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Reciprocal effects between information and communication technology literacy and conventional literacies

Timo Gnambs *

Leibniz Institute for Educational Trajectories, Germany

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ABSTRACT

Information and communication technology (ICT) literacy encompasses a range of cognitive abilities that facilitate the effective use of digital technologies. Two studies on German students investigated the role of reading comprehension and mathematical competence in the development of ICT literacy in adolescence. A variance decomposition analysis (N = 13,335) revealed that both competence domains together accounted for nearly half of the explained item variances in two ICT literacy assessments. Additionally, a cross-lagged panel analysis (N = 4,872) demonstrated that reading and mathematical competencies predicted ICT literacy growth over three years, while ICT literacy also had reciprocal effects on domain-specific competencies. These findings emphasize that ICT literacy is not merely a technical skill set but is also closely related to other cognitive abilities.

The ability to effectively use information and communication technologies (ICT) has become a crucial competence in modern societies, shaping various aspects of daily life including education, work, and social participation (e.g., Falck et al., 2021; Hertweck & Lehner, 2025; Lei et al., 2021). While diverse factors such as motivation, personal interests, and habitual usage patterns have been shown to contribute to the development of ICT competence across the life course (e.g., Karpiński et al., 2023; Senkbeil, 2022, 2023; Zylka et al., 2015), it is widely recognized that also cognitive abilities play a critical role in how individuals acquire and apply ICT skills (Engelhardt et al., 2021; Weber & Greiff, 2023). Theoretical frameworks on digital competence emphasize that ICT proficiency extends beyond technical knowledge (e.g., Fraillon & Duckworth, 2025; Senkbeil et al., 2013; Vuorikari et al., 2022). Rather, a broad set of cognitive abilities from rather basic problem-solving abilities to acquired competencies such as reading comprehension contribute to an individual's ability to use digital environments effectively. Despite widespread agreement that digital competencies comprise various cognitive and noncognitive factors, empirical research on the cognitive basis of ICT skills remains scarce (but see Engelhardt et al., 2020; Senkbeil, 2022; Senkbeil & Ihme, 2020; Wicht et al., 2021).

The present study examines the relationship between ICT literacy and two competence domains, reading and mathematics, that are considered fundamental abilities for successful participation in modern society (Weinert et al., 2019) and may also play key roles in shaping individuals' ability to process, evaluate, and use digital information. After outlining several theoretical assumptions and describing possible effect mechanisms, two studies on German students are presented that examine how reading and mathematical competencies contribute to ICT skills. Furthermore, reciprocal influences between these domains are explored to highlight the dynamic interplay between ICT literacy and conventional literacies across students' educational trajectories.

1. The literacy concept and models of intelligence

The concept of literacy, as commonly used in educational psychology, refers to domain-specific competencies such as reading and mathematics that are essential for effective participation in modern society (Weinert et al., 2019). Unlike curriculum-based knowledge taught in schools, literacy emphasizes functional competencies, meaning the ability to apply knowledge in real-world situations. Being literate in a given domain thus entails not only possessing relevant knowledge, but also being able to correctly apply that knowledge to concrete, everyday problems. While initially focused on reading, writing, and numeracy, the concept of literacy has considerably expanded over time to encompass a wider range of domains reflecting essential skills for modern life. These include disparate skills such as scientific literacy (Rudolph, 2024), health literacy (Tavousi et al., 2022), and increasingly also ICT literacy (Fraillon & Duckworth, 2025).

In contrast, traditional models of intelligence conceptualize competencies primarily as a form of crystallized intelligence (Cattell, 1987),

* Corresponding author at: Leibniz Institute for Educational Trajectories, Wilhelmsplatz 3, 96047 Bamberg, Germany.
E-mail address: timo.gnambs@lifbi.de.

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that is, accumulated knowledge and skills acquired through education and experience. The Cattell-Horn-Carroll (CHC) model (McGrew, 2005), for example, more specifically distinguishes between quantitative knowledge (i.e., the ability to comprehend mathematical concepts), reading/writing (i.e., basic reading and writing abilities), and comprehension knowledge (i.e., a person's acquired knowledge) which alongside various domain-general abilities such as fluid reasoning, working memory, and processing speed constitute broad cognitive abilities (Stratum II) that together form general ability at the apex of a hierarchical cognitive model (Stratum III).

While mathematical and reading literacies as well as other literacies (e.g., science) align closely with specific facets in the CHC model, literacies typically extend beyond static knowledge. Because they emphasize the application and transfer of knowledge to novel or complex contexts (Weinert et al., 2019), literacies also draw on domain-general cognitive abilities, particularly fluid reasoning. Educational literacies can therefore be understood as forms of domain-specific crystallized intelligence interacting with domain-general cognitive abilities, especially in cognitively demanding tasks. These determine how well individuals can cope with challenges in modern, information-rich society.

2. Defining ICT literacy

The terminology used to describe the knowledge and skills required for proficient use of digital technologies such as computers, smartphones, or online services varies widely across scientific discourse and policy documents. Terms such as ICT literacy, technology literacy, computer literacy, and digital literacy are often used interchangeably to refer to a set of essential competencies for individuals in digital society (Godaert et al., 2022). Among these, ICT literacy is frequently viewed as a meta-competence that encompasses both technical and cognitive skills enabling individuals to effectively use digital technologies in personal, academic, and professional contexts (ETS, 2002; Senkbeil et al., 2013). Typically defined from a functional perspective (Weinert et al., 2019), ICT literacy not only subsumes basic operational knowledge of digital applications, but also includes information-related competencies that allow individuals to locate, critically evaluate, and apply digital information in various contexts (Fraillon & Duckworth, 2025; Siddiq et al., 2016). As a result, ICT literacy is often understood as a combination of technical abilities (e.g., computer skills), higher-order cognitive skills (e.g., problem-solving), and acquired competencies (e.g., reading) that support digital activities such as information retrieval, content creation, communication, and creative expression in digital environments (Calvani et al., 2008; Engelhardt et al., 2021; ETS, 2002).

A related but distinct concept is the ability for problem-solving in technology-rich environments (PSTRE; Kirsch & Lennon, 2017), which is commonly used in research on adult digital competencies. PSTRE focuses on individuals' ability to solve goal-directed tasks in digital contexts and emphasizes practical, work-related problem-solving strategies with digital technologies, like filling out forms or troubleshooting software. In contrast, ICT literacy is broader in scope and also includes information-related competencies, such as the critical evaluation of digital content and the ability to locate, process, and communicate information effectively. An even more comprehensive perspective is given by the digital competence (DigiComp) framework (Vuorikari et al., 2022) that describes digital skills required for active citizenship, employability, and lifelong learning. Unlike ICT literacy, which is primarily assessed as a cognitive construct, DigiComp explicitly also includes ethical, social, and security-related dimensions such as online safety, data privacy, and digital well-being. While there is a pronounced overlap between the two constructs, DigiComp extends beyond ICT literacy by also addressing behavioral and ethical dimensions of digital engagement. Therefore, ICT literacy can be understood as the cognitive foundation within an overarching concept of digital competence. It provides the necessary technical and cognitive skills underlying an individual's ability to engage effectively with digital technologies.

