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The development of social, gender, and migration-related disparities in digital competencies during adolescence

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ABSTRACT

The ability to use digital technologies effectively is unevenly distributed among adolescents. Youths from lower socioeconomic backgrounds, girls, and migrants frequently exhibit lower digital competencies, which can contribute to long-term educational and occupational disadvantages. To design educational strategies that promote digital equity, it is essential to understand when and for whom these inequalities emerge. This longitudinal study examined the development of social, gender, and migration-related disparities in digital competencies during adolescence. Using data from the German National Educational Panel Study (N = 4872), we examined digital competencies that were assessed three times between ages 12 and 18 with standardized achievement tests. Latent growth curve analyses revealed distinct developmental patterns: socioeconomic disparities were initially large (Cohen's $d =$ 0.22) but decreased over time (Cohen's $d =$ 0.16); gender differences favoring boys were small at first (Cohen's $d = 0.07$) but widened during adolescence (Cohen's $d = 0.18$); and the migrant gap was already substantial in early adolescence (Cohen's $d =$ 0.18) and remained stable later on. Comparative analyses for math and reading literacy highlighted partial parallels between digital inequalities and traditional educational inequalities. Overall, the results indicated persistent social, gender, and migration-related disparities in digital competencies throughout adolescence. Because these gaps remained considerable in later adolescence, they appear insufficiently addressed by the current educational system. To reduce digital inequalities, educational interventions may need to begin even before adolescence and target younger children in order to prevent disparities from becoming firmly established.

Modern technologies, including computers, smart devices and more recently, generative artificial intelligence, have profoundly changed the ways in which people learn, communicate, and interact with each other. Students rely on the Internet to search for information and resources for their course assignments, take notes using portable devices and apps, collaborate on group projects through online platforms, and enroll in remote learning courses for self-paced studies. Making optimal use of modern technologies requires not only access to them but also the development of specific abilities that enable their proficient use (Senkbeil, 2022; Vuorikari et al., 2022). Such abilities not only impact academic performance but also influence career choices and determine long-term occupational success (e.g., Falck et al., 2021; Hertweck & Lehner, 2025; Lei et al., 2021). At the same time, a recent international comparative study revealed that about half of 14-year-olds possessed only rudimentary digital skills (Fraillon et al., 2024). These students are unlikely to be able to use modern technologies effectively for purposeful activities. Moreover, despite the ongoing trend towards further digitalization in many educational fields (e.g., Giannakos et al., 2025; Zancajo et al., 2022), the share of digitally at-risk students has increased in recent years (Eickelmann et al., 2024).

The heterogeneity in digital skills observed in many studies (e.g., Fraillon et al., 2024; Gnambs, 2021; Hübner et al., 2023; Senkbeil, 2022) has raised concerns about a new digital divide that contributes to systematic disadvantages in important life areas among adolescents, including education. Meta-analyses and international comparative studies show systematic differences in digital competencies that often align with demographic characteristics such as students' gender or social background (e.g., Campos & Scherer, 2024; Kennedy et al., 2024; Scherer & Siddiq, 2019; Siddiq & Scherer, 2019), often exacerbating inequalities for already disadvantaged groups. Little is known, however, about how disparities in digital competencies change throughout adolescence. If schooling can successfully address digital skill development, preexisting differences and digital inequalities should diminish. However, digital competencies are rarely a core subject in educational

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institutions, at least in Germany. Rather, they are more influenced by nonformal learning situations outside of school (Senkbeil, 2023).

Therefore, this study investigates the development of digital competencies across adolescence to examine changes in digital disparities from ages 12 to 18 among German students (see Fig. 1). The focus of these analyses is on the impact of diverse person and family characteristics including socioeconomic status (SES), migrant background, and gender that have been shown to contribute to a digital divide among students (see Campos & Scherer, 2024; Gnambs, 2021; Kennedy et al., 2024; Scherer & Siddiq, 2019; Siddiq & Scherer, 2019). To explore whether the observed changes in disparities are unique to digital competencies or represent a general trend in literacy during this period, differences in digital competences are contrasted with respective differences in math and reading competencies.

In this way, the present research aims to contribute to our understanding of the emergence of social inequalities, which have so far been primarily documented for traditional competence domains such as reading and mathematics (e.g., Borgonovi & Pokropek, 2021; Nennstiel, 2023; Skopek & Passaretta, 2021). Comparable research for digital competences however remains scarce. Identifying systematic changes during adolescence would point to a critical developmental period for digital competence in which disparities may either widen or be reduced. This information is important, as adolescence is a period in which educational and occupational aspirations are formed (e.g., Basler et al., 2021), making inequalities particularly consequential (Falck et al., 2021; Hertweck & Lehner, 2025). The findings may therefore inform the design of educational strategies and policies aimed at promoting equity and reducing barriers that otherwise risk perpetuating social, gender, and migration-related disadvantages in an increasingly digitalized society.

1. The concept of digital competencies

Digital competence, sometimes also referred to as digital skills or digital literacy, refers to individuals' abilities to effectively use technological devices, software, and digital platforms for various purposes such as communication, information management, and creative expression. The concept of digital competencies builds on earlier definitions of computer literacy (e.g., Haigh, 1985) and encompasses not only technical proficiencies needed to use digital technologies, but also the cognitive skills required to understand and evaluate digital content (e.g., critical thinking, problem-solving), and the socioemotional skills

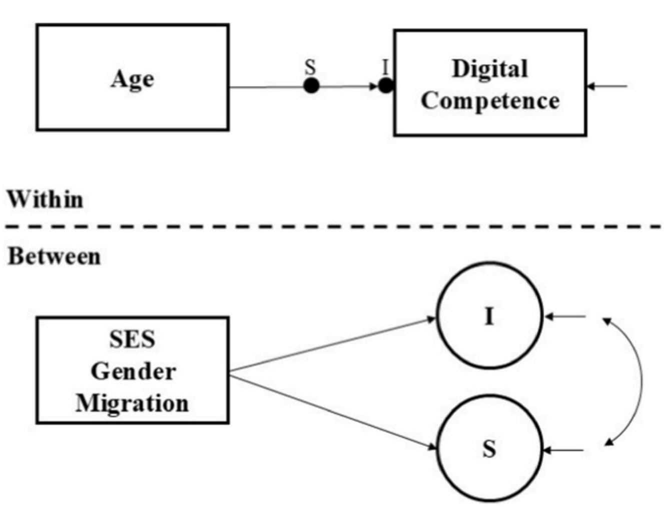

Fig. 1. Multilevel Model for Social, Gender, and Migration-related Disparities in Digital Competence
Note. Filled circles indicate random effects for the intercept (I) and slope (S). Effects for control variables and quadratic age effects are not displayed. SES = Socioeconomic status.

necessary to communicate and collaborate in digital environments (Van Laar et al., 2017). Over the past two decades, numerous definitions have emerged that emphasize different aspects of digital competencies depending on their context and application (e.g., Fraillon & Duckworth, 2025; Vuorikari et al., 2022). One of the most comprehensive definitions is formulated in the digital competence for citizens framework guiding European policy (Vuorikari et al., 2022). It describes digital competencies as "the confident, critical, and responsible use of, and engagement with, digital technologies for learning, work, and participation in society" (p. 3). The framework specifies over 20 distinct domains grouped into five areas that refer to information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving. It provides a comprehensive perspective of what it means to be digitally proficient in a modern society.

Other approaches, such as the concept of ICT literacy adopted in international comparative research, align with this definition but place greater emphasis on declarative knowledge and procedural skills. ICT literacy describes the ability to investigate, produce, and communicate information in digital environments to enable participation in school, work, and societal contexts (Fraillon & Duckworth, 2025). This definition emphasizes the integration of technical competencies with general cognitive capacities that allow individuals to access, evaluate, create, and share information with digital technologies (ETS, 2002). Narrower perspectives sometimes emphasize specific skills, such as data literacy (Gebre, 2022), critical online reasoning (Molerov et al., 2020), or computational thinking (Zeng et al., 2023), that are components of more general frameworks (e.g., Vuorikari et al., 2022) or expand the conceptualization of other definitions (e.g., Fraillon & Duckworth, 2025) to highlight their importance for an informed and critical individual in the digital age.

Consequently, digital competence is best understood as an umbrella term that refers to diverse constructs reflecting an individual's ability to efficiently use digital technologies for specific goals. Although the precise components of digital competencies may vary depending on the adopted theoretical framework, most concepts concur that they integrate technical skills and cognitive abilities (Fraillon & Duckworth, 2025; Gnambs, 2025; Senkbeil, 2022).

2. Disparities in digital competencies

Digital competencies among adolescents are distributed unevenly in many countries worldwide (Kennedy et al., 2024). In Germany, approximately 40 % of eighth-year students fail to achieve basic levels of digital skills (Eickelmann et al., 2024). These students struggle to identify relevant information using digital technologies or to edit digital content without close guidance. At the same time, about 20 % of students in Germany excel in these tasks by demonstrating the ability to independently produce digital content without outside help and to critically evaluate the relevance of online information. These differences in digital skills can have far reaching implications for students' educational and occupational trajectories. For example, digital competencies correlate cross-sectionally (Lei et al., 2021) and also longitudinally (Hurwitz & Schmitt, 2020) with academic performance, indicating that digitally competent students are also more successful in school. Moreover, students with lower digital competencies are less likely to choose career paths in science, technology, engineering, and mathematics (STEM) domains (Hertweck & Lehner, 2025), thus, limiting their professional and income opportunities over the life course (Falck et al., 2021).

