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Mobile learning in the classroom – Should students bring mobile devices for learning, or should these be provided by schools?

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Abstract
In recent years, the importance of mobile devices has increased for education in general and more specifically for science and mathematics education. In the classroom, approaches for teaching with mobile devices include using student-owned devices ("bring your own device"; BYOD approach) or using school-owned devices from central pools (POOL approach). While many studies point out features of mobile learning and BYOD that are conducive to learning, a research gap can be identified in the analysis of effects of mobile device access concepts on teaching–learning processes. Thus, this study aimed to empirically compare BYOD and POOL approaches in terms of learning performance and cognitive performance (subject knowledge development, cognitive load, concentration performance). Furthermore, the analyses included specific characteristics and preconditions (gender, socioeconomic status, fear of missing out, problematic smartphone use). A quasi-experimental study (two groups) was conducted in year 8 and 9 physics classes ($N=339$ students) in which smartphones are used for different purposes. The present data show no group differences between the BYOD and the POOL approach in the group of learners with respect to subject knowledge development, cognitive load, and concentration performance. However, individual findings in subsamples indicate that the POOL approach may be beneficial for certain learners (e.g., learners with low fear of missing out or learners tending toward problematic smartphone use). For school practice, these results indicate that organizational, economic, and ecological aspects appear to be the main factors in deciding about the mobile device access concept.

Keywords Mobile learning · Bring your own device · BYOD · POOL · Smartphones · Physics education

1 Introduction

Today, digital technologies influence almost every area of life, and their impact continues to grow. In the field of education, digital classroom technologies offer enormous opportunities (e.g., teaching of complex knowledge structures or allowing for the consideration of learners regarding race, ethnicity, or language; Neumann & Waight, 2020), but at the same time they introduce numerous challenges (e.g., training of digital competencies: Pettersson, 2017; artificial intelligence in education: Chen et al., 2020).

Over the past 20 years, mobile devices, first notebooks and then smartphones and tablet computers, have gained particular importance. Mobile learning has become critical due to the wide range of subject-specific digital applications (e.g., language education: Kacetl & Klímová, 2019; mathematics education: Bano et al., 2018; science education: Staacks et al., 2018). In addition, mobile learning has the potential to foster seamless learning, where learning can be imbedded in everyday routines (e.g., Kali et al., 2018; Song, 2018). Furthermore, mobile learning provides access to educational content for learners from underprivileged racial, ethnic, gender, or language groups (Bere & Rambe, 2019; Song et al., 2021). However, the use of mobile devices also always carries the risk that they are not used for learning-related purposes as intended, but are used off-task (Masood et al., 2020; Upshaw et al., 2022; Zhao, 2023), which distracts learners from the actual learning objective. Anshari et al. (2017, p. 30363) thus raise the question of whether smartphones act as a "learning aid or interference" in the classroom.

The occurrence of off-task smartphone use does not appear to be the same for all learners but depends on certain characteristics. For example, studies show that both gender and socioeconomic status influence the occurrence of off-task smartphone use (Ariel & Elishar-Malka, 2019; Zhou et al., 2022). There are also other individual characteristics that can also influence the extent of off-task smartphone use, such as Students' fear of missing out, which is "defined as a pervasive apprehension that others might be having rewarding experiences from which one is absent" (Przybylski et al., 2013, p. 1841) or different forms of problematic smartphone use, so that smartphones are used, for example, in situations in which their use appears inappropriate or their use is clearly excessive (Allahverdi, 2022; Elhai et al., 2021).

This immediately raises the question of how digital devices can be made available for learning, since they could either be provided by the learners, according to the "bring your own device" approach (BYOD) or made available from a pool of devices belonging to the school (POOL). In the literature, these two mobile device access concepts represent opposite ends of a spectrum that also includes mixed approaches, e.g., when schools purchase the devices, but learners use them individually (e.g., Morris et al., 2016; Keane & Keane, 2022; Krause et al. , 2024). From a learning perspective, very different advantages and disadvantages can be derived for both approaches. While learners are very familiar with their personal devices in the BYOD approach, these reveal potential for cognitive distractions (Al-Said, 2023; Mavhunga, 2016) using social media, for example, and consequently risks for academic performance (Sunday et al., 2021; Zhao, 2023). With the POOL approach, access to social media etc. can be significantly more restricted, but the limited availability of personal digital devices may, for example, increase students' fear of missing out (Przybylski et al., 2013), which in turn can have a negative impact on learning (Rozgonjuk et al., 2019). Yet, only a single study (Krause et al., 2024) has performed a comparative investigation regarding how these different approaches of smartphone access in schools influence learning.

2 Literature review

2.1 Mobile learning in education

Mobile learning "intersects mobile computing with e-learning; it combines individualized (or personal) learning with anytime and anywhere learning" (Motiwalla, 2007, p. 582). Recent meta-studies (Sung et al., 2016) and review articles (Bano et al., 2018; Crompton et al., 2016; Zydney & Warner, 2016) have revealed a heterogeneous picture regarding the effectiveness of mobile learning. While in some studies the use of mobile devices positively influenced learning achievement (Hwang et al., 2011; Ravizza et al., 2014) and working memory performance (Liebherr et al., 2020) compared to traditional forms of learning, other studies did not identify such differences (Aharony & Zion, 2019; Hochberg et al., 2020; López-Moranchel et al., 2021) or even demonstrated negative effects (Limniou, 2021).

2.2 Off-task smartphone use in class

As soon as smartphones are available in the classroom, they are also used for non-learning purposes (Chen et al., 2016; Kay et al., 2017; Kim et al., 2019; Ma et al., 2020). Off-task smartphone use, also referred to as smartphone multitasking (Ochs et al., 2024), includes social media, surfing the internet, instant messaging, or digital games (Kay et al., 2017). Studies show that learners use smartphones for non-learning purposes up to 25% of the time and disruptions can be observed every three to four minutes (Kim et al., 2019). Ma et al. (2020) were able to show that when using smartphones as clickers, over 40 percent of learners started non-learning-related activities immediately after the session began and sometimes (repeatedly) continued these for more than five minutes. The types of distraction caused by smartphones can be diverse and include internal aspects, such as cognitive disengagement or negative emotions, as well as external aspects, such as multitasking with peers or notifications on devices (Deng et al., 2024).

As explained below, studies show significant negative consequences for learning performance, see Sect. 2.2.1, and cognitive performance, see Sect. 2.2.2, as a result of off-task smartphone activities. Study results also indicate long-term negative influences of off-task smartphone use on academic performance overall in addition to these rather short-term consequences (Amez & Baert, 2020; Kates et al., 2018; Sunday et al., 2021; Troll et al., 2021; Zhao, 2023).

Based on a study by Ward et al. (2017), numerous studies according to a meta-analysis by Böttger et al. (2023) showed that even the mere presence of a personal smartphone can have a negative impact on learning.

However, it should be noted that there are also studies that show that distractions caused by smartphones or similar devices do not have a negative impact on learning. For example, a study by Dekker et al. (2024) shows that push notifications do not change the extent of smartphone use or distractions in the learning process. Similarly, Graben et al. (2022) find evidence that smartphone games (with and without push notifications) do not lead to poorer learning performance.

The findings are therefore not entirely clear, but at least indicate a potential risk from off-task smartphone use.

2.2.1 Off-task smartphone use and cognitive performance

The distraction of learners through off-task smartphone use leads to negative consequences for cognitive performance (Masood et al., 2020; Upshaw et al., 2022; Zhao, 2023). According to studies by Masood et al. (2020) and Zhao (2023), this applies to the increase in cognitive distraction due to social media (multitasking) during class. Upshaw et al. (2022) showed that off-task smartphone activities generally have a negative impact on learners' cognitive control and attention. Overall, this appears critical for learning processes against the background of cognitive load theory (Sweller et al., 1998), as the cognitive load of learners is directly influenced by their cognitive distraction or control (Lavie, 2010).

2.2.2 Off-task smartphone use and learning performance

Former research shows that off-task smartphone use leads to poorer learning performance (Dietz & Henrich, 2014; Gingerich & Lineweaver, 2013; Waite et al., 2018; Wood et al., 2012). Gingerich and Lineweaver (2013) as well as Dietz and Henrich (2014) revealed that learners who wrote text messages in class achieved significantly lower performance on learning quizzes. The use of instant messaging as well as further off-task activities also appears to have a negative effect on the quality of learning-related notes (Waite et al., 2018; Wood et al., 2012) as well as learning tests. As already explained, these short-term negative consequences can also pose a long-term risk to learners' academic performance (Amez & Baert, 2020; Kates et al., 2018; Sunday et al., 2021; Troll et al., 2021; Zhao, 2023).

