

Moving forward: why digital competency-centered education needs a broader focus

Manuela Gruenangerl¹, Dimitri Prandner²

¹Department of Communication Studies, University of Salzburg, Austria, ²Open Research Data Lab, University of Linz, Austria

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Abstract

Digital skills, knowledge, and competencies are widely regarded as essential for societal participation, yet their development is often explained primarily through sociodemographic characteristics. This paper examines whether the role of formal education is overestimated when motivational dispositions toward technology are taken into account. Using data from an Austrian population survey (n = 2,307), a regression-based path model analyses the relationships between technology commitment, self-assessed digital skills, digital knowledge, digital competencies, and sociodemographic control variables. The results show substantial inequalities in digital knowledge and competencies across the population. While tertiary education remains a strong positive predictor, digital competencies are driven mainly by digital knowledge rather than self-assessed skills. Self-reported skills largely reflect motivational orientations shaped by technology commitment. The findings highlight the need for motivation-sensitive educational approaches that address attitudinal barriers alongside knowledge development.

Note: The fourth wave of the Digital Skills Austria survey was co-financed by RTR GmbH and the OeAD.

Keywords: digital competencies; digital knowledge; technology commitment; formal education; digital inequality

1 Introduction

Over the last two decades, digital skills, knowledge and competencies have become a central prerequisite for societal participation, shaping everyday activities from shopping and scheduling doctors' appointments to using public service tools (Carter & Perriam, 2021; Livingstone et al., 2023). Accordingly, they are seen as essential not only at individual level – e.g. explaining an individuals' positions in society – but also relevant for the broader societal developments such

as safeguarding democratic principles or fostering sustainable ways of life (e.g. Vuorikari et al., 2022). As a result, digitalization-related topics have become a key aspect of education and are widely discussed regarding their role in school and university curricula as well as in lifelong learning (Bygstad et al. 2022). This focus appears sensible, as formal education is frequently treated as a key explanatory variable in both policy and research, with educational institutions assumed to provide the knowledge base and favorable learning opportunities necessary to develop digital skills and enhance digital competencies. Yet, when designing educational programs or trainings in the digital field, target groups are mainly specified using demographic markers e.g. elderly, women or NEET youth (e.g. de Oliveira & Pasqualotti, 2024; Neagu et al., 2021). While this may be practical from a policy perspective, research shows that the explanatory power of sociodemographic variables has declined drastically over the last few decades, and that digital skills, knowledge and competencies cannot be explained sufficiently by them alone. Instead, they are shaped by a combination of individual, social, and structural conditions, including attitudinal dispositions (e.g. Morandini et al., 2020). Technology-related motivational factors, such as technology commitment (Neyer et al., 2016) appear crucial for understanding individuals' abilities to navigate the digital space.

Against this background, the question arises, how strongly formal education contributes to digital competency development once motivational dispositions are considered, and whether its role may be overestimated when viewed in isolation. Using a dataset from an Austrian general population study (n=2307) a path model is applied to identify relevant pathways for enhancing digital competencies while controlling for sociodemographic factors. The paper contributes to a more differentiated understanding of the relative roles of formal education and motivational factors in digital competency development.

2 Background and Reasoning

Research on digital competencies and skills emerged from earlier debates on the “digital divide,” which initially emphasized *access* - who is online and who is not – before shifting toward more nuanced discussions of digital inclusion. For a long time, these debates were closely linked to questions of social inequality and deep societal fault lines (van Deursen et al., 2016). Accordingly, a substantial body of literature has focused on traditional categories of social inequalities (e.g. Kapeller, 2023), showing at a descriptive level that such fault lines persist. At the same time researchers started to highlight that the explanatory power of these variables is weakening, and that they even become insignificant in regression or SEM-based analysis (e.g. Gruenangerl & Prandner, 2023). This pattern mirrors findings from research on other key issues of the 21st century like climate change awareness or social inclusion (Beiser-McGrath & Huber, 2018; Driscoll 2019).