Differences in digital competencies are often systematically linked to students' demographic characteristics. In Germany, in particular, there are pronounced disparities in student achievement throughout primary and secondary school (Skopek & Passaretta, 2021). For example, students from lower socioeconomic backgrounds—indicated by factors such as parents' lower educational attainment or employment in less prestigious jobs—tend to exhibit significantly lower digital skills (e.g., Ren et al., 2022). Meta-analyses and contemporary educational large-scale studies estimate the respective SES gap at an average effect size of Cohen's $d =$ 0.43 to 0.33 (Kennedy et al., 2024; Scherer & Siddiq, 2019). Similarly, students with a migrant background who were born outside their country of residence or speak a language at home other than the primary language of instruction often show lower digital competencies, with effect sizes ranging from Cohen's $d =$ 0.15 to 0.29 (Kennedy et al., 2024). Gender differences in digital competencies present a more complex picture. While some studies have reported higher digital skills among girls as compared to boys (Campos & Scherer, 2024; Siddiq & Scherer, 2019), other have found the reverse (Qazi et al., 2022). This inconsistency may be partially a consequence of developmental factors. Longitudinal studies suggest that gender differences in digital competencies may gradually emerge during adolescence (Gnambs, 2021; Hübner et al., 2023).

2.1. Theoretical perspectives on the SES gap in digital competencies

Several theories offer explanations for disparities related to family background. The uneven distribution of economic, social, and cultural capital is often considered the decisive source for the achievement gap in digital competencies between low- and high-SES children (e.g., Hatlevik & Christophersen, 2013; Ren et al., 2022). Early explanations, for example, digital divide theory (Van Deursen & Van Dijk, 2019), argued that digital inequalities stemmed from poor access of low-SES families to digital devices, which limited their children's opportunities to develop basic digital skills. However, as smartphone and computer penetration has become nearly universal (see Rathgeb & Schmid, 2024), differences in access alone fail to explain SES-based inequalities. Instead, the focus has shifted to how digital technologies are used, the quality of digital engagement, and the opportunities they provide, thus, putting the home environment in the focus.

Proponents of cultural capital theory (Bourdieu, 1986) suggest that children may acquire digital skills at home (e.g., Ren et al., 2022). High-SES families are more likely to provide access to resources such as educational games, ebooks, and online learning platforms that foster advanced digital competencies. In contrast, children from lower SES backgrounds more often use technology for passive consumption such as watching videos or engaging in social media (e.g., Weber & Becker, 2019; Zillien & Hargittai, 2009). The accumulated digital skills and knowledge in a family, sometimes referred to as digital capital (Ragnedda et al., 2020), is considered a major contributor to SES-related disparities in digital competencies.

Parental practices may also play an important role (e.g., Lau & Yuen, 2016; Rodríguez-de-Dios et al., 2018). Social reproduction theory (Bourdieu & Passeron, 1990) describes how parents transmit educational and cultural advantages through guided interactions and structured support. High-SES parents who are often proficient in using digital tools themselves (e.g., Zilian & Zilian, 2020) can guide their children in using digital technologies in productive ways. For example, Rodríguez-de-Dios and colleagues (2018) showed that parental involvement positively correlated with student digital competencies, particularly in families with access to educational resources. In contrast, parents with poor digital skills may inadvertently limit their children's exposure to productive uses of technology because they use digital devices primarily, for example, for entertainment rather than learning and problem-solving (Lau & Yuen, 2016). Additionally, high-SES parents also monitor their children's use of digital devices more effectively (Nikken & Opree, 2018), for example, by restricting passive uses such as excessive gaming, thus, further contributing to disparities in how children use technology for skill development.

Beyond parental influences, the SES-based gap in digital skills may also be amplified by peer networks (DiMaggio & Garip, 2012). Friendships are frequently formed among individuals with similar socio-demographic backgrounds (Chabot, 2024). Social learning theory (Bandura, 1977) suggests that peers often act as models within these networks and, thus, shape behaviors and achievement (Van Ewijk & Sleegers, 2010). For high-SES students, peer groups may encourage the productive use of digital technologies, for example, by collaboratively evaluating the credibility of digital content or participating in shared online activities. These interactions may extend the digital competencies initially acquired within their families, creating a self-enforcing spiral that further enhances their skills.

2.2. Theoretical perspectives on the migrant gap in digital competencies

Although migrant background is often associated with lower SES (Panichella et al., 2021), some of the mechanisms explaining digital disparities go beyond the effect of SES. Usually, the mechanisms point to lower digital competencies in students with a migrant background.

Many digital tools and platforms rely on language skills. Adolescents from migrant backgrounds who are not yet fluent in the host country's language may, therefore, experience extraneous cognitive demands. According to cognitive load theory (Sweller, 2024), processing an unfamiliar language may limit the mental resources available for acquiring new skills when engaging with digital tasks. This dual burden is likely to affect performance in digital environments similarly to its effects in academic domains such as science, math, or reading (e.g., Lopez-Agudo, González-Betancor, & Marcenaro-Gutierrez, 2021; Van Laere et al., 2014).

Stereotype threat theory (Appel & Kronberger, 2012) provides another explanation for the digital divide. Many immigrant groups are subject to negative achievement stereotypes that portray them as underperforming relative to native students. Confrontation with these stereotypes often hinders performance, affects self-perceptions, and activity choices which may lead to lower achievement over time. While the phenomenon has been demonstrated in verbal and math domains (Appel, Weber, & Kronberger, 2015; Froehlich et al., 2022), it is plausible that it also extends to the use of digital tools.

Finally, social reproduction theory (Bourdieu & Passeron, 1990) emphasizes the role of parental cultural and social capital in academic achievement and attainment. Cultural capital includes competencies, skills, or values that are relevant to a given society, while social capital refers to networks and resources to which they provide access. As such capital tends to be context-specific, it is not easily transferred to the host country, resulting in losses when the family migrates. This applies not only to cultural but also to social capital as migrant families often form segregated social networks (e.g., Nauck, 2001) that include other migrants who have experienced similar losses. Lower cultural and social capital often translates to lower levels of academic achievement (e.g., Israel et al., 2001; Sullivan, 2001).

2.3. Theoretical perspectives on the gender gap in digital competencies

Current literature offers several complementary explanations for gender differences in digital competencies that, at their core, highlight the role of gender stereotypes and self-schema leading to lower competencies in girls. According to social cognitive theory of gender development and differentiation (Bussey & Bandura, 1999), gender identity is shaped as a result of an interplay between personal, environmental, and behavioral factors. In this ongoing process, individuals learn and internalize gendered expectations and attitudes present in their immediate environment and broader society through modelling, enactive experience, and direct tuition. This results in gendered self-schemas, motivations, and behaviors. However, people also actively shape their own gender development and environment through agentic engagement and behaviors (Bussey & Bandura, 1999). Since computers and technology have male connotations and are stereotypically more compatible with the male than female gender roles (Cheryan et al., 2013; Master et al., 2016; Miller et al., 2024), female adolescents may learn and internalize that boys are more suited for this field. This may lower their computer self-efficacy and discourage them from engaging in productive digital activities, which ultimately results in lower digital competencies.

A similar explanation is offered by situated expectancy-value theory (Eccles & Wigfield, 2020) which posits that gender stereotypes, as part of the cultural milieu, shape expectations of success and subjective task values, which in turn affect achievement-related choices and performance. Therefore, due to the male connotations of computers and technology, female students may value digital technologies less and harbor lower expectations of succeeding in them compared their male peers. This, in turn, may lower their engagement in productive uses of digital technologies leading to lower digital competencies.

Self-concept and comparison processes represent another mechanism proposed in the literature (Cheryan et al., 2013; Dasgupta, 2011; Master et al., 2016). When deciding on their engagement in a domain, students compare their self-perceptions with knowledge about a given domain and assess the extent to which the two align. As a result of such comparisons, female students, when faced with male connotations of computers and technology, may develop a sense of a mismatch between their self-perceptions and the stereotype. This can lead to decreased feelings of belonging, self-efficacy, and an increased sense of threat, reducing interest and engagement in the domain, ultimately leading to lower digital competencies.

In line with this reasoning, past research has revealed substantial gender differences in technology-related stereotypes among adolescents that favored boys (Miller et al., 2024). Somewhat smaller gender differences in the same direction were observed for self-perceptions and emotions related to digital technologies (Cai et al., 2017; Gnambs, 2021).

2.4. Development of disparities

Most research on the digital divide relies on cross-sectional snapshots that offer limited insights into how disparities in digital competencies change over time (for notable exceptions see Gnambs, 2021, Hübner et al., 2023; Lazonder et al., 2020). Research on social and gender inequalities in other academic domains, such as reading or math, suggests that SES and gender gaps may widen, shrink, or remain stable as children grow older and progress through the educational system (e.g., Borgonovi & Pokropek, 2021; Buchmann et al., 2008; Neuendorf et al., 2020). Two competing theoretical perspectives—cumulation and compensation—offer explanations for how these gaps may develop during adolescence.

