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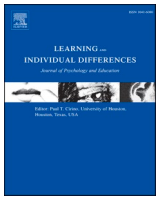

The effectiveness of game-based literacy app learning in preschool children from diverse backgrounds

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ABSTRACT

Family background factors like socio-economic status (SES) and migration background, along with child characteristics such as gender and intelligence, significantly influence early childhood competencies. Children from families with low SES and/or migration background often show weaker literacy outcomes than their peers. Game-based learning via apps can support children's competency development, but its effects may depend on children's app usage and how it interacts with child and family characteristics. We examined the effects of specifically developed literacy apps with $N = 500$ preschoolers ($M_{Age} = 60.96$ months). The intervention was successful: Children who used our literacy apps obtained greater literacy competencies compared to a control group, even after accounting for family and child characteristics. Longer app usage time was associated with literacy gains, independent of SES and migration background, with a U-shaped relation, but only among girls. Consequently, game-based learning via apps can be successful; however, individual differences should be considered.

Educational relevance and implications statement: The effects of early literacy apps developed for our study on young children's early literacy skills are mostly independent of their intelligence, gender, migration background, or socio-economic status. Moderate app usage times of half an hour per week seem especially beneficial for girls' literacy skill gain. Our findings show that our educational game-based literacy apps can act as additional means to support young children from all backgrounds in the acquisition of their early literacy skills. This kind of educational literacy apps offers parents with little financial, educational, or time resources the chance to support their children meaningfully.

1. Introduction

With the rapid development of technology, parents of young children face new challenges in their education and the design of their home learning environment. Smart devices, such as smartphones or tablet computers, are readily available, easy to use, and versatile, prompting many parents to seek digital supplements or alternatives alongside traditional learning methods (Fontenelle-Tereshchuk, 2023).

This ease of access particularly benefits structurally disadvantaged families such as families with a low socio-economic status (SES) and/or migration background, by providing opportunities to support their children's learning progress, even when financial or educational resources are limited. While parents with low SES and/or a migration background tend to have less access to financial or social resources to buy learning materials or support their children with costly activities (Kluczniok et al., 2013; Niklas & Schneider, 2010), most households now have at least one internet-enabled device that can be used to access applications (apps) (Kabali et al., 2015). This availability provides excellent potential for using learning apps as support tools for the development of children's skills, especially for structurally disadvantaged children.

Not only the social structural background of a child can affect their

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learning abilities and opportunities, but also their personal characteristics such as intelligence or gender. Girls are met more frequently with literacy learning opportunities than boys (Hemmerechts et al., 2017; Højen et al., 2022), and children with higher intelligence levels may learn and understand content at a faster pace (Deary et al., 2010). Learning apps have the potential to mitigate some of these learning differences by providing learning experiences that cater to individual preferences and abilities (Luckin & Holmes, 2016).

Various meta-analyses underscore the advantage of game-based interventions for cognitive development (Bai et al., 2020; Huang et al., 2020; Ritzhaupt et al., 2021; Sailer & Homner, 2020). However, empirical studies on game-based interventions have primarily focused on older children and adolescents. Yet, given that most learning apps in app stores are targeted at young children (Judge et al., 2015), there is a need to expand research on game-based learning apps to this age group.

Despite the vast number of so-called educational learning apps for young children in the app stores, only a few of them can be considered to be of actual educational value (Callaghan & Reich, 2018; Meyer et al., 2021). In the project Learning4Kids (Niklas et al., 2020; Niklas et al., 2022), a new set of suitable game-based apps was designed and developed by psychologists and educators in cooperation with IT experts to promote young children's school-relevant competencies.

The development of early literacy skills is particularly important for later academic success and can be supported by apps (for a review, see Griffith et al., 2020; for a meta-analysis, see Kim et al., 2021). For this reason, the present study focused on how the use of educationally valuable literacy apps can help young children from diverse family backgrounds develop their literacy skills. Special attention was paid to family and child characteristics of the participating children to find out which groups benefit the most from such apps. We aimed to identify whether structurally disadvantaged families in particular, i.e., families with low SES and/or migration background, as well as children with less beneficial characteristics such as children with lower intelligence would substantially profit from educational literacy apps designed and developed for the current study.

2. Associations of family and child characteristics with young children's literacy skills

Children's literacy skills develop long before the start of school, serving as a foundation for later reading and writing (Whitehurst & Lonigan, 1998). Whitehurst and Lonigan (1998) discriminated two intertwined literacy skill domains in their concept of emergent literacy. "Inside-out" skills refer to cognitive abilities and knowledge children need to learn to read and write. These include phonological awareness, i.e., the ability to recognise and manipulate sounds of language, and letter knowledge, i.e., the understanding and recognition of letter names, sounds, and forms. "Outside-in" skills refer to the knowledge and skills that help children understand the meaning and context of texts they attempt to write or read. This includes vocabulary development, e.g., through exposure to written and spoken language and early reading and writing skills such as exposure to books and the knowledge of their structure.

Early literacy skills are not only related to later reading skills in school (Šilinskas et al., 2017) but also to early numeracy skills (Purpura et al., 2011) as well as to emotional and behavioural skills (Westrupp et al., 2020). Their development is influenced by the environment they grow up in. Sociocultural theory (Vygotsky, 1978) suggests that children form their knowledge based on social interactions and active experiences, which are substantially shaped and influenced by their first, closest, and most frequent surrounding, namely their family (see also Bronfenbrenner, 1979).

2.1. Family characteristics: socio-economic status and migration background

The learning stimulation children receive from their parents and in their environment varies greatly, with parents' SES being one of the most influential factors associated with children's development of (academic) literacy skills (Coe et al., 2013; Demetriou et al., 2019). SES reflects a child's social origin and typically comprises parents' financial resources and educational levels (Baumert & Maaz, 2006). According to capital theory (Bourdieu, 1986), a family's resources shape their social position and opportunities. A higher SES implies access to more financial, social (e.g., networks), and cultural (e.g., knowledge) resources than a lower SES. As a result, parents with higher SES often have more financial means, broader networks of people who can support their children's academic and career paths, and can offer culturally enriching activities that promote school success, such as visits to theatres or museums.

Supporting Bourdieu's (1986) theory, empirical research demonstrates a correlation between the SES and children's academic achievement (for a meta-analysis, see Sirin, 2005). A higher SES, i.e., greater (financial, cultural, social) resources and higher levels of education, can provide children from higher SES families with increased access to learning opportunities, higher-quality parent-child interactions, and a supportive social network that fosters school success. Accordingly, studies have shown that children from families with higher SES received more literacy stimulation (Kotzerke et al., 2013; Niklas & Schneider, 2013).

These differences are also reflected in children's academic outcomes. In a meta-analysis by Mol et al. (2008), substantial differences in children's early literacy support by parents were found in families with low versus high SES. As a family's capital resources interact and accumulate over time (Bourdieu, 1986), they are often tied to an individual's migration background. Families who have lived in a country for generations have had more time to accumulate resources than first- or second-generation families. This interaction between accumulated resources and length of time a family has lived in a certain country makes it difficult to disentangle the SES from migration background. Especially in Germany, where this study is conducted, the SES is closely entangled with a migration background (Autorengruppe Bildungsberichterstattung, 2016). There are many different definitions and operationalisations for an individual's migration background (for German definitions, see Petschel & Will, 2020). In this study, we define a child as having a migration background if either the child or at least one parent was not born in Germany.

The majority of families with a migration background in Germany speak a language other than German at home (Autorengruppe Bildungsberichterstattung, 2016). On average, as another language spoken at home is usually accompanied by a migration background and thus by fewer accumulated capital resources, this often correlates with lower literacy skills in German (Relikowski et al., 2015; Wendt & Schwippert, 2017) and a less stimulating literacy environment (Højen et al., 2022; Valcárcel Jiménez et al., 2023). Empirical studies on the relation between migration background and early literacy skills struggle to disentangle the close connection between migration background and SES.

For instance, Niklas et al. (2011) reported that a migration background was associated with significantly weaker literacy skills already at the preliminary preschool year – this effect remained after controlling for children's age, intelligence, and SES (Niklas et al., 2012). In contrast, Dummert et al. (2014) did not find such significant associations between children's migration background and their early literacy skills. However, the authors criticised the unrepresentative composition of their German sample which had a low proportion of people with a migration background. In a study by Valcárcel Jiménez et al. (2023), preschoolers with a migration background were significantly less proficient in literacy skills. This association weakened when considering television exposure, which was substantially higher among children with a

migration background compared to those without. However, much of the effect of migration background could be explained by families' SES. Socio-economic origin thus appears to play a more important role in children's literacy skill development than migration background, even though the two are closely related in Germany.

2.2. Child characteristics: gender and intelligence

In addition to family characteristics, children's individual characteristics also tend to be associated with the stimulation they receive and the skills they develop. One characteristic that can be related to the way children grow up and the attitudes and learning opportunities they are met with is their gender (Butler, 1999). Early on, children encounter gender roles (Picho & Schmader, 2018), and parents tend to provide different learning stimulation and hold differing attitudes toward boys and girls, often creating more stimulating literacy experiences for girls (Højen et al., 2022). This appears to have a particular effect on children's reading self-concept (Niklas & Schneider, 2012), which, in turn, can affect later academic achievement (Susperreguy et al., 2018).

Becker and McElvany (2018) found gender differences in reading among third- to sixth-graders, which were more pronounced among children from low-SES families compared to those from higher-SES families. While Dummert et al. (2014) also reported that girls showed greater literacy skills in elementary school, Niklas and Schneider (2012) did not find such differences among preschoolers. This suggests that gender may not become an influential factor in literacy skills before the start of formal schooling.

Another child characteristic influencing learning outcomes is intelligence. In his decade-spanning work, Hattie (2008) showed that intelligence strongly affects school achievement. Several studies found substantial evidence for positive associations between intelligence and academic achievement (Schneider et al., 2014; for a meta-analysis, see Kriegbaum et al., 2018). Moreover, research indicates that intelligence benefits learning particularly in areas in which learners possess limited prior knowledge such as early literacy (Beckmann & Goode, 2010; Beier & Ackerman, 2005; Dinsmore et al., 2014; James et al., 2019; Li et al., 2012; Schneider & Preckel, 2017). Previous studies consistently show that intelligence is related to children's literacy skills; higher competencies are associated with higher intelligence scores (Demetriou et al., 2013; Ferrer et al., 2007; Watkins & Styck, 2017). The meta-analysis by Peng et al. (2019) not only shows that greater intelligence is related to better reading, but that this relation is also affected by children's SES in interaction with their age. Younger children from higher SES backgrounds were found to have better reading skills than those from lower SES backgrounds. Hereby, the authors highlight the ramifications of family and child characteristics.