In addition to these remarks, a heuristic summarizing the literature can be found in Fig. 1. The overall potential negative cause-and-effect relationship between non-learning-related smartphone use, cognitive distractions, and academic performance, see Fig. 1, can be described as follows: “Smartphone multitasking, which in turn is positively related to cognitive distractions and ultimately leads to a decline in academic performance” (Zhao, 2023, p. 3151).

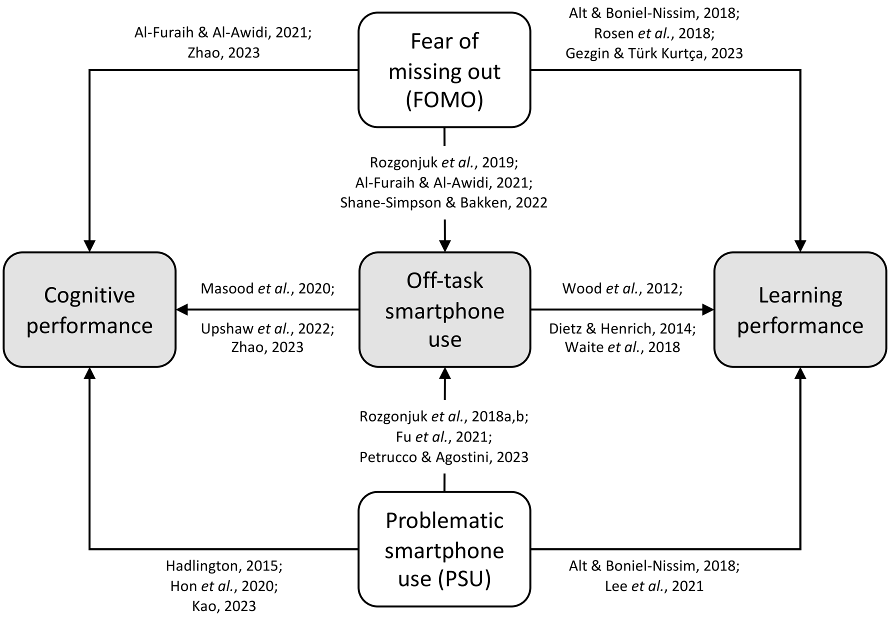

Fig. 1 Literature-based research heuristic for off-task smartphone use, cognitive performance and learning performance against the background of students' fear of missing out and problematic smartphone use

However, as can also be seen from the current literature and considered in Fig. 1, general and especially technology-related characteristics of the learners (moderator variables) also influence the relationships mentioned.

2.3 Characteristics of learners and effects on off-task smartphone use in class

Many studies analyzing mobile learning with smartphones consider potential influences from gender and socioeconomic status (SES).

According to Ariel and Elishar-Malka (2019), differences in smartphone distractions can be attributed, among other things, to the fact that learners have different information and communication technology literacy depending on their gender. As shown by Chen et al. (2017) and Kay et al. (2017) typical off-task activities are attributed more to social media in girls and more to playing games in boys. Furthermore, Zhou et al. (2022) showed that problematic smartphone use, see Sect. 2.3.2., is more likely to be observed in boys than in girls. However, other studies, for example van Deursen et al. (2015), revealed the opposite and described girls to show more problematic smartphone usage behavior.

The differences described by Ariel and Elishar-Malka (2019) as a cause are also related to the learners' SES. For SES, it also applies that students with low SES tend to show more critical aspects of smartphone use (Tao et al., 2017; Zhou et al., 2022) such as, for example, smartphone addiction (Aljomaa et al., 2016). Kliesener et al.

(2022) also confirmed these findings, but showed no correlation between SES and problematic smartphone use.

2.3.1 Fear of missing out

Students' fear of missing out (FOMO) has been shown to indirectly influence teaching–learning processes through many "daily disruptive activities due to interruptive notifications" (Rozgonjuk et al., 2019, p. 103,590). This includes various distractions such as smartphone multitasking (Rosen et al., 2018) and learning disengagement (Al-Furaih & Al-Awidi, 2021) in general, but also social media (Shane-Simpson & Bakken, 2022; Zhao, 2023).

This off-task smartphones use in turn lead to lower cognitive performance depending on FOMO, as Al-Furaih and Al-Awidi (2021) as well as Zhao (2023) were able to show. There are also deteriorations in learning performance due to FOMO, which are shown in the literature by the fact that learners with FOMO tend to surface rather than deep learning (Alt & Boniel-Nissim, 2018; Gezgin & Türk Kurtça, 2023) and achieve poorer exam results (Rosen et al., 2018).

2.3.2 Problematic smartphone use

Furthermore, several empirical studies have found that mobile learning is influenced by problematic, addictive forms of media technology use, such as problematic social media use and problematic smartphone use (PSU; Allahverdi, 2022; Elhai et al., 2021). In the classroom, these can lead to general distractions (Lee et al., 2021; Petrucco & Agostini, 2023) but also more specifically to procrastinating behavior (Rozgonjuk et al., 2018a). These distractions can be traced back to off-task social media use (Rozgonjuk et al., 2018b) or simultaneous smartphone use and multitasking (Fu et al., 2021). With regard to cognitive performance, the results of Kao (2023) indicate that PSU reduces learners' attention. In addition, Hadlington (2015) and Hong et al. (2020) show that cognitive failures in daily life are increasingly observed in connection with PSU. PSU also appears to have a negative impact on learning performance in the form of deep learning (Alt & Boniel-Nissim, 2018) and exams (Lee et al., 2021). Furthermore, Soomro et al. (2019) show that PSU can have a negative impact on learners' classroom connectedness and that they participate to a lesser extent in communication within the class or individual learning groups, for example.

The study situation thus indicates that both gender and SES as person-related variables and FOMO and PSU as technology-related variables should be included in analyses of non-learning-related smartphone use and resulting cognitive distractions.

2.4 Mobile device access concepts

The presentation of the potential for using smartphones in mobile learning, but also the possible associated risks and negative influencing factors open up the following questions for practice: How should smartphones be accessed by students?

Here, a very rough distinction can be made as to whether mobile devices are student-owned or school-owned (Keane & Keane, 2022; Lai et al., 2013; Morris et al., 2016), whereas also more differentiated approaches can be found in the literature (Krause et al., 2024; Little, 2014; Tairov, 2021). These other approaches include the "get your own device" (GYOD) approach, which is closely related to BYOD, in which students acquire personal devices according to clear specifications from the school, which are thus owned by the students, personalized and can also be used beyond school applications in their free time. The "choose your own device" (CYOD) approach is similar, in which the school does not specify a single possible device, but rather a reduced selection of possible devices (Tairov, 2021). From the school's perspective, however, the specifications mean that there is a lower risk of technical difficulties due to a significantly reduced heterogeneity of devices. The fourth approach between GYOD and POOL is the "corporate owned, personally enabled" (COPE) approach (Little, 2014). This approach, which originates from the business world, provides for devices to be provided by the school but made available to the students for a longer period of time so that they can also personalize them (Tairov, 2021). However, the devices do not become the property of the students.

There are numerous reasons why the use of student-owned devices appears to be attractive for both schools and learners: In most learning environments worldwide, students' mobile devices, often smartphones, are available in class anyway (Pew Research Center, 2019). This means that schools do not have to invest in the purchase of devices or assign staff to maintain them. In addition, personal devices are familiar to the students. However, a detailed analysis of the current literature also reveals challenges for the use of student-owned smartphones. These can be mostly traced back to the off-task smartphone use in class and corresponding distractions.

To investigate how different mobile device access concepts can lead to different learning and academic performance against the background of the literature and research heuristics presented, concrete mobile device access concepts must be considered.

The classic form of using mobile devices corresponds to the way desktop computers were used in the decades before tablet computers and smartphones were introduced: "the institutions traditionally procure, provide and control the technology" (Traxler, 2010, p. 149). This approach is referred to below as POOL because of the device pools provided by schools. Particularly during the 2010s, schools invested significantly to provide mobile devices to a notable number of learners (Brown & Green, 2017). Studies on the POOL approach reveal a heterogeneous picture regarding student assessment. On the one hand, findings indicate that many learners only appreciate the value of a school-provided device when their personal device is not available (Traxler & Riordan, 2004). On the other hand, a study on the use of iPads provided by the school showed that many students rate them as useful for education (Ditzler et al., 2016).

If the heuristics on which the article is based are considered, it can be assumed that POOL basically enables only a few off-task activities by learners when using smartphones and that only a few distractions should result. However, the potential for FOMO appears to be increased if the learner's own smartphone is not available (Kneidinger-Müller, 2019), which in turn could have a negative impact on learning.