Cumulation effects in digital competences suggest that achievement gaps tend to widen over time. Processes often referred to as “Matthew effect” may occur where early advantages lead to further benefits in the long run (Cunha & Heckman, 2007). Adolescents from high-SES backgrounds, who often benefit from digitally nurturing family environments, have access to competence-enhancing resources and parental feedback that foster the productive use of digital technologies. As a consequence, the digital gap is expected to deepen over time relative to their low-SES peers who face fewer opportunities for meaningful engagement with technology and skill development. In the German context, school tracking that sorts students into different ability groups may reinforce these disparities by creating unequal learning environments (e.g., schools with different digital equipment) and differing levels of peer support (Van Ewijk & Sleegers, 2010). Additionally, technology-related stereotypes associated with the male gender also undergo changes throughout childhood and adolescence (Miller et al., 2024). While girls tend to maintain gender-neutral (or even self-serving) views up to approximately age 13, male-focused stereotypes become more prominent thereafter. Consequently, these shifting gender stereotypes are likely to exert an increasing influence on the acquisition of digital competencies as adolescents mature. Taken together, these factors could explain why initially small differences in digital competencies may develop into sizeable achievement gaps during adolescence.

Compensation effects, on the other hand, propose that SES and gender gaps in digital skills could diminish over time. This perspective argues that ceiling effects may limit the accumulation of additional advantages for high-SES students or boys who have already reached a sufficient level of digital competencies to achieve their goals in a digital environment. As a result, further skill acquisition may not be desirable for them as compared to their low-SES peers or girls, who need to catch up. Standardized curricula and educational goals in German schools, which often focus on achieving basic competencies for all students rather than supporting high achievers, may reinforce this trend (Baumert et al., 2012). Moreover, while parental influences play an important role in shaping digital skills during childhood, its impact may decline in adolescence as peer networks become more important in adolescents’ social and academic life.

2.4.1. Empirical evidence

Empirical findings on the longitudinal development of digital competencies in general and digital disparities in particular are scarce (see Gnambs, 2021; Hübner et al., 2023; Lazonder et al., 2020; Senkbeil, 2022). However, the available evidence tends to support a modest widening of digital inequalities. For example, Lazonder and colleagues (2020) observed that Dutch children from high-SES families improved their digital skills more substantially over two years compared to their low-SES peers. Although the respective effect size of Cohen’s $d = 0.43$ suggested a notable effect, the small and selective sample limits the generalizability of these results. Similarly, longitudinal data from German students suggest that gender differences in digital competencies favoring boys increased between ages 15 and 18 by a Cohen’s d of 0.13 (Gnambs, 2021). These results provide tentative support for the cumulation hypothesis in digital inequalities. In other academic domains such as reading or math, however, findings have been mixed. While some studies indicated widening SES gaps during adolescence (e.g., Borgonovi & Pokropek, 2021; Nennstiel, 2023), others point to compensatory effects (e.g., Baumert et al., 2012; Neuendorf et al., 2020). Still, other studies argue that SES gaps emerge and expand before school in early childhood and remain stable thereafter (Skopek & Passaretta, 2021). Similar inconsistent results have been reported for gender inequalities in education (see Buchmann et al., 2008, for a review). These conflicting findings suggest that digital disparities may develop during adolescence, although the precise nature of these changes is still debated.

3. Objectives of present study

The present study on a sample of adolescents from a German educational large-scale assessment (LSA) expands cross-sectional research on digital inequalities (e.g., Campos & Scherer, 2024; Kennedy et al., 2024; Scherer & Siddiq, 2019; Siddiq & Scherer, 2019) by examining their longitudinal development during secondary education in Germany. Disparities in ICT literacy, an operationalization of digital competencies commonly used in international LSAs, related to family and individual characteristics such as SES, gender, and migrant background are studied to understand how these inequalities develop through adolescence (see Fig. 1). While prior studies suggested that growing disparities or cumulating inequalities are likely (Gnambs, 2021; Lazonder et al., 2020), compensation effects remain a plausible alternative explanation if schools act as equalizers to mitigate preexisting disadvantages. To provide a broader context, the study contrasts the development of digital inequalities with changes observed in math and reading literacy. Given the mixed evidence on educational disparities in these domains (e.g., Buchmann et al., 2008; Nennstiel, 2023; Neuendorf et al., 2020; Skopek & Passaretta, 2021), this comparison will offer insights into whether digital skills follow distinct developmental trajectories or align with typical patterns of educational inequalities.

4. Materials and method

4.1. Sample and procedure

This study uses data collected as part of the *National Educational Panel Study* (NEPS). The NEPS is an ongoing multi-cohort study that follows several representative samples of the German population, from newborns to adults, to observe how educational and occupational trajectories unfold over the life course (Blossfeld & Roßbach, 2019). Participants in the adolescent cohort who are the focus of the present study were selected using a stratified two-stage sampling approach to cover the population of students in secondary school (see Aßmann et al., 2019, for details). First, a random sample of secondary schools with fifth grades that was stratified by the major school types in Germany was identified. Then, two classes were randomly selected in each school. All students with parental consent were eligible to participate. The students received annual surveys and cognitive tests in small groups at school that were administered by experienced interviewers from a professional survey institute. Students who left school after ninth grade were individually surveyed at their homes. To reduce the burden for these students, a limited testing program including a subset of cognitive tests was implemented. Parents of the participating students were interviewed by phone to provide background information on their children. Further information on the cohort, sampling design, and assessment procedures are outlined in Thums et al. (2023).

The present study included a sample of N = 4872 students (48 % girls) attending sixth grades of secondary schools across different regions of Germany who participated in the assessment of digital competencies. Of these, 1943 participated at three measurement occasions,[1] that is, Grades 6, 9, and 12, while the remaining students participated only once or twice.[2] The assessments thus spanned a period of six years. In addition, the present study also makes use of measurements of math and reading competencies that were obtained in Grades 5, 7, 9, and 12. These measurements started one year prior to the assessment of digital competencies and stretched across seven years (see Supplement A for an overview of the measurement design).

In Grade 6, the students had a mean age of 11.89 years (SD = 0.50). About 25 % of them had a migrant background, meaning that, at least one of their parents or they themselves were born outside of Germany. Although the children came from various social backgrounds, as indicated by their parents' position on the *International Socio-Economic Index of Occupational Status Index* (ISEI-08; Ganzeboom, 2010) which ranged from 12 to 89, students with low socioeconomic status (SES) were slightly underrepresented (M = 55.86, SD = 20.28). On average, their parents had about 14.51 years of education (SD = 2.39). Additional information on the sample is provided in Table 1, while analyses of nonparticipation across grades are summarized in Supplement B.

[1] At the last measurement occasion, the sample included students attending twelfth grades of secondary schools with academic tracks and school leavers who switched to another educational path (e.g., vocational training) outside of regular schools. Even though the sample included a mixture of students and non-students at this point, for convenience we refer to this measurement occasion as 'Grade 12'.

[2] Students who left school after Grade 9 were individually tested at home (see Thums et al., 2023). To reduce the burden for these students, each was administered only two out of three test domains (i.e., digital, math, reading), in case of digital competence using a shortened version of the test. As a result, the digital competence test was not administered to about a third of these students. Because missingness of the digital competence test scores was introduced as part of the test design for these students, they were missing completely at random and did not introduce a systematic bias, following Rubin's (2004) missing value theory. In contrast, students attending Grade 12 of secondary school were tested at school and received all three test domains.

Table 1
Characteristics of participants at each grade.

	Grade 6	Grade 9	Grade 12 [f]
Sample size	4872	3167	2523
Number of schools	217	177	78
Age in years (M/SD)	11.89/0.50	14.91/0.48	17.76/0.41
Percentage of girls	48.40 %	49.32 %	50.14 %
Percentage with migrant background [a]	25.19 %	23.20 %	21.57 %
Percentage in academic track	47.87 %	52.40 %	62.55 %
Parents' years in education (M/SD) [b]	14.51/2.39	14.62/2.36	14.91/2.37
Parents' occupational prestige (M/SD) [c]	55.86/20.28	56.80/20.07	58.84/19.78
Parents' income (M/SD) [d]	2.85/1.42	2.90/1.41	3.04/1.44
Digital competencies (M/SD) [e]	0.00/1.00	0.07/1.00	0.21/0.97

Note. [a] The respondent or at least one parent were born outside of Germany. [b] The highest values reported by each parent for the average number of years required to obtain a given qualification (e.g., bachelor's degree) based on the classification of educational qualifications (CASMIN; Brauns et al., 2003) with values between 9 (equivalent to compulsory schooling) and 18 (equivalent to a master's degree from a university). [c] The highest occupational prestige of the students' parents based on the *International Socio-Economic Index of Occupational Status Index* (ISEI-08; Ganzeboom, 2010) with values between 11 (e.g., farmers) and 89 (e.g. judges). [d] Measured in seven income brackets from 0 (= no income) to 7 (= over 6000 Euros) with each bracket corresponding to an increase of 1000 Euros. [e] Standardized with respect to the mean and standard deviation in Grade 5. [f] Comprises of students from academic tracks in secondary school and school leavers.