Beyond sociodemographic factors, quantitative analysis demonstrated that concepts related to technology acceptance (TAM; Davis, 1989) have a substantial impact on skills, competencies and knowledge (Gruangnerl & Prandner, 2024; Zemsauer & Prandner, 2025), while markedly increasing the explanatory power of statistical models. Attitudes toward the use and adoption of technology emerge as central factors. At the same time, qualitative research highlights clear distinctions between skills (actions performed in digital environments), knowledge (what individuals know about digital technologies), and competencies (the ability to solve problems using digital technologies). While some differences are related to measurement approaches (ranging from self-reports to knowledge tests to standardized tasks), all three dimensions capture distinct and necessary aspects of navigating the digital space. Notably, all three of them are frequently linked to formal education (see Gruenangerl & Prandner, 2023; 2024).

3 Methods and Data

The analysis draws on data from the fourth wave of the *Digital Skills Austria* panel survey, which was conducted in August 2025 (CAWI, using online access panel). As in previous waves, the sample (n=2307) matches the Austrian resident online population according to age, gender, education, and regional distribution. This data set provides a robust basis for examining digital competencies in a country characterized by high heterogeneity in digital skills, making it particularly suitable for identifying explanatory factors.

As outlined earlier¹ a regression-based path model was applied. Dependent and mediating variables for this model are either parametrically behaving sum scores or factor variables. Sum scores are based on correctly answered questions in the digital knowledge test from Helsper et al. (2021) or correctly solved tasks from the digital competencies test designed for this study. Both instruments have been used in previous population studies and can be regarded as validated. The knowledge test included 17 questions on issues such as sharing photos via social media, while the competencies test comprised 15 tasks requiring the participants to use digital technology to solve everyday problems² (e.g. consulting train schedules, accessing a public service tool or identifying a network address). Self-reported digital skills were modeled as factor variables extracted via explorative PCA, following the structure provided by van Deursen et al. (2016), resulting in four dimensions (see Table 1).

¹ For all calculations in this paper SPSS Statistics, Version 31, was used as a tool for statistical analysis.

² Owing to the complexity of the test, only 15 out of 30 tasks were given to each participant. The test has been conducted twice and was validated for the study (see Gruangnerl & Prandner, 2023, pp. 21-22 and 2024, pp. 22-23)

Table 1: Overview of variables used for analysis (Digital Skills Austria IV, own calculations, deviations from 100 % occur due to commercial rounding)

Dimension	Variable/Question	Scale	Mean (Med.) % coded 1
Digital Skills, Knowledge and Competencies			
DS_TO	Digital Skills (technical & operational, n=2178)	PCA, tot. var. expl. 65 %, KMO 0,906, α 0,894, 1 factor	
DS_INP	Digital Skills (information navigation & processing, n=2183)	PCA, tot. var. expl. 65 %, KMO 0,909, α 0,892, 1 factor	
DS_CI	Digital Skills (communication & interaction, n=2151)	PCA, tot. var. expl. 66 %, KMO 0,911, α 0,895, 1 factor	
DS_CCP	Digital Skills (content creation & production, n=2138)	PCA, tot. var. expl. 67 %, KMO 0,814, α 0,865, 1 factor	
DK	sum-variable of 17 knowledge questions (n=1098)	0 to 17 correct answers, KR20 0,840	7,7 (8)
DC_A_B	Sum variable of 30 competency tasks (n=2307)	0 to 15 correct tasks (2 tests, vignette design) KR20 0,826 (DC_A) KR20 0,765	5,9 (6)
Technology commitment			
TC1	technology acceptance (n=2162)	PCA, tot. var. expl. 74 %, KMO 0,830, α 0,879, 1 factor	
TC2	perceived lack of technology comp. (n=2163)	PCA, tot. var. expl. 76 %, KMO 0,836, α 0,893, 1 factor	
TC3	techn. contr. convict. (n=2127)	PCA, tot. var. expl. 63 %, KMO 0,797, α 0,805, 1 factor	
Sociodemographic variables (Control variables)			
Age	age in years (n=2307)	14 to 89 years	49,0 (49)
Gender	male or female? (n=2307)	1 (female) / 0 (male)	53 %
Education	less than lower secondary education (n=1362)		59 %
	secondary education (n=487)		21 %
	tertiary education (n=448)		20 %