A very comprehensively described aspect in the way mobile devices are used is the so-called "bring your own device" (BYOD) approach. BYOD describes "technology models where students bring a personally owned device to school for the purpose of learning" (Alberta Education, 2012, p. 3). The BYOD approach assumes and requires that learners have mobile devices. While this availability could not be widely assumed 10 years ago (Burnett et al., 2017), it currently appears to be a given in many countries worldwide (Pew Research Center, 2019).

For the BYOD approach, many studies have explored conditions for use and implementation (Kay et al., 2017; Mavhunga, 2016; Song, 2014, 2016). In addition, studies have included the perspectives of school authorities and representatives (Alberta Education, 2012). Regarding cognitive effects within teaching–learning processes, literature on the BYOD approach offers data on positive effects of mobile device use on learning achievement (Rinehart, 2012; Zhai et al., 2016; Al-Said, 2023). Such effects are also evident against the background of studies in the field of science education, where positive effects have been found on the acquisition of specialized knowledge (Song, 2014; Hootman & Pickett, 2021) and the teaching of scientific inquiry (Song, 2014, 2016). Learner engagement also seems to be positively influenced by BYOD (Sarhandi et al., 2017; Hootman & Pickett, 2021). Negative effects of the BYOD approach are also reported in the literature and refer to possible distractions during individual or group work due to disruptions from emails or social media (Kay et al., 2017; Sarhandi et al., 2017; Welsh et al., 2018). These disruptions are also perceived and reported by learners themselves (Al-Said, 2023; Mavhunga, 2016). These distractions appear to be a central element of the research heuristics mentioned above and represent a risk for students cognitive and learning performance.

Yet, the comparative studies done in this context tend to compare the mobile device BYOD approach with traditional teaching/learning formats that do not use mobile devices or that take place within the BYOD approach. In principle, both approaches appear comparable, as they represent two typical mobile device access concepts in connection with mobile learning and can be classified in a comparable form in the context shown in Fig. 1. Thus, only a single study has yet examined the BYOD approach when it is compared to the POOL approach, where learners use devices that are purchased and managed by schools for individual lessons against the background of the given relation between off-task smartphone use, cognitive performance, and learning performance (Krause et al., 2024). Krause et al. (2024) show that there are almost no differences in learning behavior between BYOD and POOL. Only learners with a higher PSU benefit from BYOD. However, the study only analyzes differences in mathematical modeling competence in mathematics. It therefore seems relevant to examine the generalizability of the findings to other subjects and to include other variables of cognitive performance.

2.5 Summary and research questions

The integration of mobile learning in education has great potential for learning, but also appears to be associated with challenges. Negative effects on learning arise from off-task use of smartphones deteriorating learning performance (Dietz & Henrich, 2014; Waite et al., 2018; Wood et al., 2012) and cognitive performance (Masood et al., 2020; Upshaw et al., 2022; Zhao, 2023). If one considers the influence of different mobile device access concepts, such as the use of student-owned smartphones (BYOD) versus school-owned smartphones (POOL), both approaches open up significantly different potential for off-task smartphone use. To date, however, a research gap existing for comparison of these two mobile device access concepts with respect to both learning performance (subject knowledge development) and cognitive performance (cognitive load, concentration performance), so the following research question follows:

> RQ1. How does students' use of their personal mobile devices (BYOD) compared to school-owned devices (POOL) influence (a) development of subject knowledge, (b) cognitive load and (c) concentration performance of students in general?

On the one hand, it can be assumed that access to social media, instant messaging or digital games is significantly restricted with POOL compared to BYOD. This would result in fewer occasions for off-task smartphone use, fewer distractions and therefore positive influences on learning performance and cognitive performance. The associated variables analyzed in this study are (a) development of subject knowledge (learning performance) as well as (b) cognitive load and (c) concentration performance (cognitive performance), hereafter referred to as learning-related variables. The risk of significant distractions with BYOD can also be found in previous studies (Kay et al., 2017; Welsh et al., 2018). On the other hand, FOMO (Przybylski et al., 2013) in particular is potentially hindering for POOL learners, as they do not have access to their own smartphone, and this can result in negative mental states that are less pronounced with BYOD. The results of Krause et al. (2024) also indicate that no difference is to be expected between BYOD and POOL. If we also consider that no comparisons between BYOD and POOL have been made to date, the following hypothesis for RQ1 emerges:

> HYP1. BYOD and POOL approach do not differ with respect to (a) development of subject knowledge, (b) cognitive load and (c) concentration performance in general.

When considering the influence of different personal variables such as gender, SES or even FOMO and PSU, it seems sensible to include these separately in analyses, as they can influence off-task use of smartphones differently. It also seems important to derive appropriate indications of practical implications regarding specific groups. This leads to the research question:

> RQ2. How does students' use of their personal mobile devices (BYOD) compared to school-owned devices (POOL) influence (a) development of subject knowledge, (b) cognitive load and (c) concentration performance of students with different characteristics and prerequisites (gender, socioeconomic status (SES), fear of missing out (FOMO), problematic smartphone use (PSU))?

As Tao et al. (2017) and Zhou et al. (2022) were able to show, the risk of critical influences through distractions appears to be particularly relevant for learners with lower SES. It can therefore be assumed that the POOL approach, which generally enables fewer distractions, has advantages for these learners:

HYP2.1. Learners with lower socioeconomic status (SES) benefit from POOL approach with respect to learning-related variables (development of subject knowledge, cognitive load, concentration performance).

For high FOMO learners, it can be assumed that additional distractions arise for them due to the lack of availability of personal smartphones, as indicated by Kneidinger-Müller (2019). Advantages of the BYOD approach can be assumed here:

HYP2.2. Learners with higher fear of missing out (FOMO) benefit from BYOD approach with respect to learning-related variables (development of subject knowledge, cognitive load, concentration performance).

Conversely, it seems obvious that for learners with low FOMO there are fewer problems for POOL, but the fundamental problems for BYOD due to distractions:

HYP2.3. Learners with lower fear of missing out (FOMO) benefit from POOL approach with respect to learning-related variables (development of subject knowledge, cognitive load, concentration performance).

Looking at learners with higher PSU, the results of Kao (2023), but also Rozgonjuk et al. (2018a), indicate that the presence of a personal smartphone is a particular hindrance for these learners. This result is also indicated by the study by Krause et al. (2024) by comparing BYOD and POOL for mathematical modeling competence:

HYP2.4. Learners with higher problematic smartphone use (PSU) benefit from POOL approach with respect to learning-related variables (development of subject knowledge, cognitive load, concentration performance).

For learners without known problems due to addiction-like smartphone use in the sense of PSU, no differences are to be expected:

HYP2.5. Learners with lower problematic smartphone use (PSU) do not differ with respect to learning-related variables (development of subject knowledge, cognitive load, concentration performance).

3 Methods

The study used an experimental comparison group design with the two treatment conditions BYOD (mobile devices owned by students) and POOL (mobile devices owned by schools). Figure 2 provides an overview of the study design

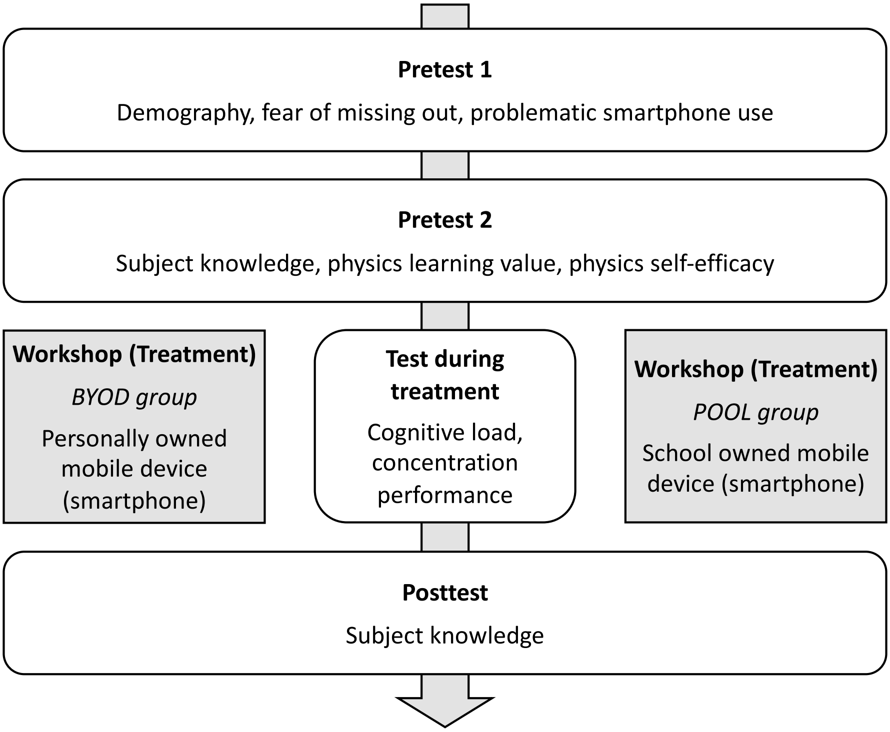

Fig. 2 Flowchart of experimental comparison group design of student-owned smartphones (BYOD) and school-owned smartphones (POOL)

and the procedure of testing and treatment. For both groups, a few weeks to days before the treatment, a questionnaire survey (pretest 1) was used to collect data for independent variables that can be considered stable over time, for example, gender and SES, see Sect. 3.3.4. The treatment comprised a four-hour workshop in physics that was completed by individual classes in school and carried out by research team members.