4.2. Ethics statement

After the educational institutions agreed to participate in the study, all students and legal guardians provided written informed consent before study enrolment. All participants could withdraw from the longitudinal study at any time. The study was conducted under the supervision of the German Federal Commissioner for Data Protection and Freedom of Information in coordination with the German Standing Conference of the Ministers of Education and Cultural Affairs and the educational ministries of the respective federal states. All data collection procedures and instruments were approved by a special data protection and security officer of the NEPS in line with national ethical and legal regulations.

4.3. Instruments

4.3.1. Digital competencies

Digital competencies in the form of ICT literacy were measured in each grade with a single achievement test that followed established frameworks of international LSAs (e.g., ETS, 2002). In these, digital competencies are defined from a literacy perspective as cognitive skills relevant for successful participation in modern societies (Weinert et al., 2019). Following the ETS (2002) definition, ICT literacy represented four process components referring to accessing, creating, managing, and evaluating information with digital technologies (see Senkbeil et al., 2013, for details). Each item referred to one or two of these components and presented realistic problems to be solved using common digital technologies such as an internet browser, search engine, or spreadsheet (see Fig. 2 for example items). The tests administered in Grades 6, 9, and 12 included 30, 60, and 32 multiple-choice items, respectively. 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 several binary subtasks. Simple items were scored dichotomously (correct/incorrect), while complex items were scored polytomously based on the number of correct subtasks. In Grade 6, all respondents received all items of the test. In contrast, the other tests used a branched testing design (see Pohl, 2013) that assigned different test versions including either easier or more difficult items to each respondent. Thus, each respondent received only a subset of the

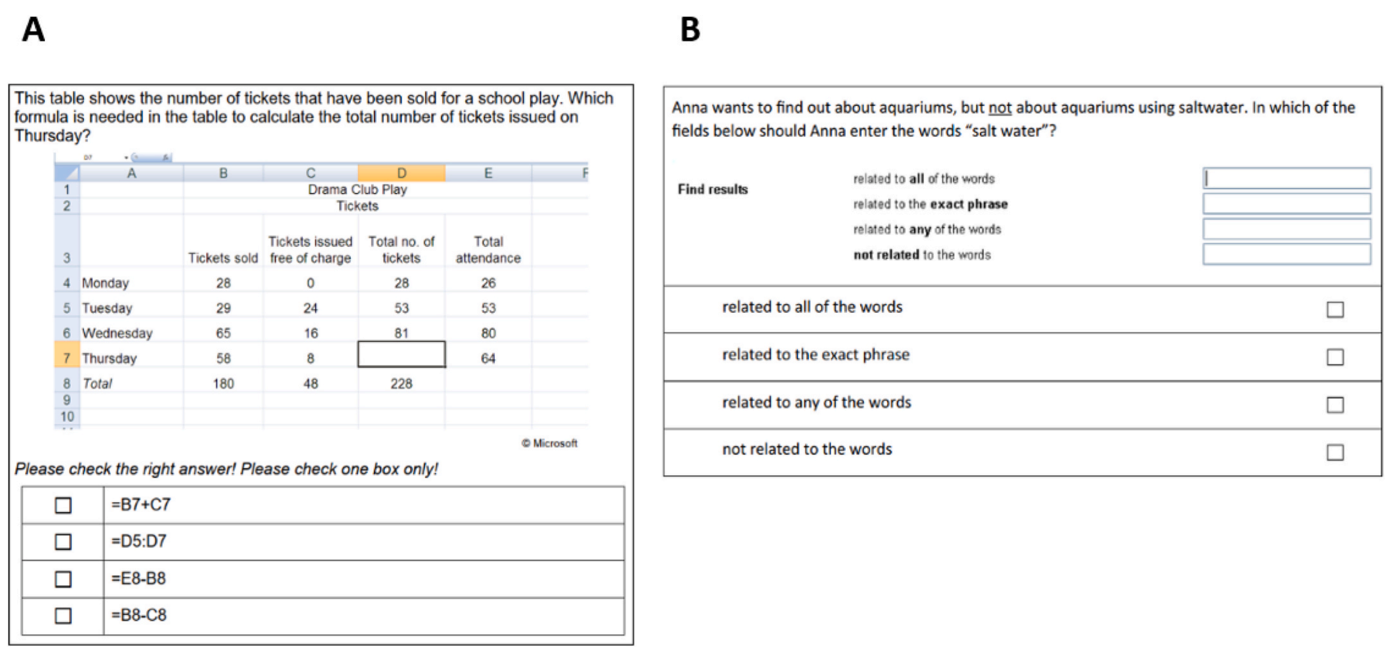

Fig. 2. Example Items of the ICT Literacy Tests
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items depending on their performance in the previous assessment. To facilitate linking on a common scale, the different test versions included several common items. For all tests, the testing time was limited to 28 min.

Although different process components were used for item development to guarantee a comprehensive construct coverage, the underlying theoretical framework conceptualized ICT literacy as a unidimensional construct (Senkbeil et al., 2013). Accordingly, the tests administered in each grade were separately scaled using the unidimensional partial credit model (PCM; Masters, 1982). Comprehensive psychometric evaluations of the item responses in each grade showed a good fit to the item response model with standardized weighted mean square statistics (*infit*; Wright & Masters, 1982) falling below 1.10 and adjusted Q_3 statistics (Yen, 1984) that did not exceed absolute values of 0.20 (see Bond & Fox, 2015; Yen, 1993, for discussions on these thresholds). Detailed item-level fit statistics and further psychometric evaluations of the administered tests are provided in Senkbeil et al. (2014) and Senkbeil and Ihme (2017, 2021). Further studies supported the convergent validity of the ICT literacy tests administered in the NEPS with assessments of ICT literacy in international LSAs (Senkbeil & Ihme, 2020). Additional analyses reported in Supplement C also attested to the approximate measurement invariance across gender and socioeconomic status. The marginal reliabilities of the tests based on the item response model (Adams, 2005) were 0.70, 0.82, and 0.65, respectively. The tests were linked across grades using independent bridge studies in which respondents received two tests at the same time (see Senkbeil & Ihme, 2017, 2021). This allowed placing the tests on a common metric using a mean/mean linking approach (see Fischer et al., 2016, for further details), thus, facilitating longitudinal mean-level comparisons. Proficiency scores were derived as 30 plausible values (Mislevy, 1991) for each student to acknowledge the uncertainty in the measurements (see Supplement D).

4.3.2. *Math competencies*

Students' math competencies were measured with achievement tests in each grade that were specifically developed for the NEPS. Following the literacy concept (Weinert et al., 2019), these tests aimed to measure competencies that are important for successful participation in modern society rather than aligning strictly with specific school curricula. The construction rationale adopted for these tests distinguished 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). The math tests administered in Grades 5, 7, 9, and 12 included 24, 23, 34, and 30 items, respectively. Each item required solving mathematical problems with (simple or complex) multiple-choice or short-constructed response formats that were embedded in real-life contexts relevant for the specific age group. Simple multiple-choice items and short-constructed responses were scored dichotomously as correct or incorrect, while complex multiple-choice items were scored polytomously as the number of correct subtasks. Because the theoretical framework defined mathematical competences as a unidimensional construct (Neumann et al., 2013), the different tests were scaled separately using the unidimensional PCM (Masters, 1982) resulting in good marginal reliabilities of 0.80, 0.76, 0.81, and 0.77, respectively. The item responses at each wave showed a good fit to the item response model with *infit* and Q_3 statistics falling below 1.10 and 0.20, respectively (see Duchhardt & Gerdes, 2012; Petersen et al., 2020; Schnittjer & Gerken, 2017; Van de Ham et al., 2018). The tests were linked across grades using common anchor items which allowed placing the tests on a common metric using a mean/mean linking approach (see Fischer et al., 2016, for further details). Students' math competencies were derived as 30 plausible values (Mislevy, 1991).

4.3.3. *Reading Competencies*

The ability to understand written texts was measured in the four grades with achievement tests that were specifically developed for the NEPS (see Gehrer et al., 2013, for the theoretical framework). The tests administered in Grades 5, 7, 9, and 12 included 32, 42, 46, and 41 items, respectively. These items referred to five texts (each with a length of about one page) with different response formats including multiple-choice or matching tasks that referred to an informational, instructional, advertising, commenting, or literary topic for each respondent. The tests were conceptualized as unidimensional measures (Geherer et al., 2013) and, thus, were scaled using the unidimensional PCM (Masters, 1982) which resulted in good marginal reliabilities of 0.81, 0.81, 0.81, and 0.80, respectively. Further psychometric properties of these tests such as item fit were satisfactory as indicated by *infit* and Q_3 statistics that did not exceed established thresholds (see Krannich et al., 2017; Kutscher & Scharl, 2020; Pohl et al., 2012; Scharl et al., 2017). Similar to the digital competence tests, the tests were linked across grades using independent bridge studies which administered two tests at the same time and, thus, allowed placing the tests on a common dimension (see Fischer et al., 2016). Again, the students' reading proficiencies were estimated as 30 plausible values (Mislevy, 1991).

