for applying fuzzy algorithms in decision-making based on evidence mined from real-world big data pools. The following research questions guide this study; 1) To what extent does the teachers' digital literacy typicality point to their cluster in the pool? 2) How can the teachers' digital literacy or self-efficacy degrees be categorized in their respective clusters?

METHODS

This research employs a quantitative research approach to examine the digital literacy skills of Finnish basic education teachers. The research utilizes large-scale secondary data collected between 2017 and 2019 through an ICT skill test developed by the Research Unit for the Sociology of Education in Finland ([Kaarakainen & Saikkonen, 2019](#)). The test measures teachers' digital competencies, self-efficacy, and in-service training adequacy. The study applies Unsupervised Possibilistic Fuzzy C-Means (UPFCM) clustering to analyze digital activity patterns and identify distinct teacher profiles. Descriptive and inferential statistical analyses, including correlation and regression models, explore relationships between key variables.

Research Objectives. The primary objective of this study is to categorize teachers based on their digital literacy skills and internet usage patterns. By identifying distinct clusters, the research aims to assess the role of self-efficacy, training adequacy, and digital activity in shaping teachers' digital competencies. Additionally, it seeks to determine the impact of factors such as urbanization level, teacher type, and information skills on digital literacy. The research contributes to the broader discourse on teacher professional development by offering insights into effective training interventions.

Instruments and Data Collection. The dataset includes responses from 4988 teachers aged between 24 and 66 years ($M = 46$, $SD = 9.5$), with 24% male and 76% female participants. The ICT skill test gathered background information such as age, gender, postal code of employment, and teacher classification (class or

subject teacher). It also included a questionnaire assessing digital usage habits, with activity frequencies rated from 0 (never) to 4 (several hours per day). Digital activity was quantified by summing these responses. Digital self-efficacy was measured through self-reported competence in ICT-related tasks and an aggregate variable, "information skills," was created based on ICT skill test items related to retrieving, processing, and sharing information.

Data Analysis. The study employs both descriptive and advanced statistical analyses. Descriptive statistics, including means, standard deviations, and frequency distributions, provide an overview of the dataset. Correlation analyses examine the relationships between digital self-efficacy, digital activity, and training adequacy. The UPFCM clustering algorithm is applied to identify teacher profiles based on their digital literacy levels automatically. Regression models further explore the impact of urbanization, teacher type, and information skills on digital competence. The findings contribute to data-driven policy recommendations for designing targeted professional development programs to enhance teachers' digital proficiency.

RESULT AND DISCUSSION

The statistical analysis of various variables is based on a dataset of 4987 observations. Focusing on the "AGE" variable, the mean age is 46.06 years, with a standard deviation of 9.49, reflecting moderate variability. The age range spans 24 to 66 years, providing a comprehensive dataset view. The skewness of -0.05 indicates a slight leftward skew, implying a gentle asymmetry in the age distribution. Additionally, the kurtosis of -0.89 suggests a platykurtic shape, meaning the distribution has lighter tails and is less peaked than a normal distribution. These findings provide valuable insights into the central tendency, variability, and shape of the age distribution within the dataset, directly addressing the research problem related to demographic characteristics.

Table 1. Descriptive Statistics

Var	Mean	Sd	Min	Max	Skew	Kurtosis
TEATY	0.4856627	0.4998445	0	1.000000	0.05735544	-1.9971107
INFOSK	1.2354310	0.3404315	0	1.972222	-0.78488998	0.7286389
IN_TRAI*	2.4716262	1.9487381	1	7.000000	1.25194243	0.2567889
URBLEV	2.4886705	0.7493961	1	3.000000	-1.07200951	-0.3979780
SELF*	3.1742531	2.4310621	1	7.000000	0.52947911	-1.4109176
DIGA*	17.9456587	4.3093913	1	35.000000	-0.12672135	0.4190039
AGE	46.063	9.490	24	66.000	-0.054	-0.889

The correlation matrix reveals intricate connections among seven key variables, suggesting a shared influence. Urbanization (URBLEV) correlates positively with age (0.32) and with self-rated health, information seeking, and technology adaptability (all at 0.39). Age has a strong positive correlation with improved self-rated health (0.65) and a moderate one with increased information seeking (0.24). The number of traits (IN_TRAI) positively correlates with being a digital native (DIGA, 0.27). DIGA shows positive correlations with INFOSK (0.38) and TEATY (0.25), indicating that digital natives have a strong interest in information and adapt well to new technologies. It is important to note that correlation does not imply causation, requiring further research to understand causal dynamics.