The decision to conduct a workshop in the subject of physics can be justified in various ways. First, there are already findings for mathematics (Krause et al., 2024), so the analysis for a different but structurally comparable school subject seems reasonable to identify fundamental trends in the comparison of BYOD and POOL. Furthermore, physics is characterized by the fact that mobile digital devices are used in a variety of ways that differ significantly from conventional use for research or communication. Applications include the collection of real data in physical experiments (Staacks et al., 2018) or interactive simulations and modeling (Wieman et al., 2008), so that learning-related applications differ significantly from private use. Finally, and closely related to this, is the argument that mobile digital devices are used very frequently in the natural sciences, especially in physics, making empirical findings particularly relevant.

During the workshop, mobile devices were continuously available for learning-related task use. For the sake of comparability, all learners worked with smartphones as mobile devices. Participating classes were each divided into two rooms. In one room learners worked with student-owned smartphones (BYOD group). In the other room learners worked with smartphones distributed by the research group (POOL group). Both groups completed another questionnaire survey (pretest 2) on further independent variables, see Sect. 3.3.4., at the beginning of the workshop. Furthermore, pretest 2 included a pretest on subject knowledge to later measure subject knowledge development as a dependent variable, see Sect. 3.3.1. During the treatment, both groups completed standardized tests (test during treatment) on cognitive load, see Sect. 3.3.2., and concentration performance, see Sect. 3.3.3., as further dependent variables providing information about students' cognitive processes. Both groups ended the workshop with a posttest on subject knowledge. In addition, videographic data of the work of individual student groups in the workshop were collected on a voluntary basis.

For the given research questions, it seems particularly relevant to highlight the extent to which BYOD and POOL differ regarding the potential for off-task use. For this purpose, different activities with reference to Kay et al. (2017) and the potential in both approaches were summarized in Table 1. Significantly more potentially distracting activities are conceivable for BYOD, which can also be used more easily by learners.

3.1 Workshop

The workshop was conducted in physics and covered middle school topics on the disciplinary core idea of energy (NGSS Lead States, 2014) based on the following driving question: How can energy for electromobility be sustainably provided by solar power? In the workshop, the learners worked in small groups (two to three students), guided by a workbook, and explored experimental tasks to answer the driving question. Learners investigated the absorption of sunlight by clouds, diffuse scattering of sunlight or the angle-dependent irradiation of sunlight and related effects on solar cells. During the workshops, smartphones were used for different purposes. First, experimental parameters and physical data (electrical power, light intensity, angle of irradiation) were determined using specifically constructed experimental material (Pusch et al., 2021) and smartphones with the app *phyphox* (Staacks et al.,

Table 1 Indication of the availability of different off-task smartphone activities (see Kay et al., 2017) for the BYOD and POOL approach

Off-task smartphone activity	BYOD	POOL
Surfing the web	Yes	Yes
Email	Yes	No*
Social media (e.g., Instagram, Facebook)	Yes	No*
Instant messaging (e.g. WhatsApp, iMessage)	Yes	No
Mobile games (e.g., Candy Crush, Pokémon Go)	Yes	No

*No apps accessible; alternative access via browser possible

2018). Second, smartphones were used to view instructional videos on how to perform the experiments. Third, smartphones were used to complete general research tasks on supplementary questions. Last, smartphones were used to collect students' results via the virtual pinboard *padlet* (Wallwisher, 2022). In this way, the continuous use of the smartphones for subject-related and general activities was ensured. More information are presented in Table A.1 and Figure A.1. in the appendix.

3.2 Sample

The study was conducted at secondary schools in Germany in the state of North Rhine-Westphalia in grades 8 and 9. A total of $N_C = 18$ classes (from $N_S = 9$ schools) and $N = 339$ students participated in the study. The pupils were on average around 14 years old ($M = 13.99$ years, $SD = 0.71$ years). The majority of pupils came from a household where German was spoken in the family ($N = 304$), while only $N = 35$ pupils came from families where German was not spoken in the household. All schools were from a type that prepares pupils for higher education and advanced academic studies. Students were randomly assigned to a treatment condition (BYOD approach or POOL approach). Further information describing the sample can be found in Table 2. Due to dropouts during data collection, slight differences emerged in the size of both treatment groups.

Preliminary power analyses confirmed that the sample was sufficiently large to statistically identify at least small effects between both approaches (type I error rate 5%, type II error rate 80%; partial $\eta^2 > 0.02$, Cohen's $d > 0.20$).

3.3 Data collection

All variables were collected in the form of written paper–pencil questionnaires.

3.3.1 Subject knowledge development

The survey of learning performance was determined by differences in learning growth over the workshop between the treatment groups and was conducted

Table 2 Sample description of the study and description of the study groups indicating age as well as gender

Approach	Gender		Age	
		N_S	M	SD
BYOD	Total	177	13.97	0.65
	Female	92	13.88	0.68
	Male	82	14.05	0.61
	Other	3	14.67	0.58
POOL	Total	162	14.01	0.77
	Female	88	13.92	0.61
	Male	73	14.12	0.93
	Other	1	14.00	-

with a self-developed test instrument on students' subject knowledge. The use of a self-developed test seemed necessary to adapt the measurement of subject knowledge development to the specific content of the workshop.

The test consisted of 15 items (12 multiple choice items, three open-ended items). While the complete set of items was used in the posttest, a subset of seven items was chosen for the pretest, as the remaining items were so content specific that learners could not be expected to answer them (such as drawing specific graphs for measurements done during the workshop). The items required learners to reproduce as well as apply the workshop content. The items were checked in a pilot study regarding their fit to the content of the workshop by experts from the field of physics education research and were adapted where necessary. Due to the breadth of the workshop content, the main goal of the pretest was to assess the fit of the items to the workshop content rather than to determine psychometric properties. Determining the internal consistency would not have been meaningful because the pretest covered numerous items with different content, so consistent response behavior could not be expected by the students before the workshop. The sets of items for the pretest and the posttest were created based on the content covered in the workshop rather than the internal structure of the test. Therefore, it is not guaranteed that they will demonstrate high values of Cronbach's alpha, as noted by Taber (2018) as well as Stadler et al. (2021). However, since the content is combined into a consistent construct in the workshop, determining reliability for the posttest seems reasonable. The reliability estimate of the posttest was Cronbach's $\alpha = 0.75$. Thus, acceptable reliability could be assumed in determining subject knowledge development (Cortina, 1993).

A standardized coding manual was created to evaluate the open-ended tasks to ensure objectivity of the assessment. Subject knowledge is indicated separately for pretest and posttest. The respective values reflect the proportion of points achieved in the respective test relative to the total number of points.

3.3.2 Cognitive load

Cognitive load as a dependent variable was used as a measure to investigate the effect of mobile learning on cognitive processes. For considering construct validity on the one hand and high situation specificity on the other, the measurement was carried out at five measurement points with the help of a single item (Kalyuga et al., 1999), since "the vast majority of studies on multimedia learning assess cognitive load by using a single item to assess perceived invested mental effort" (Klepsch et al., 2017). The five measurement points chosen for the survey correspond to the content-related tasks of the workshops, so that the measurements represent comparable cognitive processes for all learners. Cognitive load was assessed as a nine-point Likert item ("How easy or difficult was it for you to complete the tasks?"; 1 = *Very, very easy* to 9 = *Very, very difficult*) and, hence, could be assumed to be on an interval scale for analyses (Joshi et al., 2015; Wu & Leung, 2017).