4.3.4. Sociodemographic variables

The gender of the students was measured as a self-rating with two response options (0 = boy, 1 = girl). Additional gender categories (e.g., binary gender) were not presented. Students' migrant background (coded as 0 = without and 1 = with) was measured following the official German statistical categorization (Will, 2019) that indicated whether a student or at least one parent were born outside of Germany.

Three indicators were created to represent socioeconomic status, namely, parents' years in education, occupational prestige, and income. This followed prevalent recommendations to use different operationalizations that capture different aspects of socioeconomic status (Antonoplis, 2023). The *years in education* were given by an internationally comparable classification of educational qualifications (CASMIN; Brauns et al., 2003). It represents the average number of years required to obtain a given qualification (e.g., bachelor's degree) and can take values between 9 (equivalent to compulsory schooling) and 18 (equivalent to a master's degree from a university). *Occupational prestige* was measured with the international socioeconomic index of occupational status (ISEI; Ganzeboom, 2010), which considers a person's job as an intervening component between education and income. The ISEI ranges from 10 (e.g., cleaning staff) to 98 (e.g., judges). Higher values reflect a higher socioeconomic status. Finally, *household income* was measured in seven bins from 0 (= no income) to 7 (= over 6000 Euros) with each bracket corresponding to an increase of 1000 Euros. For years in education and occupational prestige, the highest value of both parents was taken, while the combined household income from both parents was used.

4.4. Statistical analyses

The research questions were addressed using latent growth curve analyses that modeled the repeated competence measurements by three additive components, that is, an intercept representing the initial level, a linear slope reflecting a constant rate of change across measurements, and a quadratic slope reflecting potentially nonlinear change trajectories. To account for the slightly different ages of the students and the varying time intervals between the assessments, a continuous time specification in a multilevel framework was adopted (Steele, 2008). This allowed examining continuous change trajectories across age and, thus, comparative analyses for the three competence domains, despite their slightly different measurement designs (see Supplement A). In these analyses, age was centered at 12 years, that is, the approximate age in Grade 6. Therefore, the intercept in all latent growth models reflected the mean competence at age 12. Then, social disparities in digital competencies were investigated by including one of the three socioeconomic indicators, gender, and migrant background as main effect and interaction with age in the model. In these analyses, digital competencies were *z*-standardized with respect to the first measurements; therefore, the regression coefficients can be interpreted in terms of standardized effect sizes. These analyses were repeated independently for each plausible value and, subsequently, combined using Rubin's (2004) rules to examine latent effects corrected for measurement error (Mislevy, 1991). Moreover, sampling weights were used to adjust for the disproportional sampling probabilities (see Hammon, Zinn, Aßmann, & Würbach, 2016). Dependencies resulting from the nesting of students in different schools were acknowledged through time-point specific random school effects for Grades 6 and 9.

Missing values were imputed 30 times with classification and regression trees using chained equations (Doove et al., 2014). To improve the imputation accuracy, the imputation model included information on the sociodemographic background such as gender, age, and school type as auxiliary variables (Collins et al., 2001). All inference tests adopted a Type I error level of 5 %. As effect sizes Cohen's *d*-like measures are reported which give the standardized mean difference between two groups. These are calculated as predicted effects for different values of a moderator based on the conditional latent growth curve models.

4.5. Transparency and Openness

The raw data analyzed in this study including the study material is available after registration at NEPS Network (2023), while the documented analysis code, including the analysis results, can be accessed at https://osf.io/vqsdx. Information on the software used for the analyses is given in Supplement H.

5. Results

Descriptive statistics including means, standard deviations, and correlations for all study variables are summarized in Supplement F. These show a pronounced increase of digital competencies from Grades 6 to 12 of Cohen's $d_{6\text{-}12} = 1.72$ (95 % CI [1.63, 1.81]). Furthermore, the test-retest correlations of $r_{6\text{-}9} = 0.70$ (95 % CI [0.69, 0.72]), and $r_{9\text{-}12} = 0.64$ (95 % CI [0.62, 0.65]) demonstrate a moderate stability across the observational period. Still, there were substantial individual differences in digital competencies in each grade. As shown in Fig. S1 of the supplementary material, the competence level of the adolescents spanned a rather broad range and included low-as well as high-ability students. Similar patterns were observed for math and reading competencies (middle and right plots) that gradually increased across grades while exhibiting pronounced individual differences at each measurement occasion.

5.1. Change trajectories of competencies

The appropriate form of the unconditional change trajectory of digital competencies from age 12–18 years without moderating effects was identified by comparing a latent growth model with linear age effects to a model that also acknowledged quadratic age effects. A model comparison using the Bayesian Information Criterion (BIC) favored the more complex model with quadratic age effects over the simpler linear model (BIC = 39187 vs. 39901). Moreover, the quadratic term was significant at $p < .001$. The linear trend indicated an increase of digital competencies by about 0.44 standard units per year (95 % CI [0.42, 0.47]), that flattened as students grew older, as indicated by the quadratic term of 0.03 (95 % CI [0.03, 0.02]; see Table 2).

Math and reading competencies also showed quadratic changes across the observational periods that implied slowing increases in competencies as students grew older. The yearly changes in competencies as reflected by the linear effects of 0.29 (95 % CI [0.27, 0.30]) and 0.27 (95 % CI [0.25, 0.28]) were, however, somewhat smaller as compared to digital competencies. The change trajectories of the predicted effects that are plotted in Fig. 3 show that digital competencies increased by about 1.66 (95 % CI [1.53, 1.79]) standard units from age 12 to 18, whereas math and reading competencies increased by about 1.19 (95 % CI [1.08, 1.30]) and 1.30 (95 % CI [1.21, 1.39]) standard units, respectively.

5.2. Moderation of socioeconomic status

The unconditional latent growth model for digital competencies was extended to include a main effect of SES and an interaction with age. Each indicator of SES, that is, parental education, occupational prestige, and income, was evaluated in independent analyses to examine the robustness of the results to the chosen operationalization of SES. As

Table 2
Parameter estimates of growth curve models.

Domain:	Digital competencies				Math competencies				Reading competencies			
Model:	Unconditional		Conditional		Unconditional		Conditional		Unconditional		Conditional	
	B	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Fixed effects:												
Intercept	0.09^{+}	0.05	0.17***	0.05	0.33***	0.05	0.56***	0.05	0.29***	0.04	0.29***	0.04
Age (linear) [a]	0.44***	0.01	0.46***	0.01	0.29***	<0.01	0.29***	<0.01	0.27***	<0.01	0.26***	<0.01
Age (quadratic) [a]	0.03***	<0.01	0.03***	<0.01	0.02***	<0.01	0.02***	<0.01	0.01***	<0.01	0.01***	<0.01
Parental education [b]			0.18***	0.02			0.19***	0.02			0.21***	0.02
Gender [c]			0.07*	0.03			0.31***	0.02			0.15***	0.02
Migrant background [d]			0.17***	0.04			0.25***	0.03			0.20***	0.03
Age (linear) x education			0.01*	<0.01			0.01^{+}	<0.001			0.02***	<0.01
Age (linear) x gender			0.02*	<0.01			0.01*	<0.01			0.00	<0.01
Age (linear) x migrant			0.00	<0.01			0.01	<0.01			0.02***	<0.01
Random effects:												
SD(Intercept)	0.64		0.63		0.68		0.63		0.67		0.64	
SD(Age)	0.08		0.08		0.07		0.07		0.06		0.06	
Cor(Intercept, Age)	0.02		0.02		0.01		0.01		0.06		0.06	
SD(School)	0.64		0.56		0.71		0.63		0.55		0.48	
Residual variance:												
SD(Residual)	0.68		0.68		0.54		0.54		0.63		0.63	

Note. B = Regression coefficient; SE= Standard error of B. Competencies were z-standardized with respect to the first measurement. [a] centered at 12 years; [b] z-standardized; [c] coded 0 for boys and 1 for girls; [d] coded 0 for no migrant background and 1 for migrant background. Based on 30 plausible values and multiply imputed data. The school-level random effect gives the sum of the two time-specific random effects.
***$p < .001$, **$p < .01$, * < 0.05,+$p < .10$.