3. ICT literacy in relation to conventional literacies

ICT literacy is a context-dependent blend of technical skills and basic cognitive abilities (Fraillon and Duckworth, 2025). While the cognitive component is seldom explicitly defined, it is sometimes suggested to encompass key abilities such as higher-order mental processes like problem-solving and conventional literacies like reading and numeracy (Calvani et al., 2008; Engelhardt et al., 2021). Accordingly, some empirical research has uncovered substantial associations between ICT literacy and various cognitive domains. For example, studies have reported bivariate correlations between ICT literacy and indicators of basic intellectual capacity such as logical reasoning ranging from 0.50 to 0.80 (Senkbeil, 2022; Senkbeil & Ihme, 2020); slightly smaller associations of about 0.40 have been reported for broader measurements of intelligence and performance in everyday computer tasks (Lintunen et al., 2024). Correlations with reading comprehension and mathematical competence fell within a similar range, around 0.60 (Holenstein et al., 2021; Wicht et al., 2021). These results highlight the close relationship of ICT literacy with both domain-general and domain-specific abilities. Several theories offer explanations for how conventional literacies support the development of ICT literacy and, conversely, how ICT literacy may enhance conventional literacies.

3.1. ICT literacy and reading

A substantial share of digital information is still text-based, especially in professional and educational settings (Eurostat, 2024). Therefore, reading comprehension is considered a crucial prerequisite for the efficient use of digital technologies (Engelhardt et al., 2021). Tasks such as searching for information, learning from blogs or Wikipedia, and communicating on social media rely on processing written content. Thus, many ICT tasks require reading to some degree, though not always higher-order reading comprehension (e.g., when installing software). Kintsch (1998) construction-integration model describes reading as a two-stage process: in the construction phase, readers generate multiple interpretations using prior knowledge, while the integration phase filters out irrelevant interpretations to form a coherent mental representation. When engaging with digital content (e.g., websites, search results), individuals follow similar steps by constructing meaning from fragmented information and integrating it into a coherent understanding. Thus, ICT literacy often requires synthesizing diverse information sources, which is facilitated by cognitive processes sometimes referred to as multiple documents literacy (Rouet, 2006). This literacy is, in turn, closely related to general reading comprehension abilities (Mahlow et al., 2020) that have been linked to ICT literacy (Engelhardt et al., 2020; Wicht et al., 2021).

Another explanation is provided by cognitive load theory (Sweller, 2024) which suggests that learning depends on working memory capacity and processing efficiency. Skilled readers process texts more fluently due to automatization (Perfetti, 2007), while those struggling with digital texts, hyperlinks, or interfaces may experience increased cognitive strains, making ICT tasks more difficult. Dual coding theory (Sadoski & Paivio, 2013) further postulates that people use verbal (linguistic) and non-verbal (visual) cognitive channels to encode novel information. Interpreting software interfaces, for example, requires linking text-based labels with icons and buttons. Similarly, tutorials for new applications often combine written explanations with schematic representations of procedures. Skilled readers integrate written texts with digital graphics and multimedia more effectively (Guo et al., 2020), which is an essential requirement for ICT literacy. These theories highlight how reading proficiency can reduce cognitive strain and improve cross-media learning, thereby enhancing ICT literacy.

Conversely, ICT literacy might also influence the development of reading skills. Multiple documents literacy theory (Rouet, 2006) suggests that readers often have to integrate information from various sources, such as websites, articles, and social media, to form a coherent understanding of a topic. Individuals with higher ICT skills engage more frequently and broadly with digital technologies (Senkbeil, 2022), using diverse sources like discussion boards, online databases, and digital news. This exposure may strengthen critical reading skills by promoting the ability to process, evaluate, and integrate complex information from multiple texts. Similarly, the rapid pace of change in digital technologies requires ongoing learning of and adaptation to unfamiliar applications. Successful engagement with new technologies may, therefore, improve cognitive flexibility, that is the ability to adapt and apply knowledge across different contexts (Shapiro & Niederhauser, 2004). Greater cognitive flexibility has been shown to improve overall reading comprehension (Escobar & Espinoza, 2025; Hung & Loh, 2021).

Taken together, various theoretical perspectives suggest potential bidirectional effects between ICT literacy and reading comprehension. While strong reading skills are considered essential for developing ICT literacy, ICT literacy, in turn, may also enhance reading proficiency.

3.2. *ICT literacy and math*

Two complementary theories describe how higher mathematical competencies may contribute to the development of ICT literacy. Cattell's (1987) investment theory explains these effects through the relationship between fluid and crystallized intelligence. People "invest" their innate problem-solving abilities to build competencies through learning and experience. Respective research shows that fluid intelligence predicts both academic achievement and the rate of learning progress (Lechner et al., 2019; Primi et al., 2010). Since mathematical problem-solving is closely linked to fluid intelligence (Peng et al., 2019), it partially reflects higher-order reasoning abilities. In the CHC model of intelligence both are considered indicators of general cognitive abilities (McGrew, 2005). This suggests that individuals who develop strong mathematical competencies will be better equipped to handle ICT tasks that require logical reasoning or algorithmic thinking. Thus, fluid intelligence investments innate to mathematical abilities drive structured problem-solving in digital environments.

While investment theory focuses on intelligence and knowledge accumulation, process overlap theory (Kovacs & Conway, 2016) explains reciprocal effects between mathematical competencies and ICT literacy through shared cognitive processes. Different domain-general and domain-specific cognitive abilities rely on a common pool of mental resources (Pokropek et al., 2022). Because both mathematical competencies and ICT literacy share overlapping cognitive processes such as those involved in working memory or attention, the skills developed in one area naturally enhance performance in the other. In other words, individuals with stronger mathematical abilities will find ICT tasks easier because they already possess executive cognitive components that also facilitate effective engagement with digital technologies.

Despite these general effects, the contribution of specific mathematical competencies to ICT literacy is likely highly task-dependent. In many everyday tasks, digital tools such as calculators or spreadsheets are used to address mathematical problems. As a result, successful completion of mathematical tasks often requires both mathematical knowledge and ICT proficiency, including familiarity with relevant software. Individuals who engage in mathematical problem-solving more frequently, thus, are more likely to use digital tools in the process, thereby incidentally strengthening their ICT skills.

The mechanisms described are likely not unidirectional; rather, they may also explain how ICT literacy contributes to the development of mathematical competence. Process overlap theory (Kovacs & Conway, 2016) suggests ICT skills strengthen domain-general cognitive processes, which are also important for mathematical reasoning. As individuals become more proficient in ICT, they improve these shared cognitive functions, which in turn supports mathematical learning. Additionally, individuals with better ICT literacy are also more likely to use mathematical software which might help individuals to develop a deeper understanding of mathematical operations and numerical problem-solving.

In summary, influences between ICT literacy and mathematical competence are likely reciprocal. Strong mathematical skills may enhance ICT literacy indirectly through the effects of fundamental cognitive abilities. Conversely, ICT proficiency may provide cognitive advantages that reinforce mathematical understanding.

4. Research objectives

ICT literacy is an essential skill in modern society that enables individuals to efficiently use digital technologies for specific purposes. However, its cognitive basis remains largely uncharted territory, particularly in relation to conventional literacies such as reading comprehension and mathematical competence. Moreover, much of the existing research relies on subjective self-assessments of one's perceived digital skills (Godaert et al., 2022), which often suffer from validity problems due to systematic over- or underestimation (Ballantine et al., 2007; Porat et al., 2018). To address these gaps, two studies on German students examine the relationship between objective measures of ICT literacy, reading, and mathematics.

The first study adopts a cross-sectional design to examine item-level data from two ICT literacy assessments. It investigates how different items impose different cognitive demands, depending on the presented task. For example, ICT tasks with longer textual content may rely more heavily on reading comprehension, whereas items involving the use of spreadsheets may depend more on mathematical competence. Therefore, this study adopts a factor-analytic approach to decompose the variance in each ICT item into components attributable to conventional literacies as opposed to general ICT literacy. In addition, two indicators of general cognitive abilities, that is, logical reasoning and perceptual speed, are included to estimate the relative contribution of reading and math abilities while controlling for basic intellectual capacity. The second study takes a longitudinal perspective and presents differential change analyses to assess whether students with higher reading or mathematical competence in Grade 9 as compared to other students demonstrate higher ICT literacy three years later. Furthermore, this cross-lagged panel analysis also considers potential reverse effects to evaluate whether prior ICT literacy influences later reading and mathematical competence.