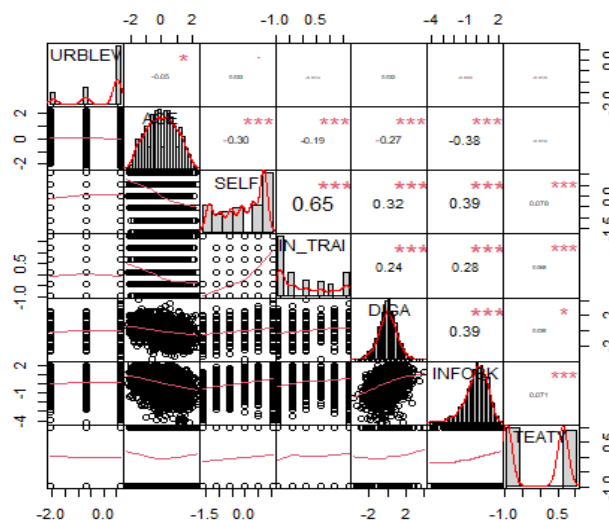


Figure 1. Correlation matrix

This significant finding sheds light on the diverse landscape of technology adoption and skill

development, paving the way for more targeted interventions and policies. The presented graphs employ different metrics to discern the optimal number of clusters. Silhouette width peaks at $k=5$, suggesting optimal clustering between 2 and 5. WSS decreases with increasing clusters, emphasizing a trade-off between quality and computational cost. The gap statistic indicates $k=3$ as optimal. In consensus, the optimal cluster count likely ranges from 2 to 5, with 3 clusters standing out. Domain knowledge can further refine the choice, recognizing multiple potentially suitable values for k .

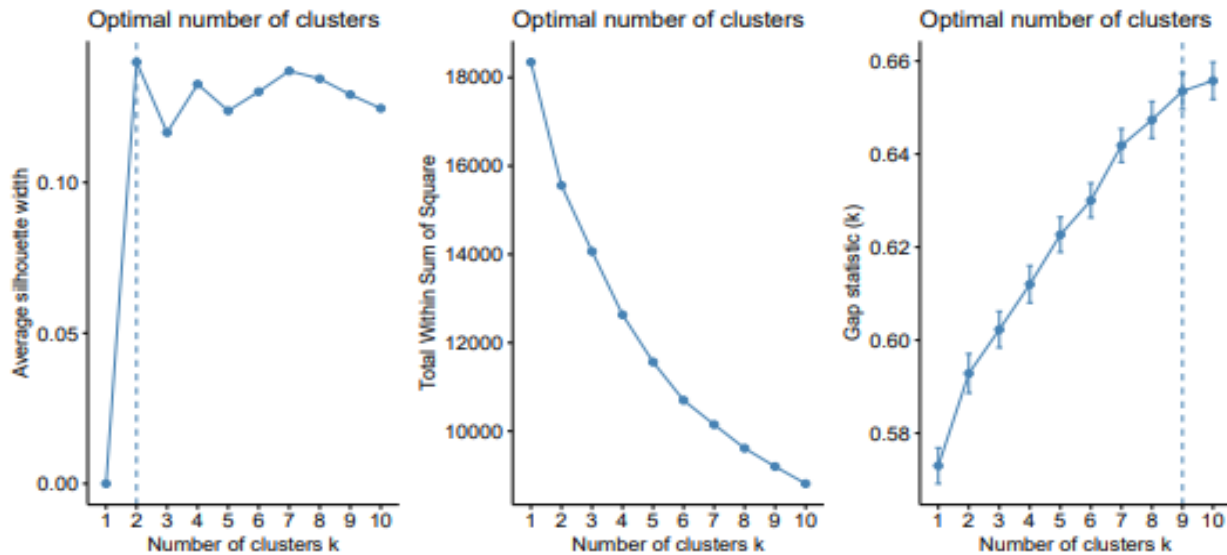


Figure 2. Optional Cluster Analysis

The descriptive statistics for membership degrees reveal distinctive characteristics within each cluster. In Cluster 1, encompassing 1332 samples, the membership degrees range from $1.6e-05$ to 0.5724259, with a mean of 0.1608575 and a median of 0.1338712. Cluster 2, comprising 1290 samples, exhibits membership degrees from $1.107097e-05$ to 0.5835346, with a mean of 0.1709570 and a median of 0.1488142.