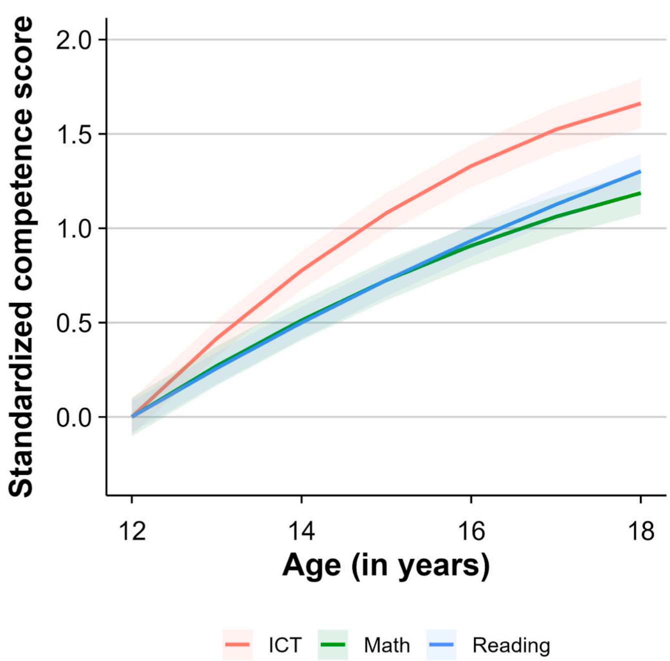

Fig. 3. Change Trajectories for Digital, Math, and Reading Competencies across Adolescence
Note. Predicted effects from growth curve model (solid lines) with 95 % confidence intervals (shadings). Competencies were z-standardized with respect to the first measurement.

summarized in Table 2, initial digital competencies at the age of 12 significantly depended on the education of the students' parents. An increase by one standard unit, which corresponded to approximately 2.4 years in parental education, was associated with digital competencies that were about 0.18 (95 %CI [0.14, 0.21]) standard units higher. The corresponding effect is illustrated in Fig. 4 (top-left plot), which shows the predicted digital competencies for students with parents having 13 years of education (equivalent to a university entrance qualification or vocational master's degree) and 16 years of education (equivalent to a bachelor's degree). The chosen values of years in education correspond approximately to the first and third quartiles of the variable in the present sample. The plot shows that students with higher educated parents tended to have higher digital competencies across the entire observational period. The results for the other operationalizations of SES, namely occupational prestige and income, replicated the basic pattern (see Supplement H). An increase of one standard unit in occupational prestige and to a lesser extent also income was associated with initial digital competencies that were higher by about 0.15 (95 % CI [0.11, 0.19]) and 0.08 (95 % CI [0.05, 0.11]) standard units, respectively.

The yearly change in digital competencies was moderated by the education of the students' parents (see Table 2). Competencies increased by about 0.01 (95 % CI [0.00, 0.02]) standard units stronger per year for students with lower SES as compared to high-status individuals, reflecting a narrowing of the competence gap from age 12 to 18. For example, the difference in digital competencies between students with parents having 13 years of education and students with parents having 16 years of education was 0.22, 95 % CI [0.35, 0.10] at age 12, which gradually reduced to a difference of 0.16, 95 % CI [0.35, 0.02] by age 18. Similar results were observed for parents' occupational prestige, albeit with a non-significant effect of 0.01 (95 % CI [0.02, 0.00]), while income did not moderate the change in digital competencies, 0.00 (95 % CI [0.01, 0.00] (see Supplement H).

Math and reading competencies exhibited highly similar moderating effects for the initial competence level at age 12 which yielded higher competencies for high- as compared to low-status students. The size of these effects was similar to those for digital competencies and fell for the two domains at 0.19 (95 % CI [0.16, 0.22]) and 0.21 (95 % CI [0.18, 0.24]; see Table 2), respectively. Regarding the moderation of change, an even larger effect of 0.02 (95 % CI [0.02, 0.01]) was found for reading competence. This corresponded to a difference in reading between students with lower and higher educated parents of 0.27, 95 % CI [0.38, 0.16] at age 12, which reduced to a difference of 0.14, 95 % CI [0.27, 0.02] by age 18. This effect was also replicated using occupational status and income as SES indicators (see Supplement H). In contrast, SES did not moderate the yearly change for math competencies (see Table 2). Thus, the competence gap in math remained largely unaffected across the observational period.

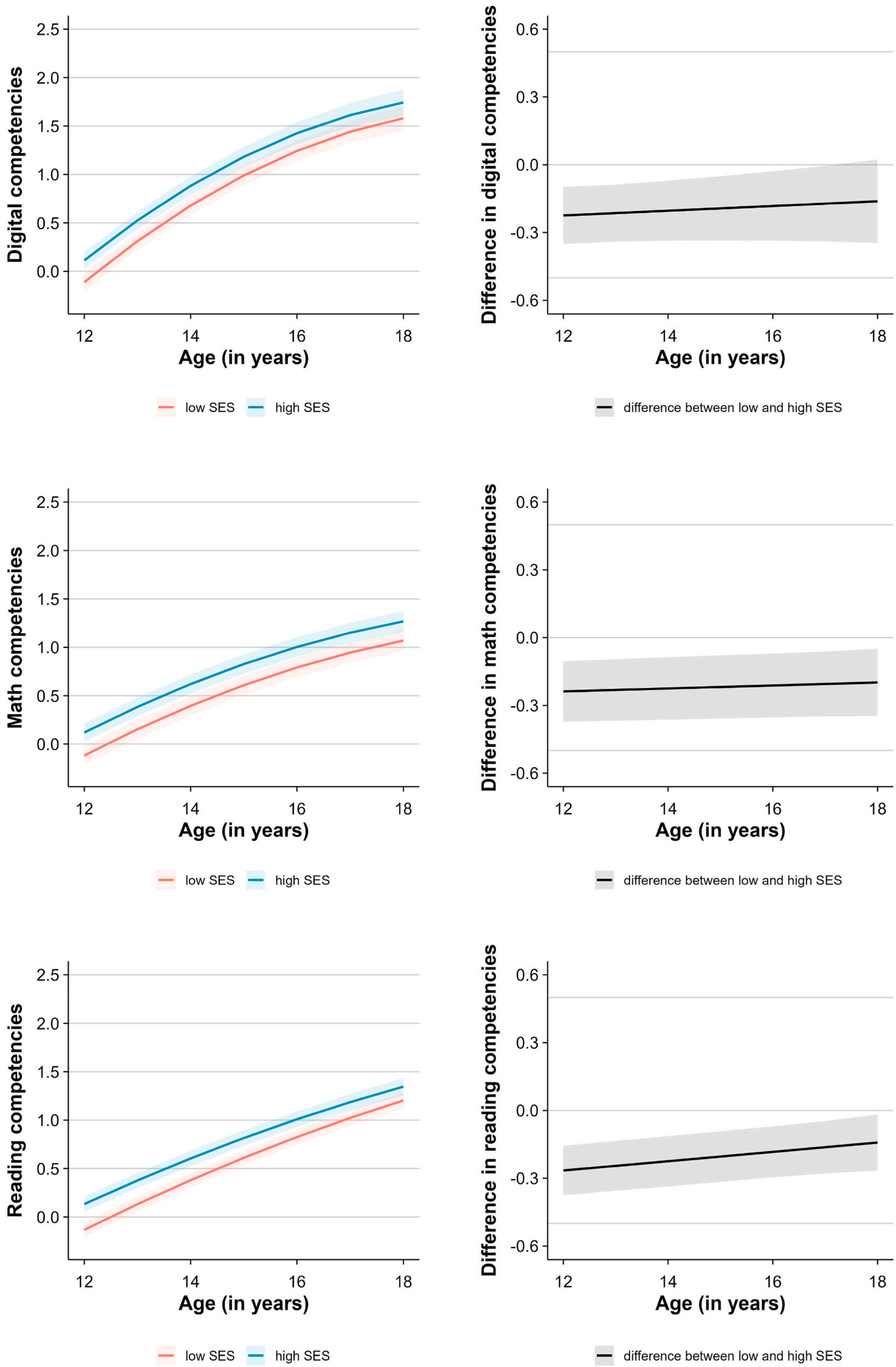

Fig. 4. Change in Digital, Math, and Reading Competencies Dependent on Socioeconomic Status
Note. Predicted effects from growth curve models (solid lines) with 95 % confidence intervals (shadings). Competencies were *z*-standardized with respect to the first measurement. SES = Socioeconomic status as parental education (low = 13 years, high = 16 years).

5.3. Moderation of gender

Although girls had lower digital competencies at age 12 as compared to boys (see Table 2), the respective effect was somewhat small, 0.07 (95 % CI [0.12, 0.01]). However, up to the age of 18 the respective gender gap increased by approximately 0.02 (95 % CI [0.03, 0.01]) standard units each year. This corresponded to a predicted difference of 0.18 (95 % CI [0.36, 0.01]) standard units at age 18 (see top row in Fig. 5). For math and reading competencies, the differences between boys and girls at age 12 were substantially larger than for digital competencies but did not change as much across the observational period (see Table 2). While predicted gender differences in math competencies increased from 0.30 (95 % CI [0.17, 0.44]) in favor of boys to 0.37 (95 % CI [0.22, 0.53]), respective differences in favor of girls remained largely constant for reading competencies, 0.15 (95 % CI[-0.26, 0.04]) and 0.15 (95 % CI [0.27, 0.02]), respectively (see middle and bottom rows in Fig. 5).

5.4. Moderation of migrant background

Students with a migrant background had digital competencies at age 12 that were lower by 0.17 (95 % CI [0.24, 0.10]) standard units as compared to students without migrant background (see Table 2). However, this difference remained rather constant and did not change in subsequent years (see top row in Fig. 6). The predicted difference between both groups was 0.17 (95 % CI [0.04. 0.30]) standard units at age 12 and 0.18 (95 % CI [0.00, 0.37]) at age 18. A similar pattern was observed for math competencies (see Table 2) that showed a non-significant decline in the difference between both groups from 0.25 (95 % CI [0.11. 0.38]) at age 12 to 0.18 (95 % CI [0.02. 0.34]) at age 18. In contrast, reading competencies showed significantly reduced competence gaps between students with and without migrant background across the observational period (see bottom row in Fig. 6). For reading competencies, the predicted competence gap decreased from 0.20 (95 % CI [0.09, 0.31]) standard units at age 12 to 0.09 (95 % CI [0.04, 0.22]) at age 18.