In addition, the 12-item scale on technology commitment developed by Neyer et al. (2016) assessing generalized attitudes towards technology was applied and collapsed into three dimensions: technology acceptance, measuring people's enthusiasm confronting technology, negative perception of technology competence, dealing with anxiety and overload concerning technology, and technology control convictions, relating to overcoming technology-related problems. Finally, control variables include demographics.

4 Results and key takeaways

The results of both tests reveal a wide dispersion of outcomes within the Austrian population. On average, participants answered 8 out of 17 knowledge items correctly; however, 8 % failed to answer a single item correctly and another 17 % solved no more than four. A similar uneven pattern emerges for digital competencies: participants solved an average of 6 out of 15 tasks, with 6 % unable to solve any task and 22 % solving at most three. Overall, more than a quarter of respondents display substantial deficits in digital knowledge or competencies. Both tests show significant differences across demographic groups. Men demonstrate higher competencies than women, though not higher knowledge. Participants aged 66+ perform worst on both tests. Participants aged 30 or younger perform significantly worse on knowledge and competencies

than the age groups 31 to 45 years (generally the group with the best results) and 46 to 65 years. Formal education shows a clear gradient, with tertiary-educated participants performing significantly better in both tests than those with secondary degrees or less³.

The path model reveals distinct patterns, linking sociodemographic characteristics, technology commitment, self-assessed digital skills, digital knowledge, and digital competencies (see Table 2). Age is negatively related to technology acceptance and all self-assessed digital skills, particularly content creation and production. Gender effects indicate lower technology acceptance and control convictions alongside higher perceived lack of technology competence among women. Nevertheless, women simultaneously report higher skills than men, mainly when it comes to information navigation and processing and communication and interaction skills. This points to a gender-related divergence between attitudes and self-perceived abilities.

As expected, educational effects are consistently positive and among the strongest in the model. It is especially tertiary education, that is positively related to technology acceptance and negatively associated with a perceived lack of technology competence. Self-assessed digital skills are primarily explained by technology commitment rather than sociodemographic factors: technology acceptance and control convictions are positively associated with all skill dimensions, whereas perceived lack of technology competence shows strong negative associations. This pattern suggests that self-assessed skills reflect motivational orientations more than actual capability. Digital knowledge is selectively related to education, technology commitment, and specific self-assessed skills. Notably, self-reported digital content creation skills are negatively related to digital knowledge on how the digital sphere works, a consistent but alarming result taken on its own. Digital competencies, in contrast, are overwhelmingly driven by digital knowledge, which clearly outweighs all other predictors, with tertiary education being the second strongest positive effect. Once knowledge is included, self-assessed skills show no direct effect on competencies.

The path model reveals the expected gap between the self-reported activities and the results of knowledge and competencies tests. While self-assessed skills largely capture attitudes and perceptions shaped by technology commitment, effective digital competencies depend primarily on knowledge-based foundations. This highlights that skill measures need to be seen as activity reports, which is not necessarily the same as the measurement of knowledge or competencies. For educational research and practice, this underscores the importance of addressing technology-related attitudes, particularly fears of insufficient competence, which cut across all demographic groups and may hinder engagement with digital technologies.

³ For age groups and formal education Kruskal-Wallis-H-Test was calculated (Sig. 0,005 for knowledge and age, for all others Sig. <0,001). For gender Mann-Whitney-U-Test was applied (for competencies Sig. <0,001; not significant concerning knowledge).