Together, these studies aim to examine the cross-sectional and longitudinal relationships between ICT literacy and conventional literacies. Theoretical considerations outlined above including multiple documents literacy (Rouet, 2006), cognitive load theory (Sweller, 2024), and dual coding theory (Sadoski & Paivio, 2013) suggest that reading comprehension contributes to ICT literacy, while multiple documents literacy also points to possible reverse effects. Similarly, Cattell's (1987) investment theory and overlap theory (Kovacs & Conway, 2016) provide a basis for expecting reciprocal relationships between ICT literacy and math competencies. Building on these theoretical perspectives, the two studies aim to address the following research questions: (a) To what extent do reading and mathematical literacies explain individual differences in ICT literacy? (b) Are there reciprocal effects over time between ICT literacy and conventional literacies?

5. Study 1: Variance decomposition of ICT items

5.1. *Methods*

5.1.1. *Sample and procedure*

The participants were part of the multi-cohort *National Educational Panel Study* (NEPS), which follows German adolescents throughout their life course (Blossfeld & Roßbach, 2019). This study analyzes two waves of data from a cohort of upper secondary school students representing the population of Grade 9 students (see Aßmann et al., 2019, for the detailed sampling strategy). In Grade 9, a total of $N = 13{,}335$ students (50% girls) with a mean age of 15.43 years ($SD = 0.62$) participated in the literacy assessments. Of these, 25% had a migrant background, meaning that either the student or at least one of their parents were born outside of Germany, and 37% were enrolled in academic tracks. In Grade 12, a subsample of the initially assessed sample from academic tracks, $N = 3{,}690$ students (56% girls), participated a second time. These students had a mean age of 17.90 years ($SD = 0.47$) and 19% of them reported having a migrant background.

5.1.2. Instruments

5.1.2.1. ICT literacy. ICT literacy was measured in each grade using achievement tests specifically developed for the NEPS that were based on established frameworks from international large-scale studies (Senkbeil et al., 2013). The tests were designed to capture digital skills in diverse areas and distinguished four process components referring to accessing, creating, managing, and evaluating information with digital technologies (see Senkbeil et al., 2013, for details). Each test item targeted one or two of these components and described realistic problems to be solved with common technologies (e.g., browsers, search engines, spreadsheets). Two example items are shown in Fig. 1. The two tests administered in Grades 9 and 12 included 35 and 27 multiple-choice items, respectively, that each had to be finished within 28 min. Simple multiple-choice items required respondents to identify a single correct response option out of four to six response options, while complex multiple-choice items presented between two to ten subtasks with binary response options each. Simple items were scored dichotomously (correct/incorrect), while complex items were scored polytomously based on the number of correct subtasks. Although the four process components guided the item development to establish a comprehensive construct coverage, the underlying theoretical framework conceptualized ICT literacy as a unidimensional construct (Senkbeil et al., 2013). Accordingly, psychometric analyses conduced on the present sample supported this assumption for both tests by confirming not only essential unidimensionality based on the partial credit model (PCM; Masters, 1982) but also negligible differential item functioning across various subgroups (see Senkbeil & Ihme, 2012, 2017a). Proficiency scores for each respondent were estimated as weighted likelihood estimates (WLE; Warm, 1989) that provide unbiased person parameters from item response models.

5.1.2.2. Reading comprehension. The ability to understand written texts was measured with 33 items in Grade 9 and 29 items in Grade 12 that were specifically developed for the NEPS (see Gehrer et al., 2013 for the construction rationale). These items referred to five different text types (i.e., information, instruction, advertising, commenting, and literary texts) and addressed three different cognitive requirements (i.e., finding information in the text, drawing text-related conclusions, and reflecting and assessing) using different response formats including multiple-choice or matching tasks. The text types and cognitive requirements were independently distributed across the items of each test. To ensure robust psychometric properties, the tests were scaled using the unidimensional PCM (Masters, 1982), resulting in good marginal reliabilities based on the item response model (see Adams, 2005) of 0.81 and 0.80, respectively. The item responses in each grade showed a good fit to the item response model, supporting essential unidimensionality and negligible differential item functioning (see Gnambs et al., 2017; Haberkorn et al., 2012). Proficiency scores for each respondent were estimated as weighted likelihood estimates (WLE; Warm, 1989).

5.1.2.3. Mathematical competence. The math tests were based on a common theoretical framework covering five content areas (quantity, shape and space, change and relationship, and data and chance) and six cognitive components required to solve the presented tasks (Neumann et al., 2013). Adhering to the literacy concept (Weinert et al., 2019), the tests emphasized the relevance of mathematical competencies for effective participation in society, rather than aligning strictly with specific school curricula. The tests comprised 22 items in Grade 9 and 31 items in Grade 12 with multiple-choice and short constructed-response formats. Each item required solving mathematical problems that were embedded in real-life contexts relevant for the specific age group. Both tests were scaled using the unidimensional PCM (Masters, 1982) and showed good marginal reliabilities (Adams, 2005) of 0.81 and 0.77, respectively. Again, the content areas and cognitive components guided the development of the items to cover the breadth of the construct, but the theoretical framework considered mathematical literacy a