Table 2. Descriptive Statistics for Clusters

Cluster	Size	Min	Q1	Mean	Median	Q3	Max
Cluster 1	1332	1.600132e-05	0.06096899	0.1608575	0.1338712	0.2346241	0.5724259
Cluster 2	1290	1.107097e-05	0.05747388	0.1709570	0.1488142	0.2596688	0.5835346

Dunn's Fuzziness Coefficients of 0.05148646 and a normalized value of -0.89702707 indicate moderate fuzziness and distinguishable cluster separation. The within-cluster sum of squares, with values of 7058.169 for Cluster 1 and 6926.573 for Cluster 2, emphasizes the clusters' compactness and separation. The overall between-cluster sum of squares relative to the total sum of squares, at 10.67%, underscores the clusters' efficacy in capturing variance and enhancing the discernibility of patterns within the dataset.

In cluster centroid, two distinct profiles, denoted Profile-1 and Profile-2, are characterized by specific quantitative values across key variables, including URBLEV (Urbanization Level), AGE, SELF (Self-rated Health), IN_TRAI (Number of Traits), DIGA (Digital Age), INFOSK (Information Seeking), and TEATY (Technology Adaptability). Profile-1 exhibits a moderately positive urbanization level, a slightly above-average age, lower self-rated health, negative values for traits, digital age, information-seeking, and technology adaptability. In contrast, Profile 2 demonstrates a slightly higher urbanization level, below-average age, positive self-rated health, positive values for traits, digital age, information-seeking, and technology adaptability. These profiles contribute nuanced insights into individual attributes within the specified variables, enhancing the granularity of our dataset analysis.

Table 3. Cluster centroid

n	Profile	URBLEV	AGE	SELF	IN_TRAI	DIGA	INFOSK	TEATY
1	Profile-1	0.043925	0.28699	-0.459413	-0.4080644	-0.2669420	-0.298723	-0.1597960
2	Profile-2	0.0580918	-0.2985	0.435173	0.3966859	0.2688441	0.316779	0.1432932



Figure 3. Final Cluster

Dunn's Fuzziness Coefficients measure cluster fuzziness or how well-defined the clusters are. In this case, the coefficient of 0.05148646 suggests a low level of fuzziness, indicating relatively distinct clusters. The normalized value of -0.89702707 reinforces this interpretation, signifying a clear demarcation between the clusters. The interpretation underscores the varying degrees of association of data points with the identified clusters, with distinct patterns observed in their membership degrees. The low fuzziness coefficients affirm the clarity in cluster delineation, emphasizing the effectiveness of the clustering algorithm in assigning data points to well-defined clusters.

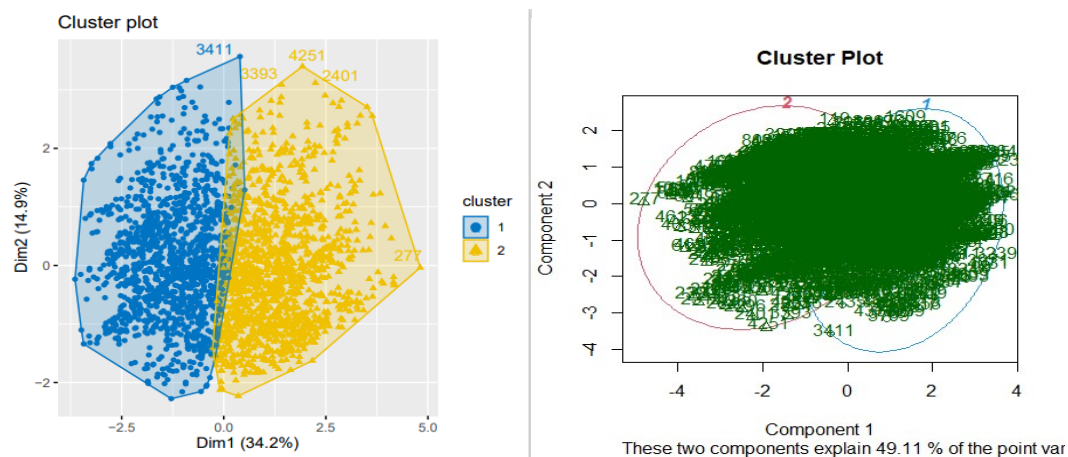


Figure 4. Fuzzy C-Means Plot

Finnish basic education teachers in each of the two digital literacy profiles, based on the UPFCM clustering analysis. Profile 1: 50.8%, higher digital literacy skills, positive self-perception, active training involvement, heightened digital awareness, increased information-seeking behavior, and a higher TEATY score. Profile 2: 49.2%, lower digital literacy skills, lower self-perception, reduced training engagement, diminished digital awareness, lower information-seeking behavior, and a below-average TEATY score.