6. Discussion

The digital divide represents a growing concern for ensuring equitable life chances for adolescences in school and beyond. A large body of research has demonstrated that differences in digital competencies are systematically associated with demographic characteristics such as SES, migrant background, and gender, often reinforcing existing inequalities (e.g., Campos & Scherer, 2024; Eickelmann et al., 2024; Kennedy et al., 2024; Scherer & Siddiq, 2019; Siddiq & Scherer, 2019). The present study contributes to this literature by investigating how digital competencies develop during adolescence and exploring how digital disparities change over this developmental period.

6.1. Development of digital competencies

The findings revealed an approximately linear increase in digital competencies of about 0.44 standard units per year, which however slowed down over time. This pattern closely aligns with competence trajectories observed in traditional academic domains such as math or reading (e.g., Bloom et al., 2008; Neuendorf et al., 2020). Interestingly, the yearly gains in digital competencies observed in this study exceeded those typically reported for math and reading in the literature ($d = 0.20$; Baird & Pane, 2019) and observed in this study ($d = 0.27$–0.29). These findings underscore that adolescence is a particularly important period for acquiring digital skills. The large variability in digital competencies also challenges the notion of adolescents as universally proficient “digital natives”, as often perpetuated in popular media (e.g., Matuson, 2025). Rather, our results and also prior research (Eickelmann et al., 2024; Fraillon et al., 2024) suggest that this may be an oversimplification because many German adolescents may lack the skills necessary for effective participation in increasingly digitalized environments.

6.2. Development of digital disparities

The observed digital disparities associated with SES, gender, and migrant background align with key theoretical expectations. Specifically, female, low-SES, and migrant students exhibited lower digital competencies compared to their male, high-SES, and non-migrant peers, respectively. These findings support prior research on the role of SES and migrant background for digital competencies (e.g., Kennedy et al., 2024). However, they diverge from some earlier studies on gender. While meta-analyses (Campos & Scherer, 2024; Siddiq & Scherer, 2019) and comparative large-scale studies (Kennedy et al., 2024) often found a slight female advantage, the current results align with other German studies (Gnambs, 2021; Hübner, 2023) that showed gender differences favoring males to gradually emerge from Grade 9 (age 15) to Grade 12 (age 18).

While the digital competence tests used across studies draw from similar theoretical frameworks to measure comparable, if not identical, constructs (see Senkbeil et al., 2013; Senkbeil & Ihme, 2020), changing normative influences might account for these diverging results. Meta-analytic findings (Miller et al., 2024) on the development of gender stereotypes in STEM fields suggest that stereotypes favoring males emerge around age 13 among girls and become more pronounced over time. This might increasingly discourage girls from engaging in technology-related activities as they grow older. As a result, early small gaps in favor of either gender (Gnambs, 2021; Kennedy et al., 2024) might develop into larger disparities favoring males in later adolescence. An alternative explanation for the widening gender gaps could be differences in leisure activities driven by gender-specific interests. Digital skill acquisition strongly relies on non-formal learning opportunities, including home environments and extracurricular activities (Senkbeil, 2023). Gender-specific preferences such as boys’ greater interest in working with objects and girls’ stronger orientation towards interpersonal tasks (Su et al., 2009; Wang & Degol, 2017), may shape these learning opportunities. Thus, gender differences in digital competence might be a consequence of differential usage patterns determined by gendered interests of boys and girls.

The observed trends in digital skill disparities varied across demographic variables. The gender gap widened from $d =$ 0.07 to $d =$ 0.18, indicating a cumulative effect in line with meta-analytic findings on the emergence of gender stereotypes (Miller et al., 2024), while the migrant gap remained relatively stable at about $d =$ 0.17, and the SES gap showed a slight narrowing over time from $d = 0.22$ to $d = 0.16$, suggesting a modest compensatory effect. A comparison of these effects to typical learning gains over the course of a normal school year can help to put them into perspective (Baird & Pane, 2019; Bloom et al., 2008). The observed changes in gender and SES gaps per year correspond to a little more than half to a full month of learning. Notable, the SES-related results were sensitive to how SES was operationalized. Although different measures of SES showed consistent disparities at baseline, changes in disparities were observed only when using parental education, but not parents’ occupational prestige or income. This aligns with general recommendations to carefully match SES measurements to the specific research question (Antonoplis, 2023). In the present case, parental education may better capture parental practice and home environments, as higher-educated parents may be more aware of the importance of digital competencies for their children’s future success and, therefore, may provide more supportive digital learning environments. In contrast, occupational prestige and income may be less indicative of children’s home environment.

The narrowing SES gap may reflect the equalizing influence of the German school system, which provides students with standardized curricula and access to classroom technologies. Peer interactions in

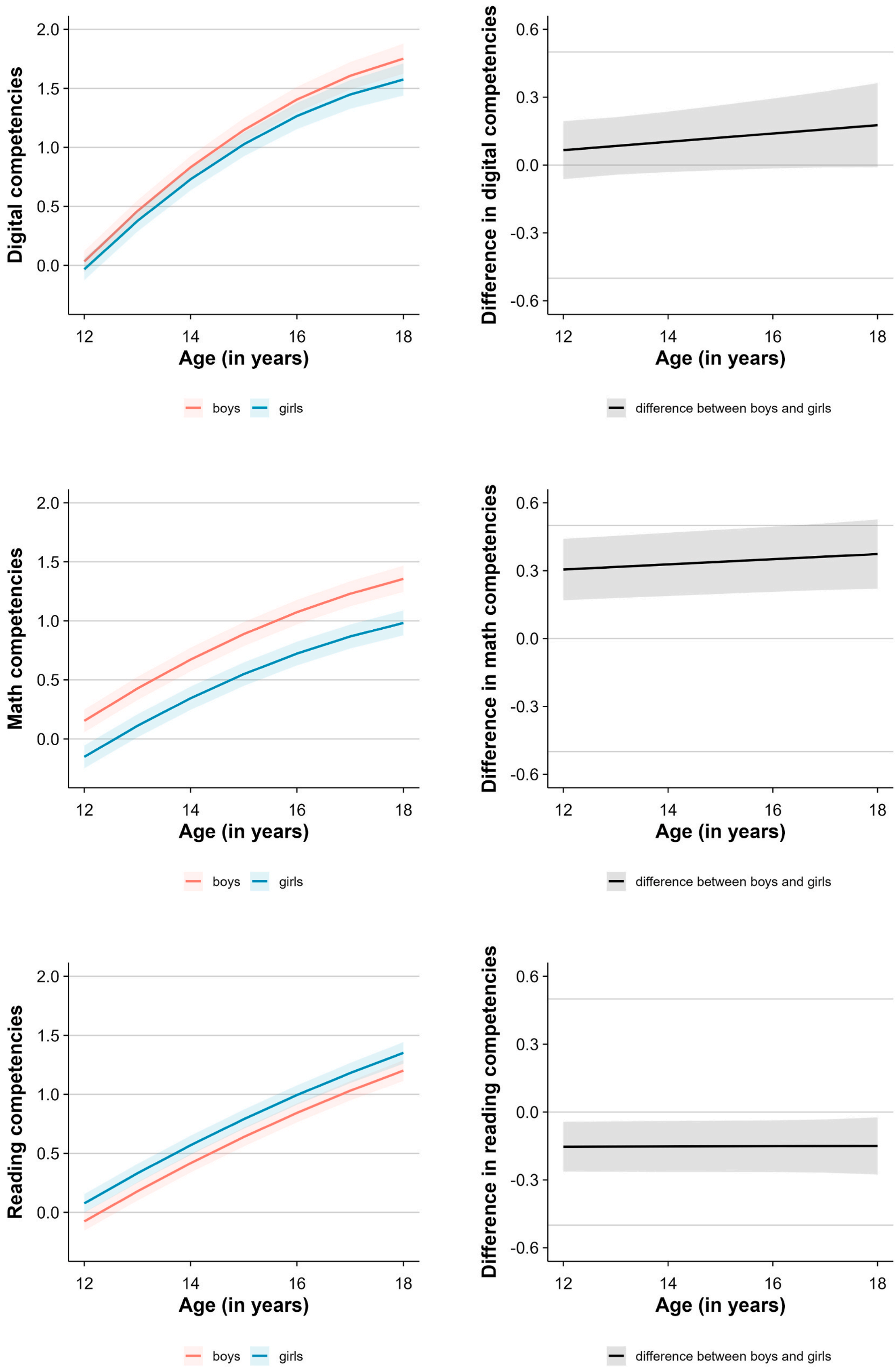

Fig. 5. Change in Digital, Math, and Reading Competencies Dependent on Gender
Note. Predicted effects from growth curve model (solid lines) with 95 % confidence intervals (shadings). Competencies were *z*-standardized with respect to the first measurement.