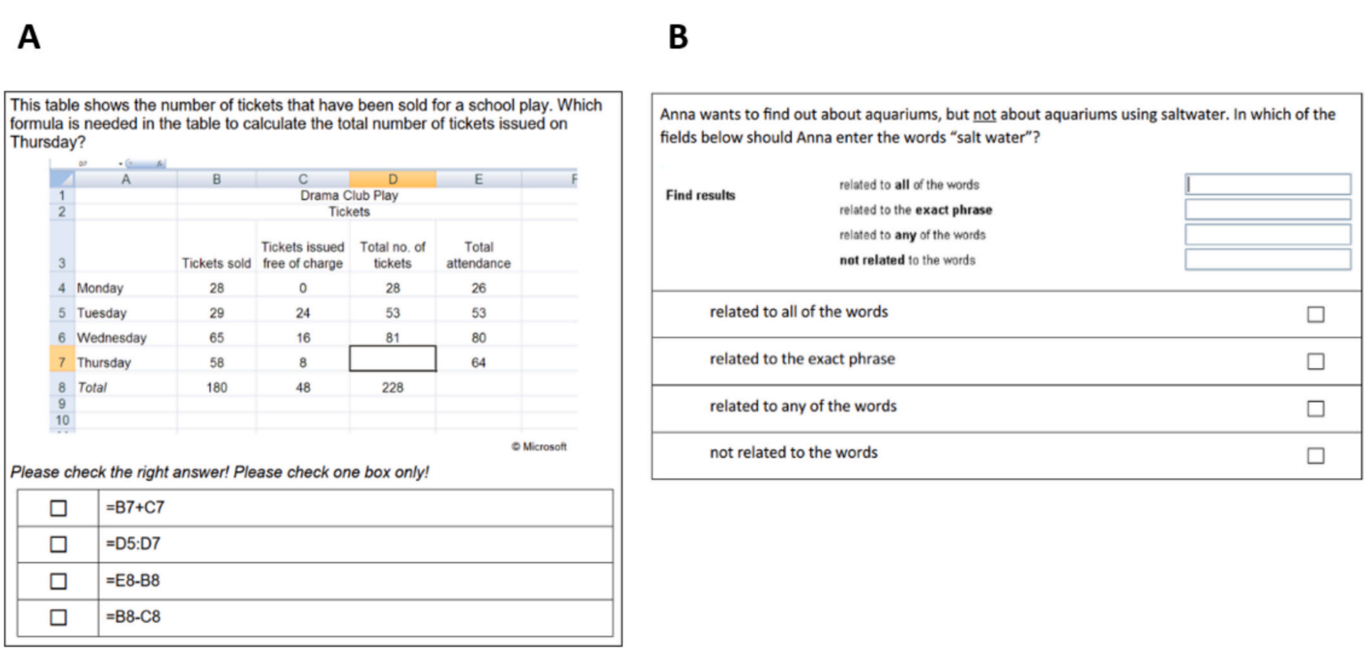

Fig. 1. Example items of the ICT literacy tests.
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unidimensional construct (Neumann et al., 2013). Accordingly, psychometric analyses conducted separately for the two tests confirmed good fits of the item responses to the PCM and suggested essentially unidimensional scales (see Duchhardt & Gerdes, 2013; Fischer et al., 2017). Person scores were estimated as WLEs (Warm, 1989).

5.1.2.4. Perceptual speed. A speeded test with three items assessed the ability to quickly identify and discriminate about visual stimuli. The search task for each item followed the concept of popular tests of mental speed (see Schmitz & Wilhelm, 2019) and required participants to match 31 figures to one of nine targets within 30 s (see Gnambs et al., 2021). The sum score across the number of correctly matched targets for each item showed an omega reliability of 0.81. The test was only administered in Grade 9.

5.1.2.5. Reasoning. Figural reasoning was measured with a test developed following the popular progressive matrices tasks by Raven (see Murphy et al., 2023). The 12 items included in the test required participants to identify a rule from a set of patterns and select the corresponding pattern from six response options that logically completed the set (see Gnambs et al., 2021). Designed as a brief cognitive measure rather than a full cognitive assessment for individual diagnostics, the sum score showed a categorical omega reliability of 0.71. The test was only administered in Grade 9.

5.1.3. Statistical analyses

The ICT test in each grade was analyzed using confirmatory ordinal factor analyses with a weighted least square estimator and a mean and variance adjusted test statistic (Beauducel & Herzberg, 2006) in *R* (R Core Team, 2024) using the *lavaan* package (Version 0.6–19; Rosseel, 2012). After confirming unidimensional measurement models for each ICT test, the latent variable models were extended to multiple indicator multiple causes (MIMIC) models (Wang & Shih, 2010). To this end, the latent factor representing ICT literacy and each ICT item score that served as manifest indicators for the latent factors were regressed on four cognitive scores (i.e., math, reading, perceptual speed, reasoning) simultaneously in a single model. No direct effects of the cognitive scores were modeled for five indicators as identification constraints, that is, the respective regression coefficients were fixed to 0. The path diagram of the respective MIMIC model is illustrated in Fig. 2. The variance explained in each indicator for which direct effects of the covariates were specified was calculated to partition the indicator variance into that explained by the latent factor and each cognitive score.

Model fit of the confirmatory factor analyses were evaluated using dynamic fit indices which were derived from 100 Monte Carlo samples following McNeish (2023). These represent thresholds for the comparative fit index (CFI), root mean squared error of approximation (RMSEA), and standardized root mean residuals (SRMR) that indicate satisfactory goodness-of-fit for the unidimensional factor models examined in the current study. The dynamic fit indices estimated with the *dynamic* package (Wolf & McNeish, 2025) suggested goodness-of-fit thresholds for the Grade 9 and 12 tests, respectively, of 0.98/0.94 for the CFI, 0.02/0.02 for the RMSEA, and 0.04/0.03 for the SRMR.

The raw data including the study material is available after registration at NEPS Network (2024). Documented analysis code and results are provided at https://osf.io/jvc87/.

5.2. Results

Goodness-of-fit indices supported satisfactory measurement models of both ICT literacy tests administered in the two grades. In Grade 9, the unidimensional factor model ($\chi^2 = 1656$, $df = 620$) showed good fit with a CFI of 0.99, a RMSEA of 0.01, and SRMR of 0.02, that did not meet the thresholds of the dynamic fit indices for non-negligible misspecification. The standardized factor loadings ranged from 0.22 to 0.66 (*Mdn* = 0.45), resulting in an acceptable categorical reliability of 0.85. For the test administered in Grade 12 ($\chi^2 = 519$, $df = 386$), fit indices were also good with CFI = 0.98, RMSEA = 0.01, and SRMR = 0.03, standardized factor loadings falling between and 0.10 and 0.47 (*Mdn* = 0.32), and a categorical omega reliability of 0.70.

The correlations between ICT literacy and the four cognitive ability scores are shown in Table 1. As expected, ICT literacy in Grade 9 showed strong correlations with reading ($r = 0.66$, $p < .001$) and math competencies ($r = 0.64$, $p < .001$), reflecting substantial shared variance across these domains. In Grade 12, these correlations were somewhat smaller, with reading and math correlating at $r = 0.44$ ($p < .001$) and $r = 0.52$ ($p < .001$), respectively. In contrast, the correlations between ICT literacy and both logical reasoning and perceptual speed were notably weaker in both grades. It is important to note, however, that these bivariate correlations do not inform about the unique contribution of each cognitive domain to ICT literacy.

In Grade 9, the MIMIC model ($\chi^2 = 1607$, $df = 636$, CFI = 0.94, RMSEA = 0.01, SRMR = 0.03) showed similar effects of math and reading on the latent ICT factor with standardized regression weights (β) of 0.41 ($p < .001$) and 0.43 ($p < .001$), respectively. Perceptual speed (β = 0.01, $p = .407$) and reasoning abilities (0.12, $p < .001$), on the other hand, had smaller effects. The direct effects on the manifest factor indicators were substantially smaller, with median absolute standardized regression weights below 0.05 for all cognitive scores. Fig. 1 (top plot) shows that the latent ICT factor accounted for *Mdn* = 46% of the explained item variances, while math and reading explained about *Mdn* = 25% and 26%, respectively. Perceptual speed (*Mdn* = 0%) and

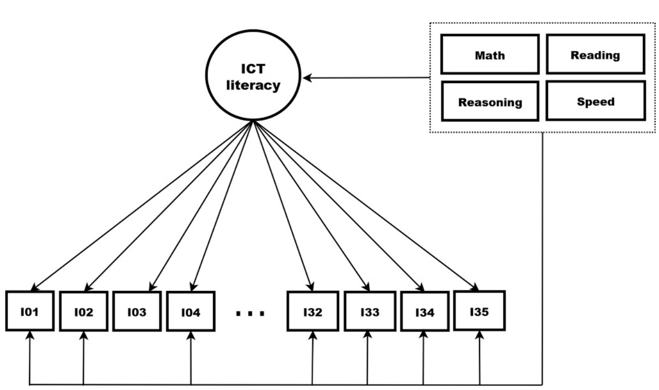

Fig. 2. Simplified path diagram of multiple indicator multiple causes model in study 1.
Note. I01 to I35 represent the item scores for the ICT literacy test, while math, reading, reasoning, and speed represent the cognitive ability scores. The direct effect of cognitive abilities on Item I03 was constrained to 0 for identification.

Table 1
Means, standard deviations, and correlations between variables in study 1.