Overall, empirical studies have well established the associations between children's family background and characteristics. However, prior research has typically focused on only one or two of these variables. The current study seeks to expand on these findings by considering all family and individual characteristics mentioned in their relation to the development of children's literacy skills.

2.3. Supporting and enhancing literacy skills through game-based learning

Given the widespread presence of digital media devices in households with young children (Kabali et al., 2015) and the considerable differences in literacy skills among children even before they enter school (e.g., Niklas & Schneider, 2010), it is advantageous to use these devices to support children's literacy development through learning apps.

There are various approaches for the design of supportive learning apps that combine learning content and game elements in different ways. The learning apps used in this study as part of the Learning4Kids project employ two specific approaches: game-based learning and gamification. Game-based learning transforms educational activities into games where players must apply their knowledge of the subject to fulfill educational objectives (Ke, 2016). To do so, the learners not only need to understand the learning content but also to develop the required generic and metacognitive skills, such as information searching and handling complex situations (Le & Weber, 2011).

Gamification, by contrast, incorporates game elements like badges, competitions, avatars, or rewards into traditional learning activities to motivate and engage learners (Deterding et al., 2011; King et al., 2013).

The game-based approach thus uses the game itself as the learning opportunity, while gamification adds game mechanics to traditional learning methods. The distinction between the two can sometimes be blurred. Although our apps follow both approaches (e.g., the "snakes and ladders" app is game-based, the "letter drawing" app comprises elements of gamification), we refer to game-based learning throughout the article for simplicity.

Game-based learning, along with digital game design and development, is now considered essential in educational contexts, leading to significant learning gains and enabling individual and group training. For example, children can train independently using tablet computers or mobile apps.

In their article, Hirsh-Pasek et al. (2015) define the junction of learning with app design and development as "the four pillars of learning". For games to successfully promote learning, these four pillars should be implemented in the game design. The first pillar is *active* or minds-on learning through the apps. The second pillar refers to creating *engaging* learning content that encourages children to play longer. The third pillar, *meaningful experiences,* bridges the gap between app content and children's existing knowledge. Finally, *social interaction* allows children to interact and socialise with others through the apps. Together, these pillars, along with minimal scaffolding, foster deep, lasting learning experiences.

The intersection of learning and app design, as outlined by the principles of Hirsh-Pasek et al. (2015), calls for dynamic and interactive learning environments. Tablet computers create flexible and stimulating learning settings, allowing children to engage in various interactive media experiences while actively constructing their knowledge (Sénéchal, 2011). Recent studies show that apps can support children's literacy skills, especially before the start of school (Amorim et al., 2022; Dore et al., 2019; Rogowsky et al., 2017; Vanbecelaere et al., 2020). For instance, Herodotou (2018) reported that most studies on two- to five-year-olds found positive effects of apps on children's self-efficacy and the development of their school-relevant domains, including literacy skills. By comparing traditional paper-based learning interventions and game-based app interventions, Rachels and Rockinson-Szapkiw (2017) reported that learning apps can be equivalent learning methods to traditional methods.

However, the question remains whether apps support the development of early literacy skills in children with diverse individual characteristics and family backgrounds. Few studies have addressed this issue. Arnold et al. (2021) and Griffith et al. (2019) found that children from low-SES backgrounds benefitted more from literacy app interventions than those in the control groups. However, both studies only included low-SES families and did not compare children from all socio-economic backgrounds.

To our knowledge, no empirical studies have investigated game-based literacy support for young children with a migration background. In Germany, SES and migration background are closely linked, and children with a migration background often start school with lower literacy skills than their peers (Niklas et al., 2011). Early digital support through literacy apps could help bridge this gap. In their meta-analysis, Tsai and Tsai (2018) showed that learning a second language – which for most children with a migration background in our sample is German – could be effectively supported through game-based methods. However, the second language these studies referred to was English; evidence for similar effects in learning German as a second language through game-based literacy apps is still lacking.

Research on children's characteristics in this context is comparably scarce. Studies on gender differences in learning outcomes through game-based methods have focused on secondary school and often indicate no significant differences (e.g., Ke & Grabowski, 2007; Papastergiou, 2009; but see Klisch et al., 2012 for greater gains in girls). However, these studies focused on math or science competencies. To our knowledge, no studies have explored gender differences in literacy skills through apps in preschool settings.

Similarly, intelligence has not been studied in this context. Previous research (Beckmann & Goode, 2010; Beier & Ackerman, 2005; Dinsmore et al., 2014; James et al., 2019; Li et al., 2012; Schneider & Preckel, 2017) suggests intelligence may moderate the effects of app usage. Specifically, children with higher intelligence might be able to benefit more from the same usage time. Consequently, it is conceivable that intelligence may influence whether and how individual children may profit from an app-based intervention. It is therefore important to examine whether only children with higher intelligence tend to benefit from such interventions (Dumont & Ready, 2023), which could indicate a need for app modifications to better support children with lower intelligence.

Given the disparities in literacy skills among young children from different backgrounds before school, the potential of learning apps to enhance these skills, and the limited empirical evidence, it is crucial to examine the interplay of these factors to better understand the connection between family and child characteristics and literacy outcomes.

3. Research question and hypotheses

Previous studies have shown that game-based learning apps can promote children's literacy skills. This study analysed the potential of a set of specifically designed educational literacy apps. We aimed to determine whether our app intervention would replicate previous findings, thereby testing our apps' educational value. More importantly, we investigated whether our intervention supports children from diverse backgrounds equally or whether children with certain characteristics benefit more (or less).

To this end, German preschool children were assigned randomly to either an intervention group receiving tablet computers with literacy apps to play with at home, or a control group receiving either tablet computers with apps focusing on numeracy or colours and shapes, or no tablet computers at all. The tablet computers were left in the families for children and parents to decide on their own when and how frequently to engage with the apps in an intervention phase of five to six months. Additionally, children's literacy, numeracy, and cognitive competencies were assessed via traditional tests before and after the intervention phase.

Research question 1 addressed the effect of the literacy app-condition in comparison to the control condition and whether children's individual and family characteristics predicted their literacy learning gains. Drawing on evidence supporting the effectiveness of app-based interventions (Griffith et al., 2020; Kim et al., 2021), we hypothesised that preschool children who received the literacy intervention would show greater literacy gains than those who did not receive the intervention. Further, we were interested whether we could find significant interactions between group allocation and the child and family characteristics.

Building on the first research question, we introduced a subsequent exploratory research question. Here, we examined whether the quantitative use of our literacy apps within the intervention group leads to different literacy skill gains based on children's family and individual characteristics. We used app usage time as a more precise indicator of intervention dosage in a per-protocol analysis, rather than simply comparing the intervention and control groups. Here, we examined four interrelated research questions. First, we examined whether usage time predicts literacy skill gains within the intervention group (research question 2a). Furthermore, on an exploratory basis, we used interactions to investigate whether app usage time was more influential for specific child backgrounds compared to others. Specifically, we aimed to determine whether longer times using our literacy apps resulted in greater literacy gains among children from families with low SES, migration background, with lower intelligence, and whether usage time effects varied between boys and girls (research question 2b). Finally, the effects of app usage may depend on the interplay of child characteristics with the different skills that the apps target and that were assessed as components of literacy. Therefore, we also explored whether the effects of usage time and its interactions varied across different components of the literacy outcome (research question 2c), and across different apps (research question 2d).

4. Materials and method

4.1. Sample and procedure

All data were collected within the framework of the longitudinal study Learning4Kids (Niklas et al., 2020; Niklas et al., 2022). Families with children of suitable age in the greater Munich area were contacted by post using addresses provided by the Munich district administration department; in addition, recruitment was carried out with the help of a recruiting company and through visits to kindergartens. The study comprises two cohorts and assesses a wide range of child skills. The current study investigated data of the first two measurement points (T1-T2; approximately 6 months in total) of both cohorts ($N = 500$, $M_{age\_total} = 60.69$ months, $SD = 4.61$, 257 girls). The families were visited at home by trained research assistants and children's literacy skills were assessed. All parents provided written consent for their and their child's participation. Data acquisition and assessments were approved by the ethics committee of the Faculty of Psychology and Educational Sciences at the University of Munich and carried out following the guidelines proposed by the Declaration of Helsinki.

The families were assigned to four groups via random number generation. Three of those groups received a tablet computer to use at home: The literacy group received apps focusing on children's verbal and literacy skills ($n = 151$), the numeracy group received apps focusing on children's numeracy and logical skills ($n = 151$), the tablet-control group received apps that did not include literacy or numeracy content but instead focused on colours or shapes ($n = 98$), and the business-as-usual control group did not receive a tablet computer ($n = 100$). Each child, i.e., each code, was assigned to group 1 (literacy), 2 (numeracy), 3 (tablet-control) or 4 (business-as-usual-control) according to the planned sample size. As the current study focuses on literacy skills, those families who received tablet computers with literacy apps ($n = 151$) will be regarded as the intervention group (1) and those families who received other apps or no tablet computers at all ($n = 349$) will be regarded as the control group (0). For an overview of the descriptive statistics of all variables, please refer to Table 1.

After the first assessment at T1, the research assistants handed the tablet computers over to the literacy- and tablet-control-group-families and briefly introduced a couple of apps to the children. Initially, for the intervention group, four apps that focused entirely on literacy skills were available for the children to play and learn with. To keep children interested and maintain intervention fidelity, new literacy apps were automatically downloaded every four to five weeks. For the last month of the intervention, the children had the opportunity to play with twelve different literacy apps in total.

To investigate to what extent children engaged with the apps, the exact usage times of each app were assessed through mobile sensing technology (Birtwistle et al., 2022). The total usage time of all apps formed the variable "Literacy Usage Time" (LUT; $\acute{\omega} = 0.95$). *Z*-standardised scores of this variable were used for inferential analyses to improve interpretability in our statistical models, which included interaction terms (Aiken & West, 1991).

Table 1
Descriptive statistics of all variables of interest.