5 Conclusions

Overall, the findings suggest that while formal education remains an important correlation factor of knowledge and competencies, its contribution should not be interpreted in isolation. Once motivational dispositions are considered, the role of education appears more differentiated than often assumed. The strong and consistent association between education, motivation, skills, knowledge, and competencies is largely driven by tertiary education. In this context, educational pathways seem to function effectively, as higher education is broadly linked to high motivation and the ability to translate skills and knowledge into competent practices.

At the same time, these positive pathways do not extend to the same degree to groups who have spent less time in educational institutions. For these individuals, formal education alone is not sufficient to foster competencies, especially when motivational barriers, limited awareness, or negative prior experiences with digital technologies prevail. This suggests that the importance of education for digital competency development may be overstated when its motivational preconditions are overlooked. From this perspective, educational initiatives outside of school and university settings play a particularly crucial role. To reach underserved groups and enable positive developmental pathways, such initiatives need to go beyond the sole teaching of technical or operational skills. Instead, they should begin at a more fundamental level by fostering awareness and understanding of how the digital environment functions, while explicitly addressing mental barriers, anxieties, and negative technology-related experiences. Finally, a stronger emphasis on critical reflection at a meta-level of digitalization-related challenges — one that approaches digital technologies in a holistic manner rather than reducing them to technical skills — may also be essential for reaching individuals who consider themselves digitally skilled but do not necessarily translate these skills into competent or reflective digital action. Taken together, these conclusions underline the need for broader, motivation-sensitive educational approaches to digital competency development.

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Table 2: Path model on digital competencies considering sociodemographic, motivational factors, digital skills assessment and digital knowledge test results

dependent variables	technology commitment						digital skills (self-assessment)								DK		DC	
	TC1		TC2		TC3		DS_TO		DS_INP		DS_CI		DS_CCP		Corr.	Sig.	Corr.	Sig.
independent variables	Corr.	Sig.	Corr.	Sig.	Corr.	Sig.	Corr.	Sig.	Corr.	Sig.	Corr.	Sig.	Corr.	Sig.	Corr.	Sig.	Corr.	Sig.
Age	-0,174	*	-0,016	n.s.	0,037	n.s.	-0,116	*	-0,051	***	-0,046	***	-0,210	*	-0,052	n.s.	-0,255	*
Gender	-0,260	*	0,177	*	-0,141	*	0,050	***	0,122	*	0,189	*	0,080	*	-0,065	n.s.	-0,061	n.s.
secondary education	0,030	n.s.	-0,047	***	-0,004	n.s.	0,018	n.s.	0,032	n.s.	0,011	n.s.	0,006	n.s.	0,095	**	0,074	***
tertiary education	0,048	***	-0,118	*	0,039	n.s.	0,078	*	0,097	*	0,054	**	0,033	n.s.	0,181	*	0,199	*
TC1							0,213	*	0,133	*	0,045	***	0,307	*	-0,069	***	0,015	n.s.
TC2							-0,416	*	-0,347	*	-0,348	*	-0,327	*	-0,196	*	-0,137	*
TC3							0,313	*	0,355	*	0,364	*	0,194	*	0,113	*	0,044	n.s.
DS_TO															-0,006	n.s.	0,041	n.s.
DS_INP															0,112	*	0,003	n.s.
DS_CI															0,173	*	0,036	n.s.
DS_CCP															-0,136	*	0,023	n.s.
digital knowledge test																	0,412	*
model quality																		
corr. R ²	0,094	*	0,042	*	0,021	*	0,413	*	0,350	*	0,314	*	0,367	*	0,289	*	0,457	*
n=	2168		2192		2137		1976		1993		1956		1942		871		871	

Notes: Reference categories for categorical Variables: male (gender), lower than secondary (education). Partial correlation coefficients shown, Sig.: * <0,001, ** <0,01, *** <0,05, n.s. not significant

sig. negative effects

<-0,100 <-0,200 >=-0,200

sig. positive effects

<0,100 <0,200 >=0,200