	M	*SD*	Correlations			
			ICT	Reading	Math	Speed
Grade 9						
ICT Literacy	0.01	0.94				
Reading comprehension	−0.02	1.26	0.66*			
Math competencies	0.04	1.22	0.64*	0.54*		
Speed	59.14	13.94	0.09*	0.09*	0.07*	
Reasoning	8.66	2.45	0.49*	0.46*	0.49*	0.12*
Grade 12						
ICT Literacy	0.91	0.70				
Reading comprehension	0.32	0.87	0.44*			
Math competencies	0.29	1.07	0.52*	0.36*		
Speed	60.95	12.27	0.03*	0.06*	0.03	
Reasoning	9.86	1.74	0.27*	0.20*	0.31*	0.11

Note. N = 13,335 (Grade 9) and 3,690 (Grade 12). Results are based on WLE (Warm, 1989) and sum scores. * $p < .05$.

reasoning (*Mdn* = 2%) contributed negligibly to the variances in ICT item scores. Although there were slight differences in the share of explained variances across items, the latent factor explained the largest share in all items.

Analyses of the test administered in Grade 12 ($\chi^2 = 2268$, $df = 386$, CFI = 0.94, RMSEA = 0.01, SRMR = 0.03) revealed similar results. Math ($\beta = 0.53$, $p < .001$) and reading ($\beta = 0.47$, $p < .001$) strongly predicted the latent ICT factor, whereas perceptual speed ($\beta = 0.01$, $p = .856$) and reasoning ($\beta = 0.12$, $p < .001$) showed weaker effects. Direct effects on the manifest factor indicators were small, with the median absolute standardized regression weights falling at 0.09 for math, 0.13 for reading, and below 0.05 for reasoning and perceptual speed. Fig. 3 (bottom plot) shows that the latent ICT factor explained about *Mdn* = 27% of the item variance. While math (*Mdn* = 35%) and reading (*Mdn* = 34%) also accounted for substantial proportions of the item variances, perceptual speed (*Mdn* = 0%) and reasoning (*Mdn* = 2%) were less relevant. Again, little variation in the shares of explained variance was observed across the different items.

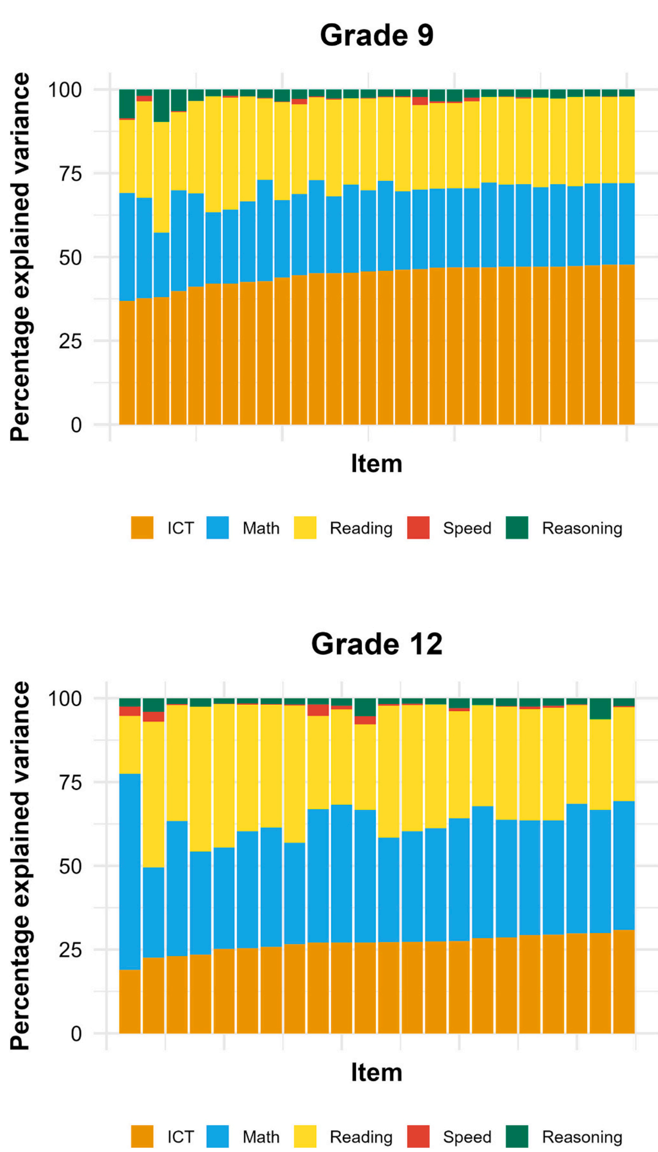

Fig. 3. Variance decomposition of ICT item scores.
Note. Items are presented in ascending order of the percentage of variance explained by the ICT factor.

6. Study 2: Cross-lagged panel modeling

6.1. Materials and method

6.1.1. Sample and procedure

The participants were part of another NEPS cohort that was initially sampled to represent Grade 5 students in secondary schools across Germany (Blossfeld & Roßbach, 2019). The analysis sample was limited to $N = 4{,}872$ students (48 % female) with an average age of 11.89 years ($SD = 0.50$) who participated in the assessment of ICT literacy in Grade 6. Approximately 25% had a migrant background and about 48% attended academic tracks. ICT literacy of these students was repeatedly assessed in Grades 6, 9, and 12, while math and reading competencies of the same sample were measured in Grades 5, 9, and 12. For those leaving school after ninth grade, a reduced testing program was conducted at home using a shortened ICT test. This reduced testing program included only two of the three test domains (ICT, math, and reading), while students who remained in school completed all three test domains. Further details on the cohort, sampling, and assessment procedures can be found in Thums et al. (2023).

6.1.2. Instruments

6.1.2.1. ICT literacy. ICT literacy was assessed in Grades 6, 9, and 12 using 30, 60, and 32 multiple-choice items, respectively, based on the framework by Senkbeil et al. (2013). In Grade 6, all students completed the same set of items, whereas the assessments in Grades 9 and 12 used a branched testing design that assigned different test versions based on the student's previous performance (see Pohl, 2013). The test versions included several common items which to facilitate linking and placement on a common scale. Each test had a time limit of 28 min. The item responses of each test were scaled separately using the unidimensional PCM (Masters, 1982), resulting in marginal reliabilities based on the item response model (Adams, 2005) of 0.70, 0.82, and 0.65 in Grades 6, 9, and 12, respectively. Comprehensive psychometric evaluations in the current sample confirmed a good fit to the adopted item response model, essential unidimensionality, and negligible differential item functioning (Senkbeil et al., 2014; Senkbeil & Ihme, 2017b, 2021). Proficiency scores were represented by 30 plausible values were drawn from the posteriori distribution of each respondent's ability based on the PCM (Mislevy, 1991).

6.1.2.2. Reading comprehension. Reading competencies were assessed with different tests following Gehrer et al. (2013) with 33, 46, and 41 items in the three grades. The tests administered in Grades 9 and 12 implemented a branched testing design with overlapping anchor items to enable linking across test forms (Pohl, 2013). All tests were scaled using the unidimensional PCM (Masters, 1982) and resulted in marginal reliabilities (Adams, 2005) of 0.77, 0.81, and 0.80, respectively. Psychometric evaluations confirmed good fits to the item response model and essentially unidimensional measurement models that were comparable across relevant subgroups (Kirsch & Lennon, 2017; Scharl & Zink, 2022; Kutscher & Scharl, 2020). Proficiency estimates were derived as 30 plausible values for each respondent based on the item response model (Mislevy, 1991).