Variable	Descriptive statistics per group: Control/Intervention				
	n	*M*	*SD*	*Min*	*Max*
Age	349/ 151	61.05/ 60.77	4.69/ 4.43	51.00/ 51.00	75.00/ 73.00
SES	349/ 151	−0.03/ 0.06	0.86/ 0.79	−2.70/ −2.54	1.32/1.32
Migration background	348/ 150	0.43/0.40	0.50/ 0.49	0.00/0.00	1.00/1.00
Intelligence	345/ 147	52.27/ 52.01	4.89/ 5.77	12.00/ 19.00	57.00/ 57.00
OMU	341/ 148	2.76/2.74	0.91/ 0.86	0.00/0.00	4.00/4.00
LUT[1]	137	590.08	509.21	0.00	1969.18
Literacy T1	344/ 149	0.01/ −0.01	0.68/ 0.71	−1.84/ −1.65	1.66/1.44
Literacy T2	344/ 146	−0.07/ 0.17	0.70/ 0.66	−2.15/ −1.89	1.33/1.24

Note. Age in months. SES = socio-economic status (z-standardised). Migration background: 0 = no migration background, 1 = migration background. OMU = overall media usage. LUT = literacy usage times in minutes. Literacy = sum score of all z-standardised literacy assessments.
[1] LUT was assessed for the intervention group (1) only.

4.2. Literacy apps

Out of the twelve literacy apps that were used in the study, eleven were specifically designed and developed within the scope of the Learning4Kids project. For an overview of the apps, see Table 2. They were mainly designed for the level of preschool children between the ages of four and five years, independent of their skill, family background, and knowledge about app and tablet usage, thus ensuring the children would easily understand the concept and the rules.

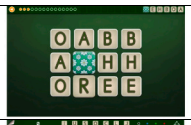
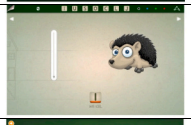
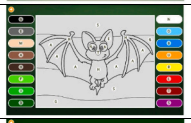
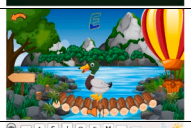
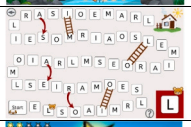
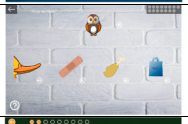
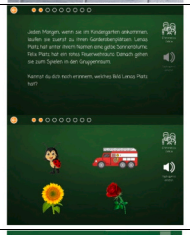
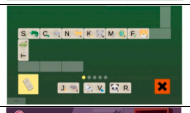
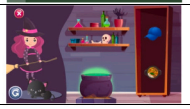
The apps were based on direct instruction (cp. Kebritchi & Hirumi, 2008), which means that instructions were given in simple language with initial training at the beginning of each game. As preschool children usually cannot read or write, no content based on reading or writing was included. Instead, verbal instructions and simple app functions were administered for children to follow. The children got the opportunity to train their literacy skills in various levels and they got feedback on correct and incorrect answers. Each level of each app started with basic precursor abilities and increased in difficulty with children's progression. This ensured that the apps remained interesting and motivating for children throughout the intervention period.

The precursor skills that were aimed to be trained included letter learning, learning vowels, rhyming, phonological awareness, word and sentence understanding, and letter drawing and sorting. The apps were further based on the "four pillars of learning" suggested by Hirsh-Pasek et al. (2015), i.e., they were designed to be active, engaging, meaningful, and social. Consequently, they not only provided individual activities but also the option for collaboration and competition (as suggested by Hirsh-Pasek et al., 2015; Ritzhaupt et al., 2021). Some of the apps were evaluated by experts according to the criteria outlined by Hirsh-Pasek et al. (2015) and received high ratings (Wirth et al., 2024). Due to financial and time restrictions, the twelfth and final app was obtained from the App Store. We introduced this app in the final month of the intervention to ensure that the majority of the intervention was carried out exclusively with apps developed by us.

Children were able to navigate through the games and across levels with simple tapping, drag and drop functions, or tracing (e.g., letter tracing). Particular attention was given to an appealing and child-friendly, but not overloading or distractive design (Mayer, 2005). For example, game avatars (e.g., an animal) were helping children to learn the game, or the games were provided on backgrounds with either no visual elements or minimal visual elements to avoid visual distraction. No distracting music/sounds were applied. Instead, verbal instructions explained the tasks to the children at the start of each level. Additionally, each letter or word was pronounced by a pre-recorded voice when children tapped them.

The learning elements of the apps focused strongly on feedback (Bai

Table 2
Overview of all literacy-apps and literacy skills they targeted.

App Name	Month	Time played in minutes total Max; *M(SD)*	Description	Screenshot	Literacy Skills	Test
Memory	1	366.97; 26.82(59.23)	This app corresponds to the traditional analogue memory game. All cards exist in pairs and are placed face down. Players turn the cards over by tapping them and memorize the letters on them. The aim of the game is to uncover two matching cards directly after each other (e.g., "A" and "A").		Active and passive letter knowledge	WVT
Letter drawing	1	361.93; 22.83(46.66)	In this app, letters are to be traced with the finger using displayed lines. Players follow a displayed arrow that guides them tracing letters.		Active and passive letter knowledge	WVT
Painting with letters	1	835.85; 53.14(106.87)	In this app, children color pictures. Both the areas of the picture and the colors are marked with letters. E.g., an area marked with "A" is to be colored with the color marked with "A" (e.g., blue).		Active and passive letter knowledge	WVT
Letter sorting	1	394.23; 23.18(50.40)	In this app, children sort a series of letters (e.g., D-A-B-C) in the correct order according to the alphabet (e.g., A-B-C-D). Pictures of animals with the corresponding initial letter simplify the matching.		Active and passive letter knowledge	WVT
Initial letter sounds	2	681.77; 25.13(62.76)	In this app, there are different levels for each letter (e.g., level "L"). Children are presented with animals one after the other (e.g., cow, lynx, lion, whale). Animals with the same initial letter as the letter of the level should be selected (e.g., lynx, lion).		Phonological awareness	WVT
Snakes & Letters	2	271.90; 27.09(58.85)	This app corresponds to the traditional Snakes & Ladders game. The board and the dice are marked with letters. This game can be played in multi-player mode.		Active and passive letter knowledge	WVT
Find the vowels	3	357.93; 8.76(28.26)	In this app, a letter is presented visually and audibly to the children (e.g., "A"). From two, three, or four objects, children are now to select the appropriate one that incorporates the letter (e.g., "panda").		Active and passive letter knowledge	WVT
Finding pairs	3	160.87; 8.69(23.10)	In this app, children are visually and audibly presented with the image of an object (e.g., "Wind"). They must now select from four other images, whose pronunciation they can listen to, the image that rhymes with the presented object (e.g., "Kind").		Phonological awareness	WVT
Sentence comprehension	4	151.52; 10.49(28.26)	In this app, children are read a short story. After each paragraph, they are asked several questions about the content of the story, which they can answer by selecting the correct image out of four (e.g., "Do you remember what season it was?" using images depicting the four seasons).		Passive vocabulary; early literacy knowledge	PPVT; EuLe
Letter-Domino	4	174.58; 7.62(23.07)	In this app, the task is to place game pieces together like in a traditional analogue domino game. The game pieces have letters and animal faces on them. The animals should match with their initial letters.		Active and passive letter knowledge	WVT
Magic potion	5	111.37; 6.81(18.07)	In this app, children help a witch brew a magic potion. For this, they need various ingredients. The witch spells out in sounds which object is needed next (e.g., P-O-T). The children must select the correct one from three given objects (e.g., the pot).		Phonological awareness	WVT
Word puzzle by PixaLink[1]	5	290.62; 5.79(28.43)	In this app, predetermined letters must be connected in the correct order to find the corresponding word for the visually depicted search object.		Early literacy knowledge	EuLe

Note. [1]The word puzzle app was not designed and developed within the framework of the Learning4Kids project.

et al., 2020), which was provided verbally (i.e., positive feedback if the answer was correct, encouraging feedback to try again if the answer was incorrect), visually (e.g., stars, balloons for correct answers), auditorily (e.g., cheering, clapping), or through badges (e.g., number of stars achieved after completing a level depending on the number of errors made) and tokens (e.g., collecting animals).

4.3. Literacy skills

To measure children's literacy skills, a variety of tests were assessed (see App. A for the descriptive statistics of all subtests). A subtest of the "Assessment of narrative and reading competencies of 4- to 5-year-old children" (EuLe; Meindl & Jungmann, 2019) tested children's early literacy knowledge: Using a picture book with simple sentences, children were asked to identify, for example, reading direction or capital letters. Correct answers were coded with "1", incorrect answers with "0". Sum scores of all answers were used (McDonald's $\acute{\omega}_{t1/t2} = 0.81/0.77$).

Children's phonological awareness and active and passive letter knowledge were assessed with five subtests from the "Würzburg preschool test" (WVT; Endlich et al., 2017). To test phonological awareness, three subtests were assessed. First, the children saw pictures of fictitious animals whose names rhymed with actual words (e.g., "Naus", similar to "Maus", the German word for mouse): The children were asked to say the correct plural form for the animals shown (e.g., several "Näuse", similar to "Mäuse", the German word for mice; $\acute{\omega}_{t1/t2} = 0.85/0.76$). Second, among four words, they were asked to identify the one word that did not rhyme with the rest (e.g., "See"—"Tee"—"*Tisch*"—"Klee"; $\acute{\omega}_{t1/t2} = 0.77/0.77$). Third, they were shown different pictures (e.g., the picture of a truck) and were asked to say the correct initial sound (e.g., /t/; $\acute{\omega}_{t1/t2} = 0.88/0.88$). To test for passive and active letter knowledge, children should recognise certain letters. Four letters were presented (e.g., "R"—"D"—"P"—"B") and the research assistant asked them to point out one specific letter (e.g., "Please show me /r/."; $\acute{\omega}_{t1/t2} = 0.78/0.81$). Additionally, children were presented with one letter (e.g., "N") they had to name actively (e.g., "/n/"; 0.87/0.88). In all five subtests, correct answers were coded with "1", incorrect answers with "0". Sum scores of all answers were used.