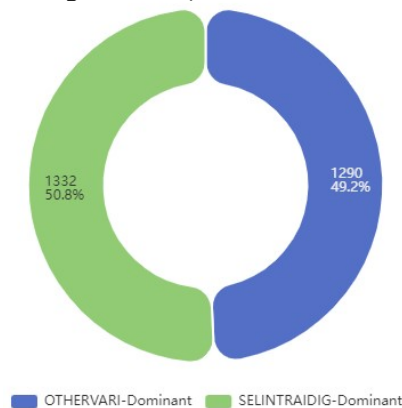


Figure 5. Profile membership

The pie chart highlights the need for tailored interventions to support teachers with lower digital literacy skills and ensure all teachers stay current with digital trends. The COVID-19 pandemic has significantly changed educational practices, especially e-learning and online education (Ahmad et al., 2022). The transition to online learning presents different aspects of teachers' experiences and challenges. Carrillo and Flores (2020) conducted a comprehensive literature review that focused on the different approaches used by teachers during their exchanges and highlighted the critical need for adaptive teaching strategies to be competitive in the job market. Their findings suggest that successful online teaching depends on teachers' ability to manage educational innovations and solve technological problems while increasing their learning engagement to meet students' needs (Kosherbayeva et al., 2024; Arpentieva et al., 2019). In the Netherlands, van der Spoel et al. (2020) examined teachers' experiences during the pandemic and examined the dichotomy between the expected and actual outcomes of online teaching. Effective online teaching management and the skills teachers must develop are now important in professional development (Begimbetova et al., 2024). Similarly, Gao and Zhang (2020) and Kassymova et al. (2019) examined teachers' cognitive processes related to online learning. These studies described the psychological pressures and the need for emotional support teachers experience when adapting to new teaching methods.

Online learning has become a hot topic of research for many researchers around the world. Lie et al. (2020) examined secondary school language teachers in Indonesia, identified key factors that influenced their participation in online learning during the pandemic, and highlighted the importance of teacher motivation and the need for structured professional development programs that can enhance the effectiveness of online learning. Furthermore, Panisoara et al. (2020), Kassymova (2018), and Xu et al. (2024) investigated burnout and technostress in teachers' motivation to teach. Their results suggest high-stress levels may negatively affect teachers' motivation and effectiveness in delivering lectures and classes.

The importance of social participation in online professional communities has been scientifically examined by Tseng and Kuo (2014) and Sheriyev et al. (2016); they have shown that knowledge sharing in online communities can significantly enhance teachers' professional growth. This perspective aligns with the findings by Yao et al. (2020); they analyzed the roles teachers should assume in online education. Their study emphasizes teachers' need to engage collaboratively, fostering a supportive learning environment, which is crucial in the digitalized era. Despite abundant qualitative research on teachers' online experiences, there is a significant gap in quantitative methodologies that can systematically analyze these experiences. Unsupervised fuzzy C-means (PFCM) clustering is a promising approach to address this gap. PFCM allows data to be classified into clusters, considering uncertainties in the relevant data in the context of different teaching experiences. Published studies have used different clustering algorithms in domains as diverse as medical imaging (Ji et al., 2011) and plant classification (Cáceres et al., 2010). However, the specific application of PFCM to cluster teachers' online experiences is still underexplored and unclear. Implementing PFCM allows us to identify different clusters of challenges that teachers face, thus providing a clearer picture of the online teaching landscape.