3.3.3 Concentration performance

Concentration performance as another dependent variable to describe learners' cognitive processes was measured by the complete d2-R attention and concentration test (revised version; Brickenkamp et al., 2010). The measurement was done at a selected time point during the learners' processing of the workshop content. Like the choice of measurement time points for cognitive load, the measurement time point was chosen in such a way that the time point was relative to the processing of the tasks to ensure that the learners were tested in comparable (cognitive) situations. For interpreting learners' concentration performance (e.g., the number of correctly crossed symbols minus the number of incorrectly crossed symbols; Baghaei et al., 2019; Brickenkamp et al., 2010), high values indicate high concentration performance and, thus, little distraction. The concentration performance scoring displayed excellent internal consistency (estimates range from 0.90 to 0.97; Bates & Lemay, 2004; Brickenkamp, 2002) and good to excellent retest reliability (estimates range from 0.71 to 0.94; Brickenkamp, 2002; Brickenkamp et al., 2010). Interval scaling can be assumed for this scale.

3.3.4 Demographic variables, technology-related variables, physics-related variables and further variables

In the data collection for independent variables, see Table 3, a distinction is made between two purposes of these variables.

First, data were collected for variables that represent learner characteristics in the sense of Sect. 2.3. and could moderate effects of approaches to smartphone use (BYOD, POOL). These variables are considered in the analysis of the influence of learner characteristics on research question RQ2. As explained in Sect. 2.3., the variables to be considered here include gender ("How do you identify?" (female, male, other)) and students' SES. However, due to data protection and ethical requirements, the learners' SES could only be collected indirectly. A procedure was chosen that

Table 3 Overview of variables with number of items, scale of measure, and reliability (Cronbach's α)

Variable	No. of items	Scale of measure	α
Demographic variables			
Gender	1	Nominal	
Home language	1	Nominal	
Technology-related variables			
Fear of missing out (FOMO)	10	5-point Likert	0.77
Problematic smartphone use (PSU)	9	Dichotomous	0.68
Physics-related variables			
Physics learning value	5	5-point Likert	0.87
Physics self-efficacy	7	5-point Likert	0.82
Further variables			
General cognitive ability	30		0.89

derives indications of the SES from the migration background of individuals, which in turn is collected indirectly via the language spoken at home ("Which languages do you speak at home?"). A corresponding procedure can be found in the literature (Volodina et al., 2021) and shows a significant correlation between SES and home language ($r = 0.28$, $p < 0.01$). For the evaluation, a nominal scaling was carried out accordingly, considering learners with German as their home language (indicating higher SES) and one or more home languages without German (indicating lower SES). However, it should be noted as a limitation that this approach only allows indirect and limited conclusions to be drawn about SES. Further data to determine learner characteristics were collected for FOMO (10 items; adapted from Przybylski et al., 2013; German version from Reer et al., 2019) and PSU (nine items; adapted from van den Eijnden et al., 2016; German version from Reer et al., 2023).

Second, data were collected for variables that are known to influence subject-related teaching–learning processes and learning performance as well as cognitive performance in a more general manner. Consideration of these variables served to ensure that the comparative studies of the BYOD approach and the POOL approach each had comparable conditions regarding the prerequisites of the learners. These variables were considered for comparing the BYOD approach and the POOL approach in both research questions RQ1 and RQ2. Data to control for learners' different prerequisites were collected for general cognitive ability (30 items; taken from the Matrices and Series Completion subtests of the Culture Fair Intelligence Test [CFT], where both subtests displayed the highest loadings on general cognitive ability; Weiß, 2019), physics learning value (five items; adapted from Tuan et al., 2005), and physics self-efficacy (seven items; adapted from Tuan et al., 2005). Additional information is presented in Table A.2. and A.3. in the appendix.

4 Results

The results for both research questions are described separately below. Data were analyzed with IBM SPSS Statistics (Version 29). Both for the description of correlations and for group differences, the specification of effect sizes was done according to Cohen (1988): Pearson correlation coefficient $|r| \geq 0.10$ small, $|r| \geq 0.30$ medium, $|r| \geq 0.50$ large effect size; Cohen's $|d| \geq 0.20$ small, $|d| \geq 0.50$ medium, $|d| \geq 0.80$ large effect size; partial $\eta^2 \geq 0.01$ small, partial $\eta^2 \geq 0.06$ medium, partial $\eta^2 \geq 0.14$ large effect size.

In advance, Pearson correlations were examined to identify relationships between covariates (general cognitive abilities, physics learning value, physics self-efficacy) and dependent variables (subject knowledge development, cognitive load, and concentration performance). The mean value over the five measurement time points was taken as the total value for cognitive load over the course of the workshop. The results show small to moderate correlations for some of the variables, see Table 4.

For the subsequent analyses, covariates that were related to any of the dependent variables were included in analyses of covariance for the contrast between BYOD and POOL. For this exploratory approach, analyzing correlations seems useful. When deriving covariates from regression models, which also seems conceivable in

Table 4 Pearson correlation coefficients for linear correlation analysis between independent and dependent variables

	General cognitive abilities		Physics learning value		Physics self-efficacy	
Subject knowledge (pretest)	0.175	***	0.011		0.085	
Subject knowledge (posttest)	0.263	***	–0.023		0.069	
Cognitive load	–0.064		–0.345	***	–0.294	***
Concentration performance	0.126	*	–0.197	***	–0.115	*

* $p<0.05$. ** $p<0.01$. *** $p<0.001$

principle, dependencies between covariates could prevail that do not become effective later in analyses.

4.1 Analyses for RQ1: General

The analyses of the sections within 4.1. refer to RQ1 and the associated variables (a) subject knowledge development, see Sect. 4.1.1., (b) cognitive load, see Sect. 4.1.2. and (c) concentration performance, see Sect. 4.1.3.

The covariates considered in our study were chosen for theoretical reasons and/or available prior evidence of their relevance in the context of our study. Then, the investigation of group differences between the BYOD approach and the POOL approach in general was performed taking covariates into account with reference to the respective correlation analyses. Group comparisons were performed by independent sample *t*-tests or (one-way or mixed) analyses of covariance (ANCOVAs). Consideration of the covariates identified by the correlation analysis was intended to ensure that group comparisons with respect to relevant influencing factors considered possible differences in covariates between groups. The the comparison of both analyses should serve to better identify the existence and origin of findings. For example, it is conceivable that effects appear statistically significant in analyses without correction for confounding variables (t-tests), while difference analyses with correction for confounding variables (ANCOVAs) do not detect any effects, as the variance of the confounding variables between groups appeared to be causal. However, due to the influence of the covariates on the statistical power of the analyses, it is also conceivable that only larger samples can make effects appear significant when covariates are included. For this reason, the different information of both analysis methods should be determined and presented in the respective results.

4.1.1 Subject knowledge development

To determine group differences in subject knowledge development between the BYOD and POOL approaches, an analysis of covariance (mixed ANCOVA) was conducted. Subject knowledge was selected as the dependent variable. The within-subjects factor was represented by the two measurement time points of subject knowledge (pretest, posttest). The between-subjects factor was the approach for using mobile devices (BYOD, POOL). Based on the results of the correlation analysis, see Table 4, only the general cognitive abilities were considered as covariates.

The results are presented in Fig. 3. They first show a significant main effect with a large effect size, $F(1.00, 384.00) = 643.58$, $p < 0.001$, partial $\eta^2 = 0.63$, and, thus, a positive subject knowledge development in both groups between pretest and posttest. As interaction effects, no significant group difference for subject knowledge development between BYOD and POOL were found for the influence of the smartphone use approach, $F(1.00, 387.00) = 0.10$, $p = 0.751$, partial $\eta^2 = 0.00$.

4.1.2 Cognitive load

First, to analyze group differences between BYOD and POOL, total cognitive load values for both groups were compared. For this purpose, the mean values were aggregated across the five measurement points. A comparison of the means shows that the total cognitive load of the learners in the BYOD approach ($M = 4.12$, $SD = 1.28$) was higher than the total cognitive load of the learners in the POOL approach ($M = 3.95$, $SD = 1.31$), see Fig. 4(a). However, an independent samples t-test shows that this group difference is not statistically significant, $t(395.00) = 1.30$, $p = 0.195$, Cohen's $d = .13$).