Finally, children's passive vocabulary was assessed with nine sets from the German version of the "Peabody Picture Vocabulary Test" (PPVT; Lenhard et al., 2015). Each set comprises twelve items and each item consists of four pictures. The research assistant said a word (e.g., "hedge") and the child had to point to the correct picture out of the four pictures shown. Correct answers were coded with "1", incorrect answers with "0". All incorrect answers were subtracted from the overall item count. The outcome served as sum score for the analyses ($\acute{\omega}_{t1/t2} = 0.90/0.93$). Due to differences in maximum scores between the PPVT and the other tests, all sum scores were z-standardised and summed up into the variables "Literacy T1" and "Literacy T2" for both T1 and T2 (McDonald's $\acute{\omega}_{t1/t2} = 0.81/0.82$).

4.4. Learners' backgrounds

4.4.1. Socio-economic status

The socio-economic status (SES) was measured through family income, parents' highest educational attainment, and the highest prestige value of parental occupation (Wegener, 1988). In the prestige scale, 283 categories of the International Standard Classification of Occupations (ISCO) are ranked according to their socially ascribed prestige. The scale ranges from 20 (unemployed) as the lowest value to 186.8 (physician) as the highest value and the complete range was found in our sample. All indicators of SES were z-standardised and mean values were used for the analyses to improve interpretability in interaction analyses (Aiken & West, 1991; $\acute{\omega} = 0.74$).

4.4.2. Migration background

If at least one of their parents or the child was not born in Germany, children were considered to have a migration background. In the full sample, $n = 210$ children were coded with a migration background (42 %; $n = 288$ no migration background). In the intervention group, $n = 52$ children had a migration background (38 %, $n = 85$ no migration background). This proportion of children with migration background is very similar to the proportion of approximately 41.6 % for children aged 0–5 years in Germany (as of 2022; Statistisches Bundesamt, 2023).

4.4.3. Intelligence

Children's intelligence was measured via the "Columbia Mental Maturity Scale" (CMMS; Burgemeister et al., 1972). Higher scores indicated greater intelligence. *Z*-standardised values of children's test scores at T2 were used for the analyses (split-half reliability in German contexts is between 0.92 and 0.96; Esser, 2002).

4.4.4. Overall media usage

In order to control for children's overall media usage, their parents were asked to indicate how much time their children spent with digital media on average per week on a 5-point Likert scale at T2. The parents could indicate >25 h per week (4), 10–25 h per week (3), 5–10 h per week (2), 1–5 h per week (1), or <1 h per week (0).

4.5. Missing data

Due to errors in usage recording, usage times of $n = 13$ participants were identified as missing. We imputed these data using multiple imputation via the Multiple Imputation by Chained Equation (MICE) approach (van Buuren & Groothuis-Oudshoorn, 2011). First, all variables were z-standardised. LUT was squared with itself, as descriptively a quadratic relation between LUT and literacy outcomes at T2 was evident. Then, interactions between all predictor variables and both LUT and LUT^2 were computed to prevent potential quadratic correlations and interactions with LUT from being underestimated in the imputed data sets during imputation. Literacy at T2 was reported as quadratic outcome variable of LUT (Vink & van Buuren, 2013). In this way, 100 imputed data sets were generated using predictive mean matching for continuous variables, the procedure suggested by Vink and van Buuren (2013) for the quadratic effect, and logistic regression for dichotomous variables. Regression models were then calculated with the 100 data sets and the results were pooled according to Rubin's rules (Schafer & Olsen, 1998).

One outlier (> +3SD) with a usage time >2500 min was excluded for inferential analyses, as well as one outlier with an intelligence score <10 (< -3SD).

5. Analysis plan

Analyses were conducted with R.4.2.1 (R Core Team, 2022). To examine the first research question (effects of child and family characteristics on literacy gains), we set up multiple regression models. First, children's literacy scores at T2 were controlled for literacy scores at T1 to model baseline-corrected learning gains. Second, we included a dummy variable indicating condition (0 = control group, 1 = intervention group) as predictor to examine the effect of group membership. Third, we included child characteristics (intelligence, gender), background variables (migration background, SES), and the control variable age to investigate whether group allocation had an effect even when considering all variables of interest.

Next, we analysed not only the main effects of group allocation while controlling for child characteristics but also examined in more detail whether child and family characteristics predict the literacy gains when considering group allocation. Specifically, we expanded the multiple regression models by incorporating interaction terms between group allocation and child intelligence, gender, and age, and family migration

background and SES.

To examine research questions 2a and 2b (effects of app usage for children with different characteristics and backgrounds), we set up four additional regression models, using exclusively data from children in the intervention group (see App. C). We again used literacy scores at T2 as the outcome and controlled for literacy scores at T1 (model 0). In model 1, we included literacy app usage time (LUT) as a predictor to examine research question 2a (effects of usage time). Since descriptive analyses indicated a quadratic relation between LUT and literacy scores at T2, we included both linear and quadratic terms of LUT. In model 2, we added children's characteristics (intelligence, gender) and family background (SES, migration background) as predictors as well as overall media usage (OMU) as a control variable. In models 3a-f, we added interaction terms between LUT, LUT^2, and one predictor at a time. Finally, in model 4, we included interactions between LUT, LUT^2, and all variables simultaneously. The aim of models 3a-f and model 4 was to identify the best-fitting model to examine research question 2b (interactions of usage time with child and family characteristics). We established this by selecting the best model according to the relative fit criteria AIC, BIC, and the sample-size adjusted BIC (aBIC).

Finally, we extended our final model to multilevel models, aiming for exploratory insights into varying effects of all predictor variables across the different literacy skills that comprised our overall measure (research question 2c), as well as varying effects of usage time across the different apps (research question 2d; see STab. 1 and STab. 2 in the electronic supplemental).

6. Results

6.1. Descriptive analysis

Bivariate correlations between all variables can be seen in Table 3. Children from higher SES families, with higher intelligence scores, and without a migration background showed significantly greater literacy skills at T1 and T2 than children from lower SES families, with lower intelligence scores, and with a migration background. Older children and girls had significantly greater literacy skills at T1 and T2. Usage times of literacy apps were positively correlated with literacy skills at t2. Children with a migration background were more likely to be from low-SES families. Children with higher intelligence scores were more likely from families with higher SES and/or without a migration background. Younger children were more likely to more frequently engage with media than older children. Girls scored significantly better in the intelligence measure than boys.

6.2. Effects of group allocation on literacy gains

In a pre-analysis, literacy skills at T1 were found to explain 69 % of the variance in children's literacy skills at T2 (Table 4, model 1). We investigated the effect of family (SES, migration background) and child (gender, intelligence) characteristics on pretest-controlled literacy gains to assess the relation between background characteristics and literacy gains before accounting for our app intervention (Table 4, model 2). Our findings indicate that children from families with higher SES, without a migration background, with greater intelligence scores, and older children showed greater literacy gains than children from families with lower SES, with a migration background, with lower intelligence scores, and younger children. Girls and boys did not differ substantially in their literacy gains.

To investigate our first research question, group allocation (intervention versus control) was added to the linear regression model of the pre-analysis (Table 4, model 3). As expected, group allocation was found

Table 4
Results of linear regression models testing effects of group (Model 2) and covariates (Model 3) on pretest-controlled literacy gains.

Parameter	Estimate	*SE*	*t*	*p*	R^2
Model 1					
Intercept	0.02	0.02	0.94	0.348	
Literacy T1	0.83	0.03	32.90	< 0.001	
					0.69
Model 2					
Intercept	0.04	0.03	1.38	0.17	
Literacy T1	0.73	0.03	24.16	< 0.001	
SES	0.06	0.02	2.71	< 0.01	
Migration background	−0.08	0.04	−2.28	0.02	
Gender	0.02	0.03	0.57	0.57	
Intelligence	0.07	0.02	3.64	< 0.001	
Age	0.01	0.00	2.56	0.01	
					0.71
Model 3					
Intercept	−0.06	0.02	−3.15	< 0.01	
Literacy T1	0.83	0.02	34.68	< 0.001	
Group allocation	0.26	0.04	7.33	< 0.001	
					0.72
Model 4					
Intercept	−0.04	0.03	−1.45	0.147	
Literacy T1	0.73	0.03	25.66	< 0.001	
Group allocation	0.26	0.03	7.61	< 0.001	
SES	0.05	0.02	2.46	0.01	
Migration background	−0.08	0.03	−2.22	0.03	
Gender	0.02	0.03	0.65	0.52	
Intelligence	0.08	0.02	4.22	< 0.001	
Age	0.01	0.00	2.75	< 0.01	
					0.74

Note. Group allocation: 0 = control group, 1 = intervention group. SES = socio-economic status (z-standardised). Migration background: 0 = no migration background, 1 = migration background. Gender: 0 = boys, 1 = girls. Intelligence was z-standardised. Age in months.

Table 3
Bivariate correlations between all variables of interest.

Variable	1	2	3	4	5	6	7	8
1. Literacy T1								
2. Literacy T2	0.84**							
3. SES	0.41**	0.42**						
4. Migration background	−0.35**	−0.36**	−0.28**					
5. Intelligence	0.40**	0.42**	0.25**	−0.18**				
6. Gender	0.09*	0.09*	−0.01	−0.02	0.09*			
7. Age	0.12**	0.16**	−0.21**	0.04	0.08	−0.05		
8. OMU	−0.00	−0.00	0.04	−0.08	−0.06	−0.08	−0.15**	
9. LUT	−0.01	0.13**	−0.06	0.03	−0.02	−0.06	0.01	0.02

Note. Literacy = sum score of all z-standardised literacy assessments. SES = socio-economic status (z-standardised). Migration background: 0 = no migration background, 1 = migration background. Gender: 0 = boys, 1 = girls. OMU = overall media usage. LUT = literacy usage times in minutes.
* $p < .05$.
** $p < .01$.

to be a significant predictor of literacy outcomes at T2. Even after considering all child characteristics and background variables, group allocation was significantly associated with literacy skill gains (Table 4, model 4). This supports our hypothesis that children in the intervention group would achieve greater learning gains than those in the control group. This model explained a further 3 % in posttest literacy scores.

Next, we calculated multiple regression models with interaction effects between group allocation and children's characteristics (intelligence, gender, age, migration background, and SES; Table 5). No significant interaction effects were found here.