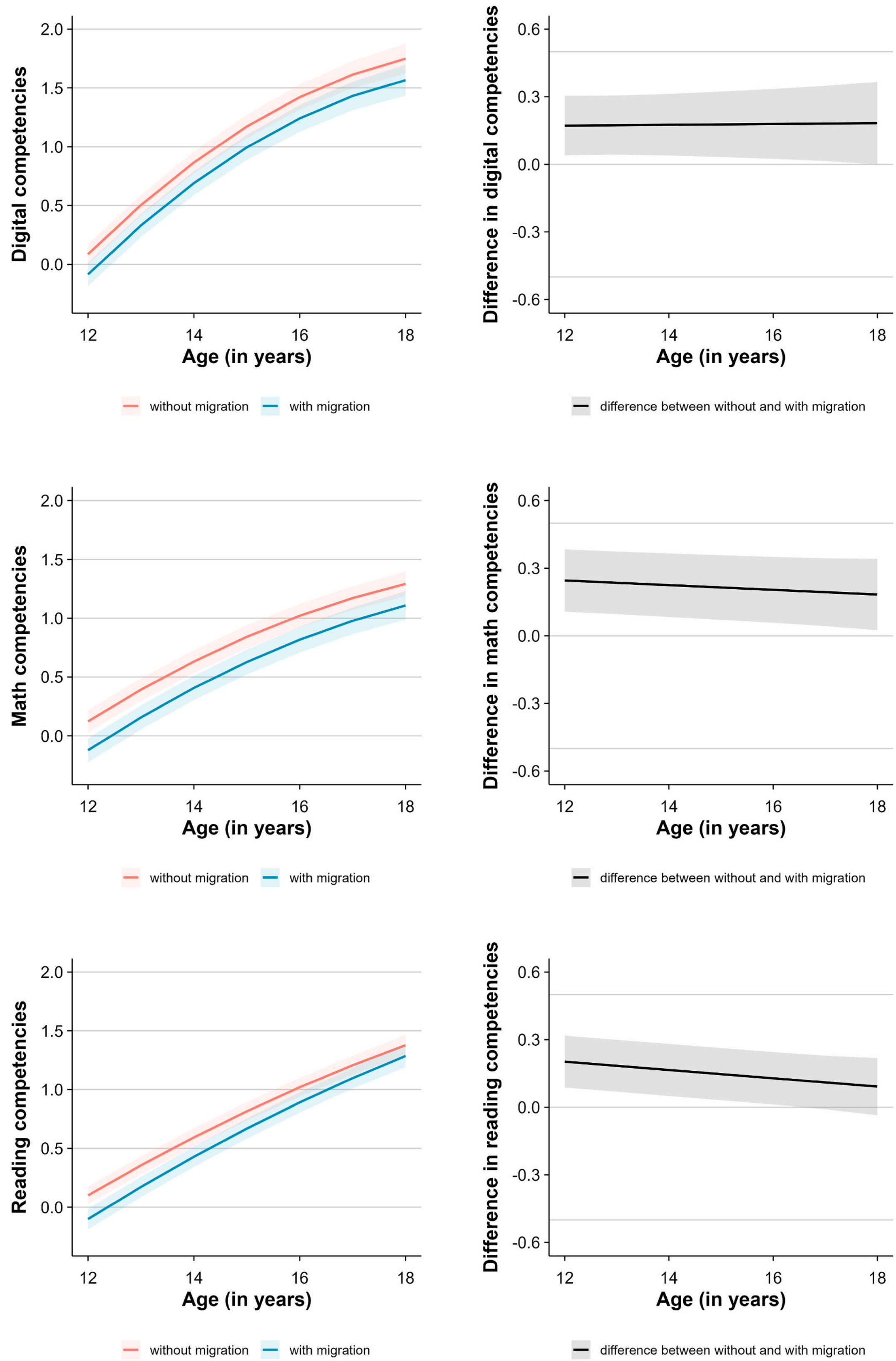

Fig. 6. Change in Digital, Math, and Reading Competencies Dependent on Migrant Background
Note. Predicted effects from growth curve model (solid lines) with 95 % confidence intervals (shadings). Competencies were *z*-standardized with respect to the first measurement.

mixed-SES school settings may additionally help lower-SES students learn from higher-SES peers and, thus, contribute to reducing disparities. However, while the German school system may act as equalizers for SES-related disparities, the persistence of the migrant gap highlights challenges that are not addressed by regular educational settings. Similar patterns have been previously observed for traditional education domains (Passaretta & Skopek, 2025).

A broader comparison across educational inequalities in the three domains (see Table 3) suggests that digital disparities more closely resemble the patterns observed for math than those for reading. Gender differences in digital and math competencies increased across adolescence, while migration-related gaps remained stable for both domains. In contrast, reading showed a decrease in migrant disadvantages, while gender differences persisted. These parallels between digital and math competencies may be attributed to similar gendered interests, stereotypes, and societal expectations that tend to steer boys toward technology and science-related fields, while discouraging girls (Miller et al., 2024; Wang & Degol, 2017). These findings underscore the importance of addressing domain-specific factors that contribute to educational inequalities and their developmental trajectories.

6.3. Limitations and directions for future research

Several limitations may affect the generalizability of the present findings. First, the study operationalized ICT literacy in line with international large-scale studies (ETS, 2002; Fraillon & Duckworth, 2025; Senkbeil et al., 2013). While this approach captures declarative and procedural skills related to established digital technologies, it does not encompass specific competencies such as computational and algorithmic problem-solving (Zeng et al., 2023), ethical and socially responsible behaviors in digital environments (Van Laar et al., 2017), or the ability to critically evaluate the accuracy and credibility of digital information (Molerov et al., 2020), which are part of more comprehensive digital competence frameworks (Vuorikari et al., 2022). Future research should, therefore, explore the development of digital inequalities in these neglected components of digital competence to highlight common and unique patterns of change.

Second, longitudinal studies inherently reflect past contexts because they rely on technologies that were relevant at the time they were conducted. Consequently, the administered tests focused on established digital technologies, such as office software or search engines, commonly encountered in everyday life when adolescents were about 10 years old but did not account for the emergence of transformative technologies in later years like generative artificial intelligence (Giannakos et al., 2025). As a result, the reported findings may not fully reflect the competencies required in contemporary or future digital environments. Replication of the present study with an updated assessment framework that incorporates these novel technologies is, therefore, encouraged to determine whether the observed effects hold for current and future populations.

Third, students' competencies and their development may depend on the intersection of individual and familial characteristics (Parker et al., 2020). For example, subgroups such as girls from lower socioeconomic backgrounds might face more serious disadvantages beyond simple main effects. However, exploratory analyses (see Supplement I) found little evidence for relevant intersectional effects on the growth parameters of digital competencies in the present sample. Future research could go beyond the considered variables and examine more detailed interactions, for example, with conventional literacies to better understand disparities in digital skills.

Finally, while several theoretical perspectives explain digital inequalities arising from SES, migrant background, or gender, these remain largely speculative because they have been rarely empirically examined. Therefore, future research should extend the analysis of group differences to investigate underlying mediating mechanisms. For example, studies could explore how normative changes in gender attitudes influence the development of gender differences in digital skills or how social homophily in friendship networks reinforces behaviors in digital environments, thus, shaping skill acquisition. Such analyses could provide a deeper understanding of the processes behind the emergence of digital inequalities.

Table 3
Summary of observed changes in disparities.

Domain	Socioeconomic status	Gender	Migrant background
Digital	(⇩)	⇧	⇔
Math	⇔	⇧	⇔
Reading	⇩	⇔	⇩

Note. ⇩ = Decrease of difference (= compensation effect); ⇧ = Increase of difference (= cumulation effect); ⇔ = No change of difference; () = Not robust.

6.4. Policy implications and conclusions

Longitudinal analyses of the digital divide across adolescence revealed pronounced individual differences in digital competencies that were shaped by students' individual and familial characteristics. Notably, social and gender disparities followed contrasting change trajectories: while social inequalities diminished over time, gender inequalities widened. In contrast, the migrant gap in digital competencies remained rather stable without much change. These findings are concerning given the role of digital competencies for adolescents' career choices and later professional success (e.g., Falck et al., 2021; Hertweck & Lehner, 2025). The disadvantages for female, low-SES, and migrant students may perpetuate broader patterns of social and gender inequalities.

The increasing gender gap also suggests that the digital divide between men and women in adult populations (e.g., Martínez-Cantos, 2017) emerges at early stages of schooling and is not adequately addressed by the current education system. From a policy perspective, preventing the formation of this gap is more efficient and effective than attempting to close it once it becomes substantial. The parallel trends in math-related disparities further emphasize that addressing gender disparities may be a particular challenge for the German education system. The persistence of digital disparities through adolescence underscores the need for targeted digital education initiatives that address existing social and emerging gender inequalities in digital competencies. Preparing adolescents for the challenges of modern, digitalized societies remains a critical task for parents and educators to ensure equal opportunities for all students.

CRediT authorship contribution statement

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

Author note

We 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) after concluding a data use agreement. Restrictions apply to the availability of these data, which is the reason why they cannot be provided by the authors of the study. Survey questionnaires are available on the NEPS study website (https://www.neps-data.de). The computer code and analysis results are provided at https://osf.io/vqsdx/.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2025.108800.

Data availability

The data is available free of charge after signing a data usage contract at https://doi.org/10.5157/NEPS:SC3:12.1.0.

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