The same nonsignificant group difference between total cognitive load scores is seen for a one-way analysis of covariance (one-way ANCOVA) with cognitive load

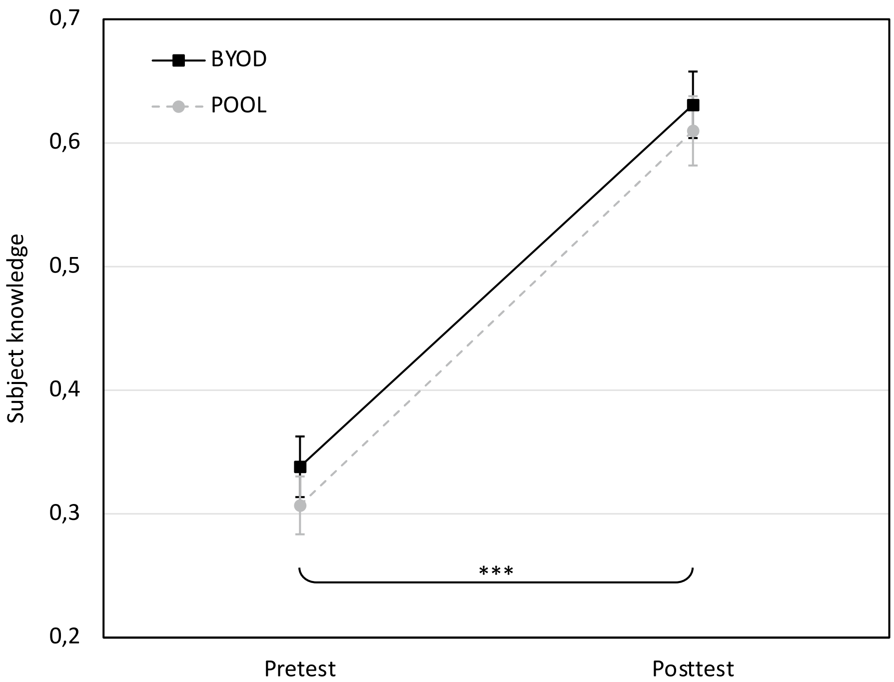

Fig. 3 Interaction plot for approach of smartphone use (BYOD approach, POOL approach) and measurement time points of subject knowledge (pretest, posttest). Note: * $p < .05$. ** $p < .01$. *** $p < .001$

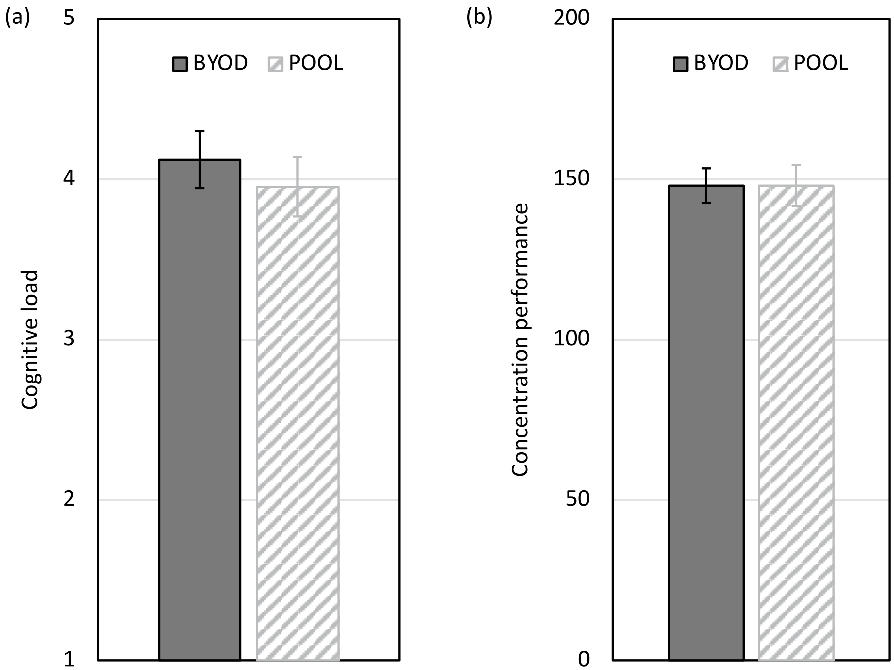

Fig. 4 **a** Average total cognitive load scores across five measurement time points. **b** Total concentration performance scores for learners following the BYOD approach and POOL approach

as a dependent variable, the mobile device access concept (BYOD, POOL) as the between-subjects factor, and, as described in the correlation analysis, physics learning value and physics self-efficacy as covariates, $F(1.00, 352.00) = 1.25$, $p = 0.265$, partial $\eta^2 = 0.00$.

In addition, analyses were done on the time course of cognitive load and the group difference between the BYOD and POOL approaches using a mixed ANCOVA. Cognitive load was selected as a dependent variable. The within-subjects factor was represented by the five measurement time points of cognitive load. The between-subjects factor was the mobile device access concept (BYOD, POOL). Based on the results of the correlation analysis, see Table 4, physics learning value and physics self-efficacy were considered as covariates. Since the Mauchly test was significant, Mauchly-$W(9) = 0.770$, $p < 0.001$, the Huynh–Feldt adjustment was used to correct for violations of sphericity.

The results are presented as the interaction plot in Fig. 5. They first show a significant main effect with a small effect size, $F(3.72, 903.78) = 3.43$, $p = 0.010$, partial $\eta^2 = 0.01$, and, thus, a slightly decreasing cognitive load over the course of the workshop. Since cognitive load was assessed as a nine-point Likert item, results indicate that learners expressed a moderate level of cognitive load.

As interaction effects, no significant group difference for cognitive load between BYOD and POOL were found for the influence of the smartphone use approach, $F(7.44, 903.78) = 1.89$, $p = 0.064$, partial $\eta^2 = 0.02$.

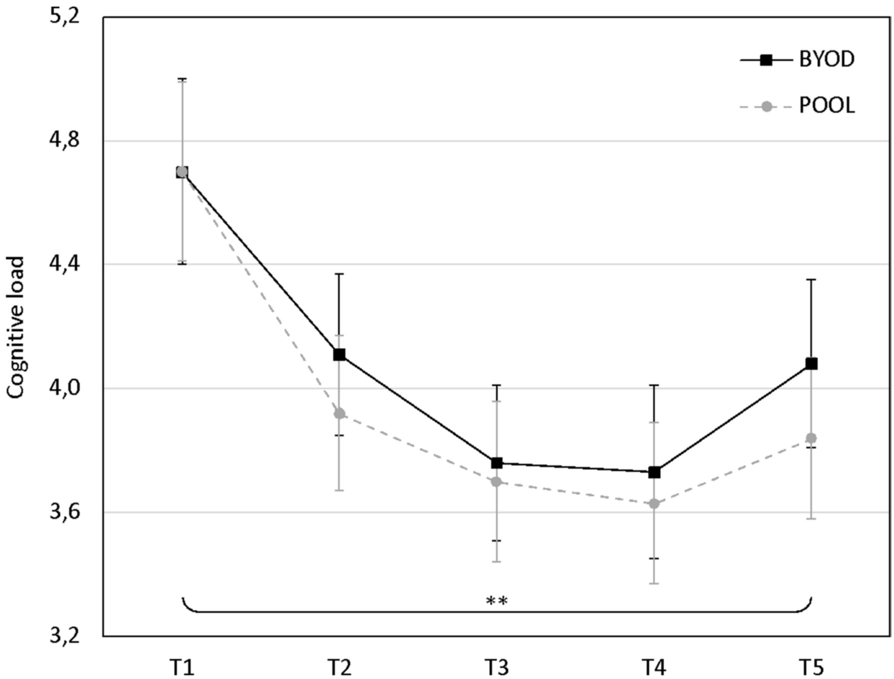

Fig. 5 Interaction plot for approach of smartphone use (BYOD approach, POOL approach) and measurement time points of cognitive load. Note: * $p<.05$. ** $p<.01$. *** $p<.001$

4.1.3 Concentration performance

A comparison of cognitive performance between learners in the BYOD and POOL groups shows that concentration performance in the BYOD group ($M=147.96$, $SD=38.35$) was higher than concentration performance in the POOL group ($M=148.07$, $SD=44.78$), see Fig. 4(b). However, an independent samples t-test shows that this group difference is statistically not significant, $t(386)=-0.03$, $p=0.980$, Cohen's $d=0.00$.

The same nonsignificant group difference between concentration performance scores is seen for a one-way analysis of covariance (one-way ANCOVA) with concentration performance as a dependent variable, mobile device access concept (BYOD, POOL) as a between-subjects factor, and, as described in the correlation analysis, general cognitive ability, physics learning value, and physics self-efficacy as covariates, $F(1.00, 344.00)=0.14$, $p=0.707$, partial $\eta^2=0.00$.