6.1.2.3. Mathematical competence. The math tests in Grades 5, 9, and 12 were developed following Neumann et al. (2013) and included 25, 34, and 30 items, respectively, in the three grades. Again, the tests for Grades 9 and 12 employed a branched testing design ot tailor item difficulty based on students' prior performance. All tests were scaled separately using the unidimensional PCM (Masters, 1982), resulting in marginal reliabilities (Adams, 2005) of 0.78, 0.81, and 0.77, respectively. Also, further analyses demonstrated satisfactory psychometric properties of the three tests such as good item fit and unidimensionality (see Petersen et al., 2020; Schnittjer & Gerken, 2017; Van den Ham et al., 2018). A set of 30 plausible values was used to represent the respondents' latent proficiencies (Mislevy, 1991).

6.1.2.4. Auxiliary variables. The analysis acknowledged several measured confounders. Students' self-reported gender was recorded as a binary variable (0 = boy, 1 = girl). Migrant background (coded as 0 = without and 1 = with) indicated whether the student or at least one parent was born outside of Germany. Socioeconomic status (SES) was measured using the highest number of years of education attained by the student's parents (Brauns et al., 2003). School type distinguished between secondary schools with (1) and without academic tracks (0). Lastly, basic cognitive capacity was measured in Grade 5 using the same instruments as in the previous study. Figural reasoning was measured with 12 items (see Gnambs et al., 2021), while perceptual speed was assessed using 3 items (see Gnambs et al., 2021). Figural reasoning scores were scaled using the unidimensional Rasch (1960) model to derive 30 plausible values for each respondent. Perceptual speed was operationalized as the number of correctly solved tasks within a 30-s time limit; the total number of correct responses served as indicator of respondents' abilities. Both tests demonstrated satisfactory reliabilities, with omega coefficients of 0.79 for reasoning and 0.80 for perceptual speed.

6.1.3. Statistical analyses

Reciprocal effects between ICT literacy, mathematics, and reading were examined using cross-lagged panel modes (CLPMs) within a structural equation modeling (SEM) framework. These models incorporated autoregressive paths to predict performance in one domain from its prior performance and prior performance in the other domains (Duncan, 1969). Residual variances for the three domains were allowed to correlate at each time point to account for concurrent associations. To more robustly estimate potential causal effects, a CLPM with lag-2 paths was specified which controlled for the performance from the *two* prior measurement occasions instead of just *one*, as in traditional CLPMs (Lüdtke & Robitzsch, 2022). This approach helps reduce bias due to unobserved confounders (Marsh et al., 2022; Marsh et al., 2023; Murayama & Gfrörer, 2024) and has been shown to yield more consistent cross-lagged effects than alternative modeling strategies (Orth et al., 2021b). Additionally, students' gender, migrant background, socioeconomic status, school track, reasoning, and perceptual speed were included as covariates in the analyses to control for measured confounders.

Because the model is just-identified, goodness-of-fit indices are not reported. To identify the most parsimonious model, several hierarchically nested models were compared. These included (a) a baseline model with no constraints on the cross-lagged effects between Grades 9 and 12, (b) models constraining the cross-lagged effects between ICT literacy and either reading or math to 0, (c) models constraining these cross-lagged effects to equality, (d) models constraining either the cross-lagged effects for math and reading on ICT literacy or the effects of ICT literacy on math and reading to equality, and (e) a model constraining all cross-lagged effects to equality (see Table 3). Model comparisons followed an information-theoretic approach based on Akaike's (1973) Information Criterion (AIC). Rather than testing each constraint in isolation, Akaike weight were computed to evaluate the relative likelihood of each model being the best-fitting among the candidate set (Burnham & Anderson, 2002). This approach facilitates a comprehensive model ranking based on the strength of the empirical evidence. Additionally, results from conventional chi-squared difference tests between nested models are reported, where non-significant values indicate support for the imposed constraints.

SEM estimation was performed in *R* (R Core Team, 2024) using the packages *lavaan* (Version 0.6–19; Rosseel, 2012) and *lavaan.mi* (Jorgensen & Rosseel, 2024). The analyses used the test statistic proposed by Yuan and Bentler (2000) and estimated cluster-robust standard errors (Savalei, 2014) to account for the hierarchical nesting of students within schools. Latent variables for the cognitive domains were modeled using 30 plausible values (Mislevy, 1991). Plausible value estimation for the three literacy domains were generated with the *NEPSscaling* package (Version 2.2.0; Scharl & Zink, 2022), while they were estimated with the *TAM* package (Robitzsch et al., 2024) for reasoning. As perceptual speed was assessed with a timed test, manifest scores were used in the analyses rather than plausible values. Missing data were addressed through multiple imputations using classification and regression trees (Burgette & Reiter, 2010) in the *mice* package (Version 3.17.0; Van Buuren & Groothuis-Oudshoorn, 2011). Accordingly, the statistical analyses were independently repeated for each plausible value and imputed dataset (see Jewsbury et al., 2024). The resulting estimates were then pooled using Rubin (2004) rules. To facilitate interpretation, all competence scores were *z*-standardized relative to the means and standard deviations in Grade 9. Thus, all regression parameters refer to a standardized scale (with $M = 0$ and $SD = 1$) for ninth-grade competencies.

The raw data and study materials are available upon registration at NEPS Network (2023). The documented analysis code and results are provided at https://osf.io/jvc87/.

6.2. Results

Fig. 4 presents violin plots illustrating the distributions of latent ICT literacy, math, and reading scores across the three measurement occasions. These distributions reveal substantial variability both within and across grades, indicating pronounced individual differences in all three domains. As expected, the latent scores for each domain showed substantial stability across Grades 9 and 12, with correlations of $r = 0.81$, 95% CI [0.80, 0.82], for ICT literacy, $r = 0.84$, 95% CI [0.83, 0.85], for math, and $r = 0.70$, 95% CI [0.68, 0.71], for reading (see Table 2). Additionally, the longitudinal cross-domain correlations with ICT literacy were $r = 0.78$, 95% CI [0.77, 0.79], for math and $r = 0.69$, 95% CI [0.67, 0.70], for reading, indicating substantial associations between ICT literacy and more traditional educational domains. Although these correlations suggest notable relationships between ICT literacy, math, and reading, they do not establish causal effects because confounders may have similarly influenced all three domains. For example, each was substantially correlated with reasoning abilities and, to a lesser extent, with perceptual speed (see Table 2). Moreover, several auxiliary variables were associated with the literacy scores in the three domains. Boys, students without a migrant background, those with higher socioeconomic status, and students attending schools with academic tracks demonstrated higher ICT literacies, with median correlations across the three time points of $Mdn(r) = 0.05$, 0.20, 0.36, and 0.46, respectively. Comparable patterns were observed for math and reading.

Reciprocal effects were examined using the CLPM with lag-2 effects. To identify the most parsimonious model, various constraints were applied to the cross-lagged effects between Grades 9 and 12. Initially, two models were estimated in which the cross-lagged effects for either math or reading were constrained to 0. Both models showed significantly ($p < .001$) poorer fit compared to the unconstrained model that estimated cross-lagged effects for both domains, indicating meaningful reciprocal effects for both domains. Subsequently, several models with different equality constraints on the cross-lagged effects were compared (see Table 3). An information-theoretic evaluation across all eight models using the AIC revealed that the baseline model without constraints on the cross-lagged paths (Model 1) had the highest probability (about 80%) of representing the true effects. The second-best model (Model 7) which constrained the cross-lagged effects from ICT literacy to math and reading to be equal had a considerably lower probability of 20%. These results suggest that the reciprocal effects between ICT literacy, reading, and math differ in magnitude, supporting the examination of the unconstrained estimates.