6.3. Effects of usage time, family, and child characteristics on literacy gains within the intervention group

We further analysed the potential benefits not only of group allocation in general, but also of the usage time of our literacy apps for children from different backgrounds (research questions 2a and 2b). For this purpose, we focused exclusively on children in the intervention group. To examine the app intervention in more detail, we used the measured app usage times of each child. After comparing the relative fit indices (AIC, BIC, aBIC; see App. B) of all models, model 3e turned out to be the model with the best fit and is therefore presented as the final model for this research question (Table 6; see App. C for the results of the other models as well as the findings for the whole sample). This model included interaction terms between gender and usage time, but only main effects for all other predictor variables of literacy gains within the intervention group.

The results show again that literacy skills at T1 are a strong positive predictor of literacy skills at T2. As hypothesised, both SES and intelligence are positively related to literacy skills at T2: Both children with greater intelligence and children with higher SES record greater literacy gains than children with lower intelligence or lower SES. The significant interaction effects between LUT and LUT^2 with gender show that girls and boys profit differentially from their literacy app usage (Fig. 1). While boys do not experience significant benefits from specific usage times, a quadratic effect emerges for girls: Girls with low and high usage times learned the least, girls with medium usage times learned the most. These findings indicate that girls profit most from an average literacy app usage time of approximately 5 min per day/35 min per week. Migration background and child age did not have any significant influence on the literacy gains.

6.4. Varying effects of predictor variables across specific literacy skills and across specific apps

To investigate whether certain literacy components were specifically promoted by app usage and whether using specific apps led to more learning gains than others, we extended our final model to multilevel models. In the first model (STab. 1 in the electronic supplemental), we split the overall literacy score into the individual literacy variables. In the second model (STab. 2 in the electronic supplemental), we split overall literacy app usage times into usage times for individual apps. Bayesian estimation was used for these models, as frequentist estimation would likely fail at this sample size. Bayesian estimation of multilevel models allows obtaining individual estimated effects for different apps and literacy skills (in contrast, under frequentist estimation, only an estimate of variation across apps or literacy skills could be obtained; see e.g. Edelsbrunner et al., 2024).

Except for the interactions between gender and LUT and LUT^2, the variation estimates across apps and literacy skills are close to 0, showing no relevant differences compared to the final model for research question 2. The only noteworthy result is the variation in the effect of migration background across different literacy components (STab. 1: random slope variation: $SD = 0.44$, $SE = 0.17$, $CI = [0.21; 0.88]$). Specifically, the association between migration background and literacy at posttest was more positive than average (average regression weight estimate across literacy components: $b = 0.00$) for the two indicators of letter knowledge ($b = 0.39$, $CI = [-0.03; 0.82]$ and $b = 0.42$, $CI = [0.01; 0.85]$), and more negative for vocabulary ($b = -0.41$, CI = [−0.88;

Table 5
Results of multiple regression models for interactions with group allocation.

Parameter	Estimate	*SE*	*t*(df)	*p*	R^2
Model 0					
Intercept	0.01	0.02	0.75	0.46	
Literacy T1	0.84	0.02	34.55	< 0.001	
					0.71
Model 1					
Intercept	−0.06	0.02	−3.39	< 0.001	
Literacy T1	0.84	0.02	36.36	< 0.001	
Group allocation	0.26	0.03	7.36	< 0.001	
					0.73
Model 2					
Intercept	−0.05	0.03	−1.48	0.14	
Literacy T1	0.74	0.03	26.49	< 0.001	
Group allocation	0.26	0.03	7.52	< 0.001	
Intelligence	0.06	0.02	3.32	< 0.001	
Migration background	−0.08	0.03	−2.47	< 0.05	
SES	0.06	0.02	2.68	< 0.01	
Age	0.01	0.00	2.99	< 0.01	
Gender	0.03	0.03	0.88	0.28	
OMU	0.01	0.02	0.36	0.72	
					0.75
Model 3					
Intercept	−0.03	0.04	−0.76	0.45	
Literacy T1	0.79	0.04	23.88	< 0.001	
Group allocation	0.18	0.07	2.42	0.02	
Intelligence	0.06	0.02	2.83	< 0.01	
Migration background	−0.09	0.04	−2.34	0.02	
SES	0.03	0.03	1.36	0.17	
Age	0.01	0.00	3.27	< 0.01	
Gender	0.03	0.04	0.75	0.45	
OMU	−0.00	0.02	−0.41	0.68	
Literacy T1:Group	−0.16	0.06	−2.63	< 0.01	
Intelligence:Group	−0.01	0.04	−0.24	0.81	
Migration background:Group	0.00	0.08	0.04	0.97	
SES:Group	0.07	0.05	1.49	0.14	
Age:Group	−0.01	0.01	−1.02	0.31	
Gender:Group	0.01	0.07	0.20	0.84	
OMU:Group	0.05	0.04	1.33	0.18	
					0.75

Note. Literacy = sum score of all z-standardised literacy assessments. Groups: 1 = intervention, 0 = control. SES = socio-economic status. Migration background: 0 = no migration background, 1 = migration background. Gender: 0 = boys, 1 = girls. Age in months. OMU = overall media usage.

Table 6
Results of the multiple regression Model 3e.

Parameter	Estimate	*SE*	*t(df)*	*p*
Intercept	−0.06	0.09	−0.66 (129.51)	0.511
Literacy T1	0.70	0.06	12.00 (128.27)	< 0.001
LUT	0.00	0.17	0.01 (86.78)	0.993
LUT^2	0.00	0.15	0.01 (80.76)	0.994
Migration background	−0.07	0.11	−0.62 (122.22)	0.540
SES	0.15	0.05	2.80 (125.18)	0.005
Intelligence	0.10	0.05	2.03 (127.99)	0.045
Gender	−0.04	0.09	−0.42 (129.37)	0.673
Age	0.02	0.05	0.37 (125.75)	0.714
OMU	0.07	0.05	1.25 (126.48)	0.213
Gender:LUT	1.20	0.28	4.26 (103.13)	< 0.001
Gender:LUT^2	−1.12	0.29	−3.79 (110.30)	< 0.001

Note. Literacy = sum score of all literacy assessments. LUT = literacy usage times in minutes. SES = socio-economic status. Migration background: 0 = no migration background, 1 = migration background. Gender: 0 = boys, 1 = girls. Age in months.

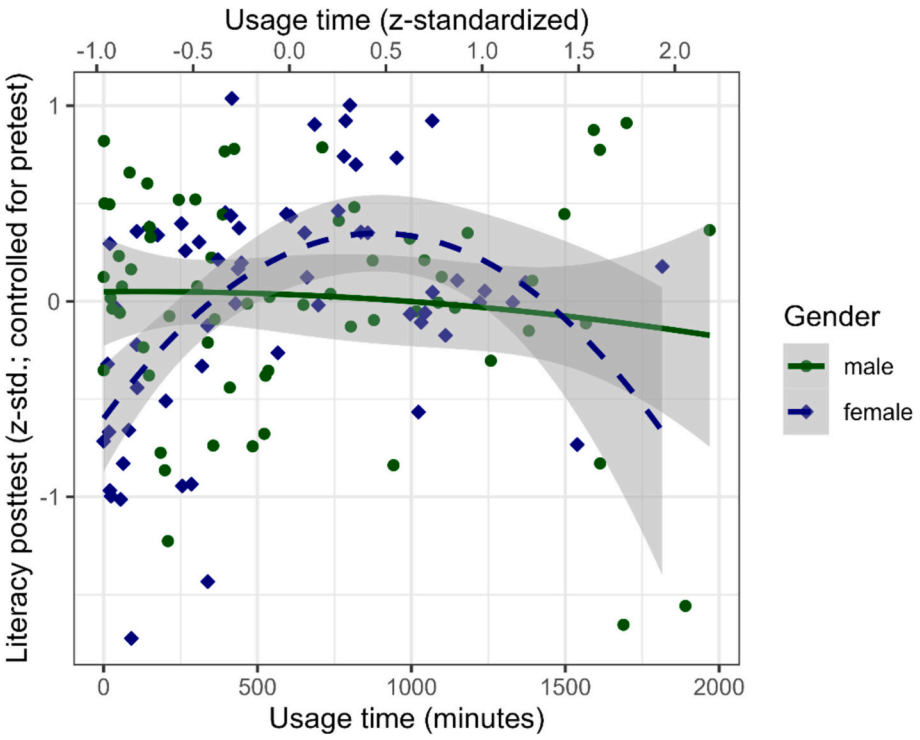


Fig. 1. Gender differences in the relationship between literacy app usage times and baseline-corrected literacy skills at T2 within the intervention group.

0.00]). Put differently, learners with a migration background showed more positive learning outcomes in letter knowledge and more negative outcomes in vocabulary. Note that these findings are exploratory and require replication, although we will discuss hypotheses that these findings may bring up for future research. The results for isolated apps (STab. 2) indicate that no specific app was responsible for particular gains in literacy skills or differences between children with different characteristics.

7. Discussion

The current study investigated to what extent a game-based literacy app intervention can benefit the early literacy competencies of preschoolers with different family and child characteristics. Socio-cultural theory (Vygotsky, 1978) and recent empirical findings (Griffith et al., 2020; Kim et al., 2021; Sailer & Homner, 2020) suggest that children's learning can be supported through high-quality game-based educational learning apps (Bai et al., 2020; Hirsh-Pasek et al., 2015).

Our findings confirm that preschool children profit from our game-based literacy app intervention. Not only could children in the intervention group show greater literacy gains than children in the control group (research question 1), but a closer look at the time spent using the apps (research question 2) revealed that there was a significant interaction between children's gender and their literacy app usage times. Our study further extends previous research by taking a closer look at children's literacy gains depending on child characteristics and family background. In the following, we will discuss our findings considering prevailing literature.

7.1. Differences in literacy gains depending on group allocation: greater gains for the literacy app intervention group

Our findings show that children in the literacy app intervention group experienced significantly greater literacy gains than those who did not receive the intervention. This supports previous research on the effectiveness of learning apps for enhancing young children's literacy skills (Amorim et al., 2022; Dore et al., 2019; Rogowsky et al., 2017; Vanbecelaere et al., 2020). Additionally, the results illustrate that our apps have educational value and are suitable for training young children's literacy skills.

Furthermore, we did not find significant interactions between group allocation and child and family characteristics. These non-significant moderation effects do not imply that no moderation effects exist in our data; to make such claims, Bayes factors would need to be calculated or confidence intervals would need to be interpreted. However, the results suggest that our intervention may be independent of child and family characteristics. Additional and more focused analyses with larger samples would be necessary to explore this further.