Our study of the digital literacy skills of Finnish primary education teachers using cluster analysis using unsupervised fuzzy C-means (UPFCM) provides valuable insights into the complex landscape of teachers' digital profiles. The following discussion elaborates on the research questions, explores the implications of the findings, and offers recommendations for educational policy and interventions. Addressing the research questions: 1) *Teachers' digital literacy type and cluster identification*. Using cluster analysis using unsupervised fuzzy C-means (UPFCM) provided a novel approach to identifying different digital literacy profiles of Finnish primary school teachers. In contrast to previous studies using clustering methods, UPFCM allowed us to identify influential variations in teachers' digital competencies. The two identified clusters – Profile 1 and Profile 2 – indicate that teachers' digital literacy skills are not evenly distributed but correspond to different typologies. This new methodological application increases the accuracy of creating digital literacy profiles and contributes to a more accurate representation of teachers' competencies; 2) *Categorizing digital literacy and self-efficacy levels*. Classifying teachers into Profile 1 (high digital literacy, strong self-efficacy, active learning engagement) and Profile 2 (low digital literacy, low self-efficacy, low learning engagement) introduces a structural framework for understanding variation in digital competence. The categorization challenges the assumption that teachers operate as a monolithic group concerning digital skills. By recognizing distinct profiles, education can move beyond one-size-fits-all curricula and instead implement differentiated professional development initiatives tailored to the specific needs of each group.

Improving the digital literacy profile. The study significantly contributes to the field by providing a refined, evidence-based classification system for teachers' digital literacy. Unlike previous studies that have relied mainly on self-reported assessments, integrating the UPFCM cluster provides a more objective and detailed analysis. Progress supports more informed decision-making in education policy and teacher education program design.

The relationship between self-efficacy and digital literacy. The study shows a strong positive correlation between self-efficacy and digital literacy, reinforcing the importance of psychological factors in acquiring digital

skills. The finding that teachers with high self-efficacy are more likely to engage in learning suggests that building confidence in digital competence is as important as providing technical instruction. This insight highlights the need for holistic teacher development programs integrating skills development and confidence-building strategies.

Generational dynamics in information-seeking behavior. A notable finding is the negative correlation between age and information-seeking behavior, which suggests that younger teachers are more active in acquiring digital knowledge. This generational gap suggests that interventions should be age-appropriate and include peer mentoring models where younger, tech-savvy teachers support their more experienced colleagues in navigating digital tools. Such targeted strategies can help bridge the generational gap and contribute to a more inclusive digital transformation of the teaching profession.

Addressing digital inequalities among teachers. Identifying teachers with low digital literacy in Profile 2 highlights the urgent need for targeted interventions. Recognizing the unique challenges of this group, institutions can implement specific support mechanisms such as mentoring programs, support learning opportunities, and personalized digital learning sessions. Addressing these gaps will ensure a more equitable distribution of digital literacy, reducing disparities that might hinder the effective integration of technology in education. The findings of this study suggest several avenues for educational policy and improvement. Based on the clustering results, it is clear that teachers require different types of support to develop their digital literacy. Some teachers may need basic training, while others may use more advanced pedagogical approaches integrating technology (Rakes et al., 2006). Researchers can use these insights to develop targeted, comprehensive professional development programs tailored to different levels of teachers' digital competence and improve educational programs (Blundell et al., 2022).

CONCLUSION

The research conducted a comprehensive analysis of the digital literacy of Finnish primary school teachers using the Unsupervised Fuzzy C-Measures (UPFCM) clustering. Using this advanced clustering method, it was possible to identify different profiles of digital literacy, focusing on changes in self-efficacy, teaching engagement, and digital engagement among teachers. By distinguishing teachers into two main groups – those with high digital literacy skills and high self-efficacy and those with low digital literacy and low teaching engagement – the study provides an evidence-based framework for targeted professional development programs. The implications of the findings go beyond theoretical contributions, offering insights that can impact education policymakers, teacher education institutions, and school administrators. By recognizing the diversity of teachers' digital competencies, education systems can move towards personalized and tailored professional development strategies. The results highlight the important role of self-efficacy in acquiring digital skills and the need for approaches to building confidence alongside technical training. Identifying generational differences in digital literacy highlights the importance of peer mentoring programs that support younger, more tech-savvy teacher colleagues using digital tools. The use of the UPFCM cluster in education research demonstrates the potential of artificial intelligence and big data analytics to inform evidence-based policy decisions. This approach allows future research to explore digital literacy trends across different educational contexts, ensuring that curricula remain relevant in an evolving digital landscape. In conclusion, the study provides a path to improving teacher digital readiness, supporting equitable access to digital resources, and encouraging digitally literate pedagogy.

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