4.2 Analyses for RQ2: Learner characteristics

The analyses of the sections within 4.2. refer to RQ2 and the associated variables (a) subject knowledge development, see Sect. 4.2.1., (b) cognitive load, see Sect. 4.2.2. and (c) concentration performance, see Sect. 4.2.3.

To consider various characteristics of learners as well as individual personal prerequisites in the analyses in the form of differential effects, certain sample subgroups were formed based on the independent variables considered in each case. The independent variables considered for this purpose were chosen based on the explanations in Sect. 3.3.4. Two cases must be distinguished in the formation of groups.

First, for gender two groups were formed directly from the characteristics (female, male). The subsamples comprised $N=180$ female and $N=155$ male students. Due to an insufficient number of learners with a different assignment ($N=4$), these could not be included in the further analyses. The home language was also used as an indication of the learners' SES for group formation. The subsamples here comprise $N=304$ learners with German as a home language indicating higher SES and $N=35$ learners without German as a home language indicating lower SES.

Second, for the variables considered as predictors (FOMO, PSU), groups were formed individually for each predictor to consist of the 25% of students with the lowest values of the respective variable (low group) and the 25% of students with the highest values of the respective variable (high group) (Gelman & Park, 2009). The resulting group sizes are shown in Table 5.

The following analyses were based on the methods used in Sects. 4.1.1. to 4.1.3. and were applied to the subsamples structured according to gender, language or the low groups and high groups of the seven different predictors. Due to the number of calculations, only statistically significant findings are reported in the following sections. An overview of all calculations including the statistically nonsignificant findings can be found in the supplemental material.

Again, independent variables that were related to any of the dependent variables were included as covariates in analyses of covariance for the contrast between BYOD and POOL, see Sect. 4.1.

4.2.1 Subject knowledge development

The analysis of the mixed ANCOVA (dependent variable: subject knowledge development; within-subjects factor: measurement time points (1 to 2); between-subjects

Table 5 Number of students in low group and high group (group sizes) for samples split at the lower and upper quarter of different predictors

Predictor	Low group	High group	Total sample	Unconsidered for this predictor
Fear of missing out (FOMO)	78 (23.4%)	88 (26.3%)	334	168 (50.3%)
Problematic smartphone use (PSU)	93 (28.4%)	57 (17.4%)	328	178 (54.3%)

factor: mobile device access concept (BYOD, POOL); covariates: general cognitive abilities) shows no statistically significant differences between the BYOD and POOL approaches in any subsample, see supplemental material (Table A.4.).

4.2.2 Cognitive load

To analyze differences between BYOD and POOL, first the total values of cognitive load were compared analogous to Sect. 4.1.2. via an independent samples *t*-test (dependent variable: cognitive load; group variable: mobile device access concept (BYOD, POOL)). The results show significant differences between BYOD and POOL for learners with certain levels of FOMO and PSU.

According to the data, learners with lower FOMO, $t(76.00)=2.19$, $p=0.032$, Cohen's $d=0.50$, and learners with higher PSU, $t(57.00)=2.25$, $p=0.028$, Cohen's $d=0.59$, each with medium effect sizes, showed lower cognitive load from the POOL approach, see supplemental material (Table A.5.).

However, these group differences are not significant for the one-way ANCOVA (dependent variable: cognitive load; between-subjects factor: mobile device access concept (BYOD, POOL); covariates: physics learning value, physics self-efficacy) for learners with lower FOMO, $F(1.00, 67.00)=3.53$, $p=0.064$, partial $\eta^2=0.05$, and learners with higher PSU, $F(1.00, 51.00)=3.51$, $p=0.067$, partial $\eta^2=0.06$, see supplemental material (Table A.6.).

For this analysis, a significant group difference among lower SES learners in favor of the POOL approach is found, $F(1.00, 26.00)$ 5.51, $p=0.027$, partial $\eta^2=0.18$.

Considering the data for the time course of cognitive load in a mixed ANCOVA (dependent variable: cognitive load; within-subjects factor: measurement time points (1 to 5); between-subjects factor: mobile device access concept (BYOD, POOL); covariates: physics learning value, physics self-efficacy), two statistically significant findings occur when accounting for the covariates, since female learners, $F(8.00, 496.00)=2.73$, $p=0.006$, partial $\eta^2=0.04$, and lower SES learners, $F(8.00, 56.00)=3.11$, $p=0.006$, partial $\eta^2=0.31$, showed a positive development of cognitive load in the POOL approach compared to learners in the BYOD approach, see supplemental material (Table A.7.).

4.2.3 Concentration performance

In terms of learner concentration performance, the data only shows statistically significant differences between the BYOD and POOL approaches in the analysis of the one-way ANCOVA (dependent variable: concentration performance; between-subjects factor: mobile device access concept (BYOD, POOL); covariates: general cognitive abilities, physics learning value, physics self-efficacy) for interaction term (between-subjects factor × covariates). Here, students with higher FOMO showed a statistically significant better concentration performance, $F(1.00, 77.00)=4.90$, $p=0.030$, partial $\eta^2=0.06$, with weak effect size in favor of the POOL approach, see supplemental material (Table A.8. and A.9.).

5 Discussion

The following discussion is based structurally on the research questions and the associated hypotheses, see Sect. 2.5.

5.1 Discussion for RQ1: General

HYP1. BYOD and POOL approach do not differ with respect to learning-related variables in general.

The results showed no differences between the BYOD and POOL approaches for any of the dependent variables, both when including and excluding different covariates that were identified before the analyses and thus confirm HYP1. Based on the available data, it can thus be assumed that the approach to smartphone use, specifically when comparing the BYOD approach and the POOL approach, does not differently influence students' learning in general. Both approaches seem to be equivalent in this respect. Possibly due to different negative influences on cognitive and learning performance, which balance each other out in comparison.

Overall, these results appear to be consistent with the heterogeneous impression of the studies described in Sects. 2.2. to 2.4. While on the one hand cognitive performance (Upshaw et al., 2022; Zhao, 2023) and learning performance (Dietz & Henrich, 2014; Waite et al., 2018) appear reduced due to more off-task smartphone use for BYOD, the lack of availability of the smartphone in POOL increases the FOMO of learners and in turn causes distractions (Kneidinger-Müller, 2019). The findings of the present study answer RQ1 indicating that mutual advantages and disadvantages seem to balance out, and no general difference between both approaches can be identified. The result also confirms the findings of Krause et al. (2024) for mathematical modeling competence as learning performance variable and extends this regarding cognitive performance.

5.2 Discussion for RQ2: Learner characteristics

Overall, considering the specific characteristics of learners, statistically significant differences were found for certain subgroups. Before discussing individual results in relation to the hypotheses, two aspects can be emphasized: First, all differences indicate advantages of the POOL approach or show both approaches to be equally conducive to learning. An advantage of the BYOD approach cannot be proven for any subgroup. Secondly, differences are only found for the variables of cognitive load and in one case for concentration performance. There were no actual differences in performance in the development of subject knowledge. This suggests that differences in other variables, such as cognitive load or concentration performance, are not sufficient to influence the actual learning efficacy of a learning sequence.

HYP2.1. Learners with lower socioeconomic status (SES) benefit from POOL approach with respect to learning-related variables.

The results of the analysis show statistically significant advantages of the POOL approach with large effect size for the cognitive load of learners, both considering the time course ($p = 0.006$, partial $\eta^2 = 0.31$) and total cognitive load ($p = 0.027$, partial $\eta^2 = 0.18$) for learners with lower SES (despite the small sample size of this group). This result confirms HYP2.1 and appears consistent with previous studies that demonstrate potential distractions when using personal smartphones, especially for learners with lower SES (Tao et al., 2017; Zhou et al., 2022). One possible cause is the typically negative correlation between SES and PSU (e.g., Pearson's $r = -0.16$, $p < 0.01$; Zhao, 2023). For example, a higher level of PSU is observed in people with lower SES and smartphone addiction also occurs more frequently (Aljomaa et al., 2016). A potential reason for this given by Aljomaa et al. (2016) is that "low income individuals overuse smartphones as a sort of compensation and for self-assertion". Since the increased PSU is in turn associated with an increased probability of off-task use (Fu et al., 2021; Petrucco & Agostini, 2023; Rozgonjuk et al., 2018a, 2018b), the finding in favor of POOL for the group of students with low SES seems plausible.

HYP2.2. Learners with higher fear of missing out (FOMO) benefit from BYOD approach with respect to learning-related variables.