Our app design can serve as an inspiration for further development of learning apps for young children. However, it remains unclear if any specific type of app was particularly effective for literacy development. Exploratory analyses, in which we examined the relation between the individual learning apps and children's literacy skills, showed that the apps were on average effective in supporting literacy gains and that this effectiveness did not differ significantly across the twelve apps (see STab. 2). Since some apps focused on specific skills (e.g., exclusively tracing letters or exclusively recognising initial sounds), it is plausible that our apps, when used together, provide a solid foundation covering all areas of emergent literacy (cf. Whitehurst & Lonigan, 1998).

Consequently, future research should aim to replicate these findings and identify key components for a comprehensive app that significantly supports children's literacy development, potentially eliminating the need for multiple apps. At the same time, examining individual learning apps could help identify those that strengthen specific literacy skills, thereby enabling targeted support for particular weaknesses, such as phonological awareness.

7.2. Effects of usage time, family, and child characteristics on literacy gains within the intervention group: how much time does it take to make a difference?

Investigating the interaction effects between LUT, LUT^2, and

children's background characteristics revealed significant findings related to gender. Girls' literacy gains appeared to depend more on app usage times than those of boys. Researchers report that children generally use media to pursue already-existing interests (Chaudron, 2015). These interests are influenced by parents through value communication and (implicitly gendered) socialisation (Mesman & Groeneveld, 2017; Neitzel et al., 2019). Baroody and Diamond (2013) showed that parents and teachers reported greater reading interest among girls than boys; however, children's self-reported and observed interests did not differ by gender. Parents perhaps attribute greater literacy interest to their daughters, encouraging them more to engage with literacy apps. Yet, descriptive analyses showed that girls' and boys' overall literacy usage time did not differ significantly. This contradicts the assumption that girls may be encouraged by their parents to use literacy apps for a longer period than boys. Instead of a quantitative difference between girls and boys, these findings point to a qualitative difference in their app usage.

Empirical findings suggest differences in parental literacy involvement (Hemmerechts et al., 2017) and home literacy stimulation (Højen et al., 2022) based on children's gender. Consequently, parents of girls may be more inclined not only to encourage greater literacy app usage but also to support this usage through active involvement. The significant effect of app usage times for girls may therefore be moderated by parental involvement or extrinsic motivation. Further research on differential app usage between children with diverse characteristics and family backgrounds is needed to explore the motivations behind children's app usage and potential differences in children's actual engagement with educational apps. However, given that the overall effect of our intervention is relatively small, the differences between boys' and girls' interactions with app usage times must be interpreted with caution.

In our data, a usage time of about 5 min per day stands out as the optimal amount of time for playing the apps to enhance girls' literacy skills. Various studies show adverse effects of excessive media use on child development (e.g., Dore et al., 2020), but there is not much research on "too little" media use and thus the minimal necessary dosage of media usage for any effects to be found. Since the most beneficial usage time was only 5 min per day, it makes sense that girls who did not use the apps at all or used them, on average, only 1 or 2 min per day did not show statistically significant gains, despite being in the intervention group.

Prolonged use, on the other hand, could indicate a lack of other important learning and developmental stimuli in children's lives during the intervention phase such as verbal interaction with caregivers, engagement in hobbies, or even sufficient time spent outside of the home. For instance, Dore et al. (2020) found negative effects of prolonged media use on children's (academic) development. However, the reported usage times in that study far exceeded the maximum recorded usage times in the present study (e.g., usage times of $\geq$4 h per day in Dore et al., 2020). The negative effects of prolonged media use are also typically associated with parental factors. In particular, a lack of parental scaffolding in connection with media use has been shown to be crucial for lower achievement gains and developmental problems (Cerniglia et al., 2021).

Given the design of the current study, one can only speculate whether the girls who played on average 5 min per day received more parental scaffolding than those who recorded very short or very long usage times. Regarding the gender differences discussed above, it is also impossible to determine whether the parents of boys accompanied the use of the tablet computers less intensively than those of girls. To address these ambiguities, measurement forms other than questionnaires should be implemented. For instance, qualitative observations of (parent-)child use of game-based learning apps, time diaries, that analyse the trends and changes of the parent-child media usages, and ecological momentary assessments, that allow real-time data collection, could explore further in which situations game-based learning with apps is most conducive to children's development.

7.3. Effectiveness of game-based literacy-app intervention for children from diverse backgrounds: A Worthwile investment?

For a more in-depth discussion of the merits and limitations of our literacy app intervention, the obtained effect size with a variance explanation of 3 % should be considered. Although this magnitude might appear moderate, translation into Cohen's d by the formula given in Lakens (2013) indicates a *d* of 0.35. A meta-analysis by Kim et al. (2021) on recent studies investigating the effects of both commercial and researcher-developed apps found the same meta-analytic effect size (for literacy interventions: effect size = 0.35). These effect sizes are comparable to those of analogue interventions (effect size = 0.39; Gersten et al., 2020), and our effect size is at the higher end compared to analogue interventions that focus on low-SES children (effect sizes between 0.22 and 0.36; Dietrichson et al., 2017). Furthermore, Kim et al. (2021) found much smaller effect sizes for the broad and general type of literacy measures that were used in our study.

Based on recent discussions about a re-interpretation of small effect sizes (Kraft, 2020), it is evident that our intervention is valuable despite the obtained effect size. The findings show that children generally benefited from the intervention and the apps are therefore useful for a diverse range of children. We see the advantage of a digital intervention in this versatility. Since many families already own tablets, which are frequently used by children (Kabali et al., 2015), high-quality literacy apps can cater to individual learning levels without requiring additional effort from families in the form of travel or additional expenses. Overall, given that the developed apps can, in principle, be used across an unlimited number of samples and populations, the investment in their development seems to be worthwhile.

In their meta-analysis on computer-supported early literacy interventions, Verhoeven et al. (2020) suggest that the small effect sizes compared to analogue interventions are due to the teacher instruction that guided and supported children's learning in the analogue assessments. Consequentially, since the use of the tablets in our study was not monitored or guided during the intervention period, it is possible that a smaller effect size was achieved than would have been possible with guidance, particularly from parents. For instance, Sénéchal and Young (2008) reported moderately large effect sizes of 0.65 in their meta-analysis on the effectiveness of parental literacy interventions for children's reading skills. When comparing the effect sizes, it seems as if the advantages of parental trainings outweigh those of digital literacy interventions. However, viewing them as mutually exclusive is not constructive and does not reflect the everyday reality in which analogue and digital learning opportunities coexist.

A comprehensive approach aims at to empower parents through training to support their children's learning while enhancing their digital proficiency in guiding their children's app usage (Lehrl et al., 2021). This ensures that children can access a blend of direct parental engagement and digital learning opportunities, thus mitigating potential limitations such as time constraints or hesitations about providing support due to a lack of language skills. Especially for children facing structural disadvantages, digital literacy interventions can lead to increased parental involvement in literacy (Wirth et al., 2020). This synthesis of social interaction and the use of cultural tools aligns with Vygotsky's (1978) socio-cultural considerations and aims to unlock children's full potential.

Our analyses showed that even when accounting for the amount of time children used the apps, SES still had a significant impact on literacy gains. Since the interaction between usage time and SES (model 3c) was not statistically significant, the remaining differences between children from higher versus lower SES families must stem from different factors than the time spent using literacy apps. While our findings indicate that the frequency of app usage can enhance literacy gains, children's actual engagement with the apps must be brought to focus. Therefore, further

research has to emphasise not only the quantity but also the quality of children's app usage (Neumann & Neumann, 2017).

Moreover, previous research has suggested differences in parental support in children's app usage based on SES and migration background. For instance, Nikken and Opree (2018) reported lower basic media proficiency among low-SES parents compared to high-SES parents. It is therefore possible that low-SES parents were less able to support their children in using the literacy apps, resulting in insufficient guidance for their children, who may not have benefited from longer app usage times.

Other studies found that low-SES parents are less likely to expose their children to educational digital content compared to high-SES parents (Anderson et al., 2001; Calvert et al., 2005). These differences may be attributed to lower education levels or a lack of media literacy that enables parents to choose appropriate programmes or learning content. To address these uncertainties and gaps in competencies, further research should explore what kind of support low-SES parents need to introduce their children to digital media in a competent, confident, age-appropriate, and meaningful manner.

7.4. Effects of family and child characteristics on literacy gains: to him that hath shall be given

In a preliminary analysis, all background characteristics were simultaneously tested for their relation to children's literacy gains. Considering these variables together provides important insights into their interrelations, controls for confounding factors, and elucidates their combined associations with literacy gains. This holistic approach not only advances theoretical understanding (e.g., Bourdieu) but also informs practical strategies for promoting equitable literacy development across diverse populations.

Regardless of whether children received our literacy app intervention, those from families with higher SES, without a migration background, and with higher intelligence showed greater literacy gains than children from families with lower SES, with a migration background, or with lower intelligence scores. This suggests a Matthew effect in the performance of children from different backgrounds concerning the differences that already exist before school enrolment: children who begin with better starting conditions can use this head start to accumulate more knowledge in the same amount of time (Dannefer, 1987; O'Rand, 1996). The best predictors of later literacy outcomes are children's prior literacy skills, which are strongly correlated with children's SES, migration background, gender, and intelligence (which, in turn, is associated with a higher SES and the absence of a migration background). Therefore, at least on a descriptive level, significant relations between literacy precursor skills and family and child characteristics emerge, extending previous findings by considering all these characteristics simultaneously.

Our exploratory multilevel models showed that migration background is not only related to overall literacy gains but also to specific literacy components, namely letter knowledge and vocabulary (see STab. 1). While children with a migration background show a much higher gain in letter knowledge compared to those without a migration background, the opposite is true for vocabulary: here, the gain in vocabulary is smaller than for children without a migration background. The greater vocabulary gains made by children without a migration background suggest that these children may be exposed to a wider range of vocabulary at home, for example through conversations with their parents, which typically occur in German, or through being read to in German (Novita & Kluczniok, 2021). For children with a migration background, these informal learning opportunities are more likely to take place in a language other than German (Autorengruppe Bildungsberichterstattung, 2016), which is why they are less likely to develop their German vocabulary to the same extent as children without a migration background. In contrast, families with a migration background may prioritise formal learning of literacy competencies and thus children may be taught letters more often than children without a migration background (Novita & Kluczniok, 2021).