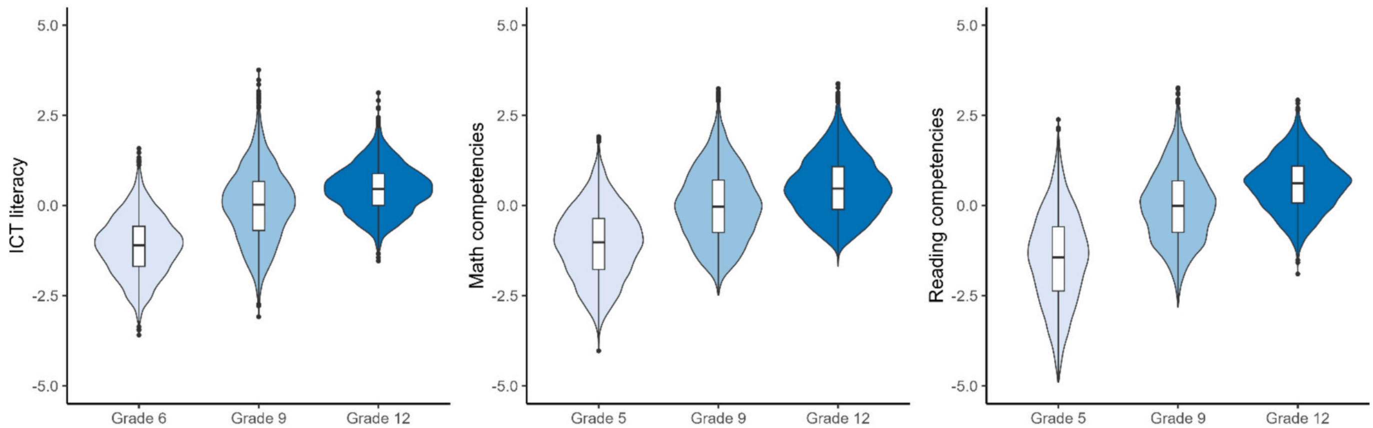

Fig. 4. Distributions of ICT, math, and reading scores across grades.
Note. Competencies were *z*-standardized with respect to the second measurement.

Table 2
Means, standard deviations, and correlations between variables in study 2.

				ICT literacy			Math competencies			Reading comprehension			Speed
	M	*SD*	MV	Grade 6	Grade 9	Grade 12	Grade 5	Grade 9	Grade 12	Grade 5	Grade 9	Grade 12	
ICT literacy													
Grade 6	−1.06	0.81	0.00										
Grade 9	0.00	1.00	35.00	0.76*									
Grade 12	0.48	0.74	48.21	0.75*	0.81*								
Math competencies													
Grade 5	−1.00	0.96	5.56	0.77*	0.75*	0.76*							
Grade 9	0.00	1.00	34.75	0.72*	0.80*	0.78*	0.84*						
Grade 12	0.62	0.92	47.17	0.68*	0.72*	0.77*	0.80*	0.84*					
Reading comprehension													
Grade 5	−1.28	1.20	5.54	0.76*	0.70*	0.67*	0.81*	0.70*	0.63*				
Grade 9	0.00	1.00	40.33	0.69*	0.75*	0.69*	0.68*	0.70*	0.62*	0.71*			
Grade 12	0.56	0.95	49.61	0.66*	0.68*	0.69*	0.66*	0.67*	0.62*	0.69*	0.70*		
Speed	44.30	13.47	5.34	0.14*	0.11*	0.10*	0.07*	0.07*	0.05*	0.07*	0.09*	0.08*	
Reasoning	0.03	0.97	5.64	0.59*	0.59*	0.60*	0.65*	0.65*	0.62*	0.60*	0.53*	0.52*	0.15*

Note. $N = 4{,}872$. MV = Percentage of missing values. Results are based on multiply imputed plausible values. Competencies were *z*-standardized with respect to the mean and standard deviation of the second measurement. * $p < .05$.

The structural effects of the CLPM without equality constraints on the cross-lagged effects (Model 1) are presented in Table 4. These showed notable stability between Grade 9 and Grade 12 for all domains (all $ps < 0.001$). In addition, math and reading in Grade 9 exhibited significant (all $ps < 0.001$) cross-lagged effects on ICT literacy in Grade 12. The standardized cross-lagged effect of math ($\beta = 0.21$) was larger than that for reading ($\beta = 0.07$), indicating that students with higher math or reading competencies in Grade 9 also had higher ICT literacy in Grade 12 compared to students with lower competencies. For the reverse direction, the standardized effects were $\beta = 0.09$ for math and $\beta = 0.13$ for reading. Thus, ICT literacy in Grade 9 also explained changes in math and reading three years later. The results for the respective effects between the first two measurements cannot be readily compared to those for Grades 9 and 12 because they did not include lag effects of the second order. Therefore, these are not evaluated further.

Together, these results suggest that students with higher math or reading scores in Grade 9 exhibited higher ICT scores in Grade 12 compared to students with lower competencies, while individual differences in ICT literacy in Grade 9 predicted changes in subsequent math and reading competencies.

7. Discussion

While there is broad consensus that ICT literacy represents a crucial competence for individuals in an increasingly digitalized world (see Falck et al., 2021; Hertweck & Lehner, 2025; Lei et al., 2021), its underlying cognitive foundations have remained a rather underexplored area. Although existing theoretical frameworks conceptualize ICT literacy as a combination of technical skills and various cognitive abilities (e.g., ETS, 2002; Fraillon & Duckworth, 2025; Senkbeil et al., 2013), the specific cognitive components contributing to ICT literacy have, with some notable exceptions (Engelhardt et al., 2020; Senkbeil, 2022; Senkbeil & Ihme, 2020; Wicht et al., 2021), seldom been explicitly outlined or empirically examined. To address this gap, the present research studied the relationship between ICT literacy and two domain-specific competence domains, reading comprehension and mathematical abilities, that are considered essential for successful participation in society (Weinert et al., 2019).

A variance decomposition analysis of two ICT literacy assessments revealed that ICT literacy partially reflects reading comprehension and mathematical competence. While variance components unique to ICT literacy accounted for over one-third of the explained item variances, reading comprehension, and mathematical competencies each explained approximately one-quarter of the variances. In contrast, the effects of basic cognitive capacities were negligible, likely due to their substantial overlap with domain-specific competencies (Peng et al., 2019; Pokropek et al., 2022). Notably, the variance decomposition showed little variation across individual items, suggesting that item-specific characteristics such as text complexity or the degree of mathematical content played only a minor role. These findings highlight that ICT literacy subsumes unique cognitive abilities such as technological skills as well as more established domain-specific competencies.

Table 3
Summary of model comparisons.

Model	χ^2	df	p	AIC	ΔAIC	Weight
1. Unconstrained cross-lagged effects	0.00	0	–	67,890	0.00	79.8%
2. No cross-lagged effects for math	40.27	2	< 0.001	68,311	421	0.0%
3. No cross-lagged effects for reading	33.86	2	< 0.001	67,902	13	0.1%
4. Equal cross-lagged effects for ICT on math and math on ICT	5.14	1	0.023	67,905	15	0.0%
5. Equal cross-lagged effects for ICT on reading and reading on ICT	3.95	1	0.047	67,901	11	0.3%
6. Equal cross-lagged effects for math and reading on ICT	16.11	1	< 0.001	67,928	39	0.0%
7. Equal cross-lagged effects for ICT on math and reading	1.68	1	0.195	67,893	3	19.7%
8. Equal cross-lagged effects for math and reading	14.60	3	0.002	67,919	39	0.0%

Note. χ^2 = Chi-squared test statistic; *df* = Degrees of freedom; p = p-value for χ^2; AIC = Akaike's information criterion; ΔAIC = Difference in AIC as compared to Model 1; Weight = Posterior probability of model. Cross-lagged effects refer to lag-1 effects between Grades 9 and 12.