For the subgroup of learners with higher FOMO, the analyses show that, contrary to hypothesis HYP2.2, they also benefit from the POOL approach, as this results in better concentration performance with a medium effect size ($p = 0.030$, partial $\eta^2 = 0.06$) compared to BYOD. There are no differences in cognitive load. The findings contradict the expectation that learners with higher FOMO would be particularly negatively affected by the absence of the smartphone, as would have been expected according to Kneidinger-Müller (2019). However, it seems possible that even the subjectively perceived restriction of the use of personal devices in the BYOD approach appears to be sufficient to increase FOMO and consequently to perceive corresponding cognitive distractions. However, this connection should be analyzed in more detail in subsequent studies.

HYP2.3. Learners with lower fear of missing out (FOMO) benefit from POOL approach with respect to learning-related variables.

When analyzing learners with lower FOMO, the findings for cognitive load in the comparison between BYOD and POOL indicate that the POOL approach has potential advantages for learning, as the cognitive effect size appears to be reduced for POOL with a medium effect size ($p = 0.032$, $d = 0.50$). This result confirms HYP2.3, which can be interpreted to mean that the influence of these variables is not or only slightly effective, especially for learners without FOMO, and that the negative potential of BYOD due to stronger cognitive distractions in the sense of previous studies by Welsh et al. (2018) or Al-Said (2023) predominates.

HYP2.4. Learners with higher problematic smartphone use (PSU) benefit from POOL approach with respect to learning-related variables.

The results for learners with higher PSU also confirm the associated hypothesis HYP 2.4. The cognitive load of students with higher PSU is reduced by the POOL approach with a medium effect size ($p=0.028$, $d=0.59$). However, there are no differences in concentration performance. As described by Kao (2023), Rozgonjuk et al. (2018a) and Krause et al. (2024), PSU can lead to increased cognitive distractions in the learning process. However, as these are more likely to be perceived with BYOD due to the availability of different activities, learners are hypothesized to benefit from the POOL approach.

HYP2.5. Learners with lower problematic smartphone use (PSU) do not differ with respect to learning-related variables.

Since PSU as a type of addictive behavior is an increasingly significant phenomenon, but also a marginal phenomenon in a larger sample in the sense of Elhai et al. (2021), it can be assumed that the learners with lower PSU represented in the sample in particular do not in fact exhibit any behavior in the sense of PSU. The results here confirm HYP2.5. and the assumption that the same prerequisites apply for learners with lower PSU as for the observation in general, see RQ1, so that both BYOD and POOL appear to be similarly conducive to learning here.

In addition to this hypothesis-driven discussion, it seems interesting that a gender-dependent difference can also be observed exploratively. Female students show a lower cognitive load with a medium effect size ($p=0.006$, partial $\eta^2=0.04$) when using the POOL approach. No difference between the approaches was observed for male students. In order to understand these findings, it seems useful to include previous studies on influences on distraction in females compared to males.

Looking at the implementation of the workshops, the learners generally had the freedom to engage in off-task activities. However, it seems more realistic that this time could be used for short social media activities (or for instant messaging) than for the more time-consuming occupation with digital games. The observations during the workshops support this impression. In this respect, it is conceivable that social media activities, which are particularly distracting for girls, were primarily perceived in the workshops, and were reduced by the POOL approach due to the lack of access to corresponding apps, see Table 1.

5.3 Limitations

Different limitations must be considered when assessing the results. First, it should be considered that the comparability of the two groups (BYOD, POOL) may have been influenced by novelty effects in the POOL group, since the students in this group worked with devices that were basically new to them. It would be desirable to review the study results in a follow-up study in which the two approaches are compared over a significantly longer period (several weeks) to enhance the reliability of the results. Further, relevant for RQ2, as shown in Table 5, subsamples were rather small due to the formation of groups, and unequal samples were created in the comparison of the low and high expression of the respective predictors. It is also important for RQ2 that the present study could only collect SES very indirectly via the students' home language due to data protection and ethical requirements. Future studies should attempt to verify the interesting findings for students with lower SES using better measures for SES. Regarding the generalizability of the findings, it must be considered that the sample only included learners in grades 8 and 9 of German high schools. Due to differences in the quality and quantity of smartphone use depending on age and socioeconomic background, it seems conceivable that studies in other age groups and at other types of schools could yield different results. Other cultural backgrounds and usage habits in other countries could also influence the results, so that data in an international comparison would also appear to be of interest. Especially in educational systems that already apply certain approaches to the use of smartphones and tablets in a more standardized way, studies appear interesting here, as long-term effects can be included. Another limitation of the findings is how the results on the use of smartphones as mobile learning devices can be transferred to tablet computers. This seems particularly relevant for schools since the COVID-19 pandemic, but it could lead to other findings regarding the form of use (BYOD, POOL) due to differences in private and learning-related use. Another major limitation of the study is the focus of the analysis of cognitive processes based on data on cognitive load and concentration performance. It would make sense to analyze and include these measures with additional data on the students' usage behavior during the workshops regarding off-task activities. However, due to the scope of the analysis of the corresponding data, which is available in the form of instructional videos, the presentation of these findings does not appear possible within the scope of this study and must be presented separately to meet the necessary quality requirements.

6 Conclusion and implications

Many schools have students use their own smartphones for mobile learning in the classroom (BYOD approach), while other schools provide pools of devices that are owned by the school and that students use temporarily in selected lessons (POOL approach). How do these mobile device access concepts differ with respect to the influence of off-task smartphone use on learning performance or cognitive performance in teaching–learning processes? And how do specific characteristics and conditions of learners influence the effectiveness of the two approaches? The present study addressed both questions based on the use of smartphones in physics lessons as an example.

The findings showed that when comparing the use of smartphones in physics classes according to the BYOD approach and the POOL approach, almost no differences were found. When considering differential effects and the influence of different predictors, such as gender, SES, FOMO, or PSU, these findings were partially confirmed, especially with respect to learning performance measured as subject knowledge development. However, some results related to cognitive performance and in particular students' cognitive load and with respect to specific characteristics of learners showed small to medium effects in favor of the POOL approach. The results of the study confirm the findings of Krause et al. (2024) and go beyond the existing findings. Looking at the literature on the comparison of BYOD and POOL, there are therefore different implications both for practice and for subsequent research.

When making recommendations for school practice, it seems sensible to distinguish between two aspects. Firstly, regarding the basic decision on a suitable mobile device access concept, no clear advantage in terms of learning can be identified from RQ1. However, this null result can be interpreted positively by schools, as it enables them to include further aspects. The extent to which the provision of POOL devices or the use of BYOD devices appears to make economic and ecological sense for schools and which organizational boundary conditions for the provision of POOL devices can thus be included in decisions. It should also be taken into account that, as stated by Krause et al. (2024), alternative approaches between BYOD and POOL as a mobile device access concept also appear possible. However, when considering individual characteristics of learners, as analyzed under RQ2, the possible advantages of the POOL approach should be taken into account. Especially for female learners or learners with low SES as well as learners with higher PSU, it may make sense to provide POOL devices. With appropriate practical experience, it could therefore make sense not to make a universal decision regarding the mobile device access concept, but to include it as a measure of individual support and to design it individually according to the requirements of learners.

For future research on mobile device access concepts, it seems reasonable to transfer the study design to other subjects or devices. In relation to the subject of physics studied here, smartphones were used for recording and measuring data in experiments. This very specific activity could have an influence on certain forms of use and distractions. In other subjects where other applications are used, qualitatively or quantitatively different effects could arise. Regarding the smartphone device type, it also seems open as to whether the tablet computer, which is currently more relevant in schools, leads to similar findings. Furthermore, only cognitive effects were analyzed in the present study. However, effects on affective constructs are also known from the literature on mobile learning and BYOD, indicating, for example, that in the BYOD setting students show higher situational interest and motivation to learn (Rinehart, 2012; Zhai et al., 2016). Therefore, such affective constructs should be included in further studies in the form of dependent variables.

It also seems sensible to determine the distractions of the different mobile device acces not only indirectly via learning performance and cognitive performance, but also to include other data, such as videos, and to analyze distractions caused by smartphones directly. How often did learners work with smartphones on-task or off-task? To what extent do distractions caused by smartphones outweigh traditional distractions in the classroom, such as private conversations between students? Corresponding objective measures should also be determined to be able to analyze differences between BYOD and POOL in more detail.

Furthermore, the data analysis also suggested that certain characteristics of learners can influence the effectiveness of both approaches. In subsequent studies, it would make sense to adapt the methodology of the study to this issue and to vary and investigate the aspects identified in the present study, for example, gender or FOMO, under more controlled conditions.

Overall, the present study makes an important contribution to the understanding of mobile learning, compares different approaches to smartphone use for the first time, and, thus, provides the basis for subsequent studies.

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Data availability Data sets generated during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest None.

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