7.5. Limitations

Researchers highlighted the importance of the quality of the child-tablet interaction (Neumann, 2014, 2016; Neumann & Neumann, 2017). Since our study examined the usage times but not the quality of usage, e.g., by observing children engage with the apps, we cannot infer from our data whether children interacted meaningfully with the apps or not, whether parents supported, or whether siblings or friends interacted with the apps, which are intriguing questions for future research.

Another limitation this study faced is the fact that only overall usage times throughout the intervention time were measured, not the exact daily distribution of the usage times per child. This would have allowed us to further investigate the potential differences between boys' and girls' usage of the apps to conclude the benefits or risks of certain usage patterns.

In theory, mobile sensing allows for such a detailed assessment of usage times. However, due to the amount of data and the framework of the current study, we were not able to measure and consider such a distinction here. Future work ought to look further into usage times frequencies to investigate whether and to what extent children differ in the frequency and duration of their app usage. Such research might have the greatest potential if it can draw on a theoretical model of usage times that allows deriving useful statistical indices regarding usage times that go beyond total usage time. Further, the present study investigates short-time effects right after the five-month intervention ended. Possibly, significant differences between children from different backgrounds based on the intervention will emerge only later on or the intervention effects found will not be maintained.

Finally, the results of this study have to be interpreted with caution as eleven out of twelve apps the children used were specifically designed and developed for the purpose of the Learning4Kids project, in the context of which the current study took place. The presented findings apply to our apps but cannot be generalised to other apps, especially commercial ones. Further research comparing the features of well-designed, scientifically based apps with commercial apps, and particularly the public communication of this comparison, is necessary to assess the quality of freely available apps. This will provide parents and educational professionals with a framework within which they can confidently select meaningful, supportive apps for their children.

7.6. Conclusion

Children from different backgrounds differ in their school-relevant competencies from an early age. In order to reduce these differences, digital methods such as support through specifically designed learning apps can be used. The positive effects of our game-based literacy apps on preschool children's literacy skill development were mostly independent of their background characteristics. For girls in particular, usage times of an average of 5 min per day related positively to learning growth, whereas for boys, the effects were mostly independent of usage time.

Ethics statement

This study was ethically approved by the European Research Council Executive Agency. This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the ethics committee of the Faculty of Psychology and Educational Sciences, University of Munich (LMU).

Consent to participate

All participating families gave written consent to participate.

Consent for publication

All authors consent to the publication of the manuscript in *Learning and Individual Differences*, should the article be accepted by the Guest Editor upon completion of the refereeing process. Formal consent to publish anonymised data was obtained by all participating families.

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CRediT authorship contribution statement

Tina Schiele: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Peter Edelsbrunner:** Writing – review & editing, Formal analysis. **Anna Mues:** Writing – review & editing, Investigation. **Efsun Birtwistle:** Writing – review & editing, Investigation. **Astrid Wirth:** Writing – review & editing, Investigation. **Frank Niklas:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

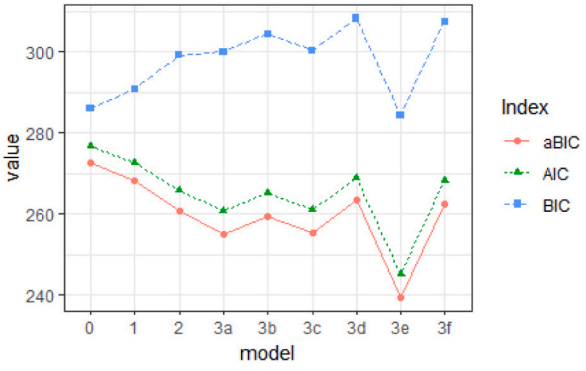
The authors have no competing interests to declare.

Appendix A. Descriptive statistics of literacy subtests at T1 and T2

Variable	Descriptive statistics per group: Control/Intervention				
	n	*M*	*SD*	*Min*	*Max*
EuLe T1	500/151	7.47/7.31	3.20/3.40	0/0	12/12
EuLe T2	495/149	8.74/8.67	2.68/2.86	0/0	12/12
PB T1	497/151	5.24/5.24	2.89/3.05	0/0	13/13
PB T2	491/147	6.03/6.05	2.90/2.99	0/0	12/12
Rhymes T1	499/151	4.04/4.06	2.35/2.40	0/0	8/8
Rhymes T2	495/149	5.03/5.32	2.20/2.18	0/0	8/8
Initial Sounds T1	498/151	3.07/3.00	2.78/2.86	0/0	8/8
Initial Sounds T2	495/149	4.21/4.88	2.82/2.58	0/0	8/8
Passive LK T1	500/151	5.68/5.63	2.79/2.73	0/0	10/10
Passive LK T2	495/149	6.90/7.90	2.72/2.27	0/1	10/9
Active LK T1	497/149	3.77/3.65	3.18/2.93	0/0	10/10
Active LK T2	495/149	5.22/6.37	3.31/3.01	0/0	10/10
PPVT T1	496/150	64.41/65.87	23.82/24.13	0/2	102/98
PPVT T2	494/148	72.19/73.97	22.60/31.01	0/0	103/100

Note. EuLe = "Assessment of narrative and reading competencies of 4- to 5-year-old children" (Meindl & Jungmann, 2019). PA = phonological awareness; subtest of the "Würzburg preschool test" (WVT; Endlich et al., 2017). Rhymes = subtest of the WVT. Initial sounds = subtest of the WVT. Passive LK = passive letter knowledge; subtest of the WVT. Active LK = active letter knowledge; subtest of the WVT. PPVT = "Peabody Picture Vocabulary Test" (Lenhard et al., 2015).

Appendix B. Fit indices (AIC, BIC, sample-size-adjusted BIC) of regression Models 0 to 3f



Appendix C. Results of multiple regression models for intervention group and full sample

	Intervention group/Full sample			
Parameter	Estimate	*SE*	*t*(df)	*p*
Model 0				
Intercept	0.01/0.02	0.05/0.02	0.22 (142.87)/0.63 (483.17)	0.829/0.532
Literacy T1	0.80/0.83	0.05/0.02	16.17 (144.70)/33.95 (484.48)	< 0.001/< 0.001

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	Intervention group/Full sample			
Parameter	Estimate	*SE*	*t*(df)	*p*
Model 1				
Intercept	−0.05/0.01	0.09/0.02	−0.52 (132.30)/0.50 (473.27)	0.606/0.618
Literacy T1	0.78/0.83	0.05/0.02	15.55 (132.92)/35.10 (477.85)	< 0.001/< 0.001
LUT	0.36/0.20	0.15/0.04	2.31 (77.36)/4.55 (308.80)	0.023/< 0.001
LUT^2	−0.31/−0.05	0.15/0.03	−2.05 (68.59)/−1.66 (198.24)	0.044/0.099
OMU	0.05/0.02	0.06/0.02	0.94 (132.15)/0.69 (452.49)	0.348/0.488
Model 2				
Intercept	−0.03/0.05	0.10/0.04	−0.25 (133.02)/1.21 (479.70)	0.802/0.227
Literacy T1	0.66/0.72	0.06/0.03	10.77 (133.69)/25.52 (470.53)	< 0.001/< 0.001
LUT	0.37/0.20	0.15/0.04	2.54 (82.15)/4.81 (316.21)	0.013/< 0.001
LUT^2	−0.28/−0.04	0.14/0.03	−1.94 (74.70)/−1.52 (213.18)	0.056/0.131
Migration background	−0.12/−0.14	0.11/0.05	−1.09 (126.71)/−2.70 (472.67)	0.279/0.007
SES	0.14/0.09	0.06/0.03	2.47 (126.92)/3.24 (465.37)	0.015/0.001
Intelligence	0.10/0.10	0.05/0.03	1.83 (131.43)/3.78 (419.81)	0.069/< 0.001
Gender	0.04/0.04	0.10/0.05	0.38 (132.92)/0.83 (477.27)	0.689/0.405
Age	0.01/0.07	0.06/0.02	0.24 (129.37)/2.89 (472.92)	0.812/0.004
OMU	0.06/0.01	0.06/0.02	1.02 (129.20)/0.30 (450.86)	0.310/0.761
Model 3a				
Intercept	−0.00/0.06	0.10/0.04	−0.01 (129.86)/1.53 (477.86)	0.990/0.125
Literacy T1	0.66/0.72	0.06/0.03	10.83 (131.42)/25.44 (467.61)	< 0.001/< 0.001
LUT	0.35/0.21	0.14/0.04	2.42 (81.15)/5.13 (332.52)	0.018/< 0.001
LUT^2	−0.24/−0.04	0.14/0.03	−1.75 (75.15)/−1.38 (225.67)	0.085/0.170
Migration background	−0.15/−0.15	0.11/0.05	−1.37 (123.81)/−2.91 (470.06)	0.173/0.004
SES	0.12/0.08	0.06/0.03	2.02 (125.80)/2.86 (460.12)	0.046/0.004
Intelligence	0.10/0.10	0.05/0.03	1.90 (130.25)/3.91 (413.29)	0.059/< 0.001
Gender	0.03/0.03	0.09/0.05	0.34 (130.37)/0.68 (475.38)	0.734/0.499
Age	0.01/0.07	0.05/0.02	0.20 (127.28)/2.92 (470.31)	0.843/0.004
OMU	0.05/0.01	0.06/0.02	0.95 (126.19)/0.26 (447.11)	0.346/0.794
Literacy T1:LUT	0.10/−0.20	0.15/0.07	0.68 (111.53)/−2.70 (403.57)	0.498/0.007
Literacy T1:LUT^2	0.02/0.21	0.15/0.07	0.15 (116.70)/2.99 (416.66)	0.884/0.003
Model 3b				
Intercept	−0.01/0.05	0.10/0.04	−0.12 (131.62)/1.38 (477.58)	0.908/0.168
Literacy T1	0.66/0.73	0.06/0.03	10.87 (132.17)/26.14 (467.54)	< 0.001/< 0.001
LUT	0.32/0.20	0.16/0.05	1.93 (84.08)/4.06 (360.97)	0.057/< 0.001
LUT^2	−0.18/−0.04	0.16/0.03	−1.16 (77.27)/−1.25 (229.65)	0.249/0.021
Migration background	−0.12/−0.12	0.11/0.05	−1.08 (124.30)/−2.47 (466.38)	0.284/0.014
SES	0.12/0.07	0.06/0.03	2.08 (124.67)/2.66 (462.17)	0.039/0.008
Intelligence	0.11/0.10	0.05/0.03	1.95 (128.14)/4.01 (417.13)	0.054/< 0.001
Gender	0.02/0.03	0.10/0.05	0.17 (131.25)/0.56 (474.04)	0.863/0.576
Age	0.01/0.07	0.06/0.02	0.23 (126.56)/2.79 (469.23)	0.815/0.005
OMU	0.06/0.01	0.06/0.02	1.05 (128.53)/0.25 (445.19)	0.295/0.805
Migration background:LUT	0.36/0.41	0.29/0.12	1.23 (101.86)/3.35 (373.11)	0.223/< 0.001
Migration background:LUT^2	−0.46/−0.44	0.27/0.11	−1.67 (106.44)/−4.02 (394.72)	0.098/< 0.001
Model 3c				
Intercept	0.03/0.06	0.10/0.04	0.34 (130.58)/1.53 (476.74)	0.734/0.127
Literacy T1	0.65/0.72	0.06/0.03	10.78 (131.65)/25.62 (468.04)	< 0.001/ < 0.001
LUT	0.37/0.22	0.15/0.04	2.51 (83.36)/5.44 (330.17)	0.014/< 0.001
LUT^2	−0.24/−0.05	0.14/0.03	−1.66 (76.04)/−1.58 (219.56)	0.101/0.116
Migration background	−0.12/−0.14	0.11/0.05	−1.10 (124.91)/−2.69 (469.91)	0.273/0.007
SES	0.10/0.07	0.06/0.03	1.71 (125.37)/2.74 (459.04)	0.091/0.006
Intelligence	0.11/0.10	0.05/0.03	2.06 (130.57)/3.90 (421.08)	0.041/< 0.001
Gender	0.01/0.03	0.10/0.05	0.10 (130.88)/0.58 (475.55)	0.921/0.560
Age	0.02/0.07	0.05/0.02	0.27 (127.18)/2.85 (470.75)	0.789/0.005
OMU	0.04/0.00	0.06/0.02	0.68 (127.59)/0.14 (449.50)	0.495/0.892
SES:LUT	−0.12/−0.12	0.18/0.07	−0.64 (111.74)/−1.57 (401.30)	0.521/0.117
SES:LUT^2	0.20/0.15	0.16/0.06	1.27 (113.99)/2.34 (411.79)	0.208/0.020
Model 3d				
Intercept	−0.02/0.05	0.10/0.04	−0.20 (131.40)/1.30 (478.35)	0.838/0.194
Literacy T1	0.66/0.72	0.06/0.03	10.66 (131.89)/25.40 (568.43)	< 0.001/ < 0.001
LUT	0.36/0.20	0.15/0.04	2.44 (82.08)/4.85 (320.92)	0.017/ < 0.001
LUT^2	−0.27/−0.04	0.14/0.03	−1.87 (74.27)/−1.43 (216.60)	0.066/0.153
Migration background	−0.13/−0.14	0.12/0.05	−1.11 (124.85)/−2.72 (470.84)	0.271/0.007
SES	0.15/0.09	0.06/0.03	2.48 (125.19)/3.15 (462.80)	0.015/0.002
Intelligence	0.10/0.10	0.06/0.03	1.67 (129.24)/3.91 (408.64)	0.098/< 0.001
Gender	0.04/0.03	0.10/0.05	0.39 (131.16)/0.71 (476.60)	0.696/0.477