Table 4
Structural coefficients for cross-lagged panel model.

	B	SE	β
Autoregressive effects for ICT			
Grade 6 ⇨ Grade 9	0.50*	0.03	0.40
Grade 6 ⇨ Grade 12	0.17*	0.02	0.19
Grade 9 ⇨ Grade 12	0.27*	0.02	0.37
Autoregressive effects for math			
Grade 7 ⇨ Grade 9	0.60*	0.03	0.58
Grade 7 ⇨ Grade 12	0.26*	0.03	0.27
Grade 9 ⇨ Grade 12	0.46*	0.03	0.50
Autoregressive effects for reading			
Grade 7 ⇨ Grade 9	0.26*	0.03	0.31
Grade 7 ⇨ Grade 12	0.13*	0.03	0.16
Grade 9 ⇨ Grade 12	0.21*	0.03	0.23
Cross-lagged effects for math on ICT			
Grade 7 ⇨ Grade 9	0.31*	0.03	0.30
Grade 7 ⇨⇨ Grade 12	0.08*	0.03	0.10
Grade 9 ⇨ Grade 12	0.16*	0.02	0.21
Cross-lagged effects for reading on ICT			
Grade 7 ⇨ Grade 9	0.08*	0.02	0.10
Grade 7 ⇨ Grade 12	−0.01	0.02	−0.02
Grade 9 ⇨ Grade 12	0.05*	0.02	0.07
Cross-lagged effects for ICT on math			
Grade 6 ⇨ Grade 9	0.22*	0.03	0.18
Grade 6 ⇨ Grade 12	0.06*	0.03	0.05
Grade 9 ⇨ Grade 12	0.08*	0.02	0.09
Cross-lagged effects for ICT on reading			
Grade 6 ⇨ Grade 9	0.35*	0.03	0.28
Grade 6 ⇨ Grade 12	0.14*	0.03	0.12
Grade 9 ⇨ Grade 12	0.12*	0.03	0.13
Cross-lagged effects for math on reading			
Grade 7 ⇨ Grade 9	0.14*	0.04	0.13
Grade 7 ⇨ Grade 12	0.06*	0.04	0.06
Grade 9 ⇨ Grade 12	0.15*	0.03	0.16
Cross-lagged effects for reading on math			
Grade 7 ⇨ Grade 9	0.00	0.02	0.00
Grade 7 ⇨ Grade 12	−0.06*	0.02	−0.08
Grade 9 ⇨ Grade 12	0.02	0.02	0.02

Note. N = 4,872. B = Regression coefficient; SE = Standard error of B; β = Standardized regression coefficient. Based on 30 plausible values. Effects for covariates are not reported. The effects of interest are highlighted.
* $p < .05$.

Analyses of reciprocal relationships between ICT literacy, reading, and mathematics suggest that the three domains mutually reinforce each other over time during adolescence. Although the cross-lagged effects from mathematics to ICT literacy were somewhat larger than those from reading, both effects were substantial. A review of standardized cross-lagged effects in psychological research (Orth et al., 2024) found average effects around 0.07, with values exceeding 0.12 considered large. In the present study, the standardized cross-lagged effects of reading and mathematics on ICT literacy were approximately 0.07 and 0.21, respectively, placing them in the upper middle range of previously observed cross-lagged effects. Another way to put these effects into perspective is to compare them to typical learning gains over the course of a normal school year. Prior research has shown that students in Grade 9 tend to improve in reading and mathematics by about Cohen's d = 0.19 and 0.25, respectively (equivalent to r = 0.10 and 0.12) across an academic year (Bloom et al., 2008). Thus, the observed cross-lagged effects in this study correspond to gains of a similar or greater magnitude, emphasizing their practical relevance.

These findings indicate that while both reading comprehension and mathematical competence contribute to the development of ICT literacy, mathematical skills appear to exert a stronger influence. Similar results have been reported in cross-sectional analyses, which showed that general problem-solving abilities have a more pronounced effect on ICT literacy than reading comprehension (Engelhardt et al., 2020). Although the analyses controlled for initial fluid reasoning and perceptual speed, it remains plausible that the observed effects of mathematics partly reflect unaccounted aspects of general cognitive abilities that developed during the same period. Importantly, these relationships were not unidirectional. Rather, the results support a reciprocal dynamic, in which ICT literacy also contributes to the growth of conventional literacies, supporting respective theoretical conjectures (e.g., Kovacs & Conway, 2016; Rouet, 2006).

7.1. Limitations

Several limitations should be acknowledged that might affect the generalizability of the present findings. First, in line with previous research (e.g., Jin et al., 2020), this study relied on knowledge-based assessments of ICT literacy to evaluate individuals' declarative and procedural knowledge of digital technologies. However, performance-based assessments, which require test-takers to actively generate solutions in interactive digital tasks, may provide a more comprehensive assessment of ICT literacy (Siddiq et al., 2016). While both types of measures are often highly correlated and capture similar constructs (Ihme et al., 2017; Senkbeil & Ihme, 2020), future research could examine whether cognitive abilities influence knowledge-based and performance-based assessment types differentially. Second, the fluid reasoning test used in this study was relatively brief and exhibited a slight ceiling effect in one of the samples (see Table 1). While the measure demonstrated adequate reliability for group-level analyses, future research should replicate the reported findings using more comprehensive assessments of general cognitive functioning to further evaluate the robustness and generalizability of the presented results. Third, there is an ongoing debate about the most appropriate way to analyze bidirectional effects with CLPMs (e.g., Murayama & Gfrörer, 2024; Orth et al., 2021a). Many of them are not well-suited for panel studies because they address improper estimands or have substantial data requirements. Following prior research (Marsh et al., 2022; Marsh et al., 2023), differential change analyses were employed to assess whether students with higher reading or mathematical abilities at one point exhibited higher ICT literacy at a later stage. Although this approach can account for many confounding influences (Lüdtke & Robitzsch, 2022), unaccounted effects of, for example, memory capacity or test motivation cannot be completely ruled. Fourth, the studies focused on German students which may limit the generalizability of the findings to other cultural or educational contexts. Therefore, replication of the presented results in other countries is highly encouraged. Finally, this study focused on two key domains, reading, and mathematics, for modern citizens. A more comprehensive exploration of the cognitive basis of ICT literacy could consider additional cognitive abilities such as fluid intelligence, memory, and attention control to develop a more holistic understanding of how basic cognitive functions contribute to ICT literacy development.

7.2. Conclusion

ICT literacy integrates various cognitive abilities that support the effective use of digital technologies. Two studies with German students consistently highlighted the importance of reading comprehension and mathematical competencies for ICT literacy. Notably, reading and mathematics accounted for approximately half of the explained item variances in ICT literacy assessments and also predicted longitudinal changes in ICT literacy over three years. These findings provide empirical evidence on the cognitive foundation of ICT literacy and emphasize that digital skills are not solely technical but are also closely linked to broader cognitive abilities.

Author note

Timo Gnambs https://orcid.org/0000-0002-6984-1276

I have no conflicts of interest to disclose. The study was not preregistered.

This paper uses data from the National Educational Panel Study (NEPS; see Blossfeld & Roßbach, 2019). The NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi, Germany) in cooperation with a nationwide network. The data that support the findings of this study are available from NEPS Network (2023, 2024) after concluding a data use agreement. The computer code and analysis results are provided at https://osf.io/jvc87/.

CRediT authorship contribution statement

Timo Gnambs: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The raw data is available after registration at https://doi.org/10.5157/NEPS:SC4:14.0.0 (Study 1) and https://doi.org/10.5157/NEPS:SC3:12.1.0 (Study 2).

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