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	Intervention group/Full sample			
Parameter	Estimate	*SE*	*t*(df)	*p*
Age	0.01/0.07	0.06/0.02	0.26 (127.48)/2.89 (470.65)	0.797/0.004
OMU	0.06/0.01	0.06/0.02	0.96 (127.58)/0.30 (451.06)	0.339/0.763
Intelligence:LUT	0.11/−0.07	0.18/0.06	0.63 (119.53)/−1.14 (406.08)	0.527/0.257
Intelligence:LUT^2	−0.09/0.07	0.18/0.07	−0.47 (120.83)/1.09 (428.83)	0.636/0.276
Model 3e*				
Intercept	−0.06/0.04	0.09/0.04	−0.66 (129.51)/1.05 (476.32)	0.511/0.292
Literacy T1	0.70/0.73	0.06/0.03	12.00 (128.27)/25.96 (465.48)	< 0.001/< 0.001
LUT	0.00/0.15	0.17/0.05	0.01 (86.78)/3.10 (339.92)	0.993/0.002
LUT^2	0.00/−0.03	0.15/0.03	0.01 (80.76)/−1.02 (218.12)	0.994/0.309
Migration background	−0.07/−0.12	0.11/0.05	−0.62 (122.22)/−2.36 (467.11)	0.540/0.019
SES	0.15/0.08	0.05/0.03	2.80 (125.18)/3.06 (460.44)	0.005/0.002
Intelligence	0.10/0.11	0.05/0.03	2.03 (127.99)/4.13 (414.67)	0.045/< 0.001
Gender	−0.04/0.02	0.09/0.05	−0.42 (129.37)/0.44 (472.67)	0.673/0.659
Age	0.02/0.07	0.05/0.02	0.37 (125.75)/2.90 (470.27)	0.714/0.004
OMU	0.07/0.01	0.05/0.02	1.25 (126.48)/0.29 (449.78)	0.213/0.772
Gender:LUT	1.20/0.42	0.28/0.11	4.26 (103.12)/3.78 (402.81)	< 0.001/< 0.001
Gender:LUT^2	−1.12/−0.44	0.29/0.12	−3.79 (110.30)/−3.60 (417.19)	< 0.001/< 0.001
Model 3f				
Intercept	−0.04/0.05	0.10/0.04	−0.43 (130.77)/1.17 (477.58)	0.671/0.241
Literacy T1	0.66/0.72	0.06/0.03	10.75 (131.76)/25.50 (468.81)	< 0.001/< 0.001
LUT	0.39/0.20	0.15/0.04	2.61 (81.75)/4.81 (315.40)	0.011/ < 0.001
LUT^2	−0.28/−0.04	0.14/0.03	−1.96 (74.00)/−1.51 (212.80)	0.054/0.133
Migration background	−0.11/−0.14	0.11/0.05	−1.00 (123.94)/−2.69 (470.67)	0.321/0.007
SES	0.15/0.09	0.06/0.03	2.56 (125.53)/3.21 (463.08)	0.012/0.001
Intelligence	0.10/0.10	0.05/0.03	1.76 (129.75)/3.84 (415.55)	0.081/< 0.001
Gender	0.04/0.04	0.10/0.05	0.40 (131.15)/0.88 (475.40)	0.686/0.377
Age	0.01/0.07	0.06/0.02	0.13 (125.88)/2.89 (470.85)	0.899/0.004
OMU	0.06/0.01	0.06/0.02	1.10 (127.50)/0.30 (448.18)	0.273/0.762
Age:LUT	0.18/−0.01	0.18/0.07	1.02 (111.86)/−0.14 (438.83)	0.311/0.892
Age:LUT^2	−0.15/−0.01	0.16/0.07	−0.94 (116.79)/0.18 (446.45)	0.349/0.854
Model 4				
Intercept	−0.03/0.05	0.10/0.04	−0.30 (118.33)/1.35 (466.67)	0.764/0.179
Literacy T1	0.69/0.73	0.06/0.03	11.79 (118.67)/25.92 (454.30)	< 0.001/< 0.001
LUT	0.01/0.16	0.19/0.06	0.06 (77.72)/2.73 (372.69)	0.951/0.007
LUT^2	0.00/−0.03	0.16/0.03	0.01 (72.31)/−0.85 (233.57)	0.991/0.399
Migration background	−0.05/−0.12	0.11/0.05	−0.49 (110.09)/−2.29 (454.58)	0.628/0.022
SES	0.12/0.07	0.06/0.03	2.05 (113.10)/2.45 (446.83)	0.043/0.014
Intelligence	0.08/0.10	0.06/0.03	1.34 (114.57)/3.88 (395.62)	0.183/< 0.001
Gender	−0.06/0.01	0.10/0.05	−0.59 (118.81)/0.28 (464.58)	0.560/0.776
Age	0.03/0.07	0.05/0.02	0.55 (109.35)/3.01 (458.77)	0.586/0.003
OMU	0.05/0.00	0.06/0.02	0.97 (117.32)/0.18 (438.35)	0.335/0.859
Literacy T1:LUT	0.00/−0.20	0.22/0.10	0.02 (107.45)/−1.87 (421.87)	0.984/0.062
Literacy T1:LUT^2	0.11/0.20	0.23/0.11	0.46 (109.73)/1.89 (426.21)	0.647/0.060
Migration background:LUT	−0.00/0.17	0.34/0.15	−0.02 (95.68)/1.14 (383.29)	0.982/0.260
Migration background:LUT^2	0.12/−0.13	0.33/0.15	0.36 (101.19)/−0.92 (398.88)	0.722/0.360
SES:LUT	−0.15/−0.05	0.20/0.09	−0.76 (107.74)/−0.62 (405.17)	0.448/0.538
SES:LUT^2	0.24/0.09	0.19/0.09	1.27 (109.09)/1.02 (410.36)	0.208/0.310
Intelligence:LUT	0.16/0.08	0.20/0.08	0.81 (109.58)/1.08 (404.15)	0.418/0.280
Intelligence:LUT^2	−0.30/−0.13	0.22/0.09	−1.34 (111.07)/−1.47 (424.42)	0.183/0.141
Gender:LUT	1.21/0.40	0.32/0.13	3.77 (97.89)/3.03 (396.55)	< 0.001/0.003
Gender:LUT^2	−1.23/−0.44	0.36/0.15	−3.44 (102.10)/−2.90 (412.54)	< 0.001/0.004
Age:LUT	0.01/−0.02	0.20/0.08	0.05 (97.79)/−0.29 (442.34)	0.960/0.769
Age:LUT^2	0.04/0.03	0.18/0.08	0.20 (102.41)/0.33 (446.89)	0.839/0.738

Note. Literacy = sum score of all z-standardised literacy assessments. LUT = literacy usage times in minutes. SES = socio-economic status. Migration background: 0 = no migration background, 1 = migration background. Gender: 0 = boys, 1 = girls. Age in months. OMU = overall media usage.

* Model 3e for the intervention group is also reported in Section 6.3 (Table 6).

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2024.102579.

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