



Article

Toward a framework for analyzing adaptive digital games' research effectiveness

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Abstract

Adaptive digital games for learning have been introduced as a motivating way for children to learn as they can provide instant feedback, embed the learning content in an attractive narrative, and adapt instruction according to individual needs of students. Although studies showed benefits of using adaptive digital educational games, a framework for analyzing research on the effectiveness of adaptive digital games is lacking. In this paper, we propose such a framework that accounts for a broad evaluation and is defined by (1) the learner variables that can affect effectiveness, (2) the adaptivity implemented in the tool, and (3) the learning outcomes being assessed. Next, this framework is used to describe recent intervention studies on the effectiveness of adaptive digital games in the context of K-12 education. We end with some concluding thoughts on the merits of such a framework for assessing the effectiveness of digital games and perspectives for future research.

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1. Introduction

Over the past years, the use of technology in education has increased, and consequently also the number of digital tools available for schools. Especially *digital games for learning*, which refer to games ‘with some learning goals in mind’ [1, pp. 2], are introduced as an effective way to reach educational purposes due to inherent features that can potentially enhance learning such as clear goals, appropriate feedback on progress, different game modes that support social interaction and attractive graphics [2], [3]. Several systematic reviews and meta-analyses [4] - [8] have in general revealed a positive trend, but empirical evidence regarding which specific features of digital games for learning are particularly effective is scarce. A factor that impedes a straightforward interpretation of the results is caused by what Girard et al. [6] labeled as the “control group problem”, referring to the great variability between studies in how the control condition is defined. Many studies have adhered to a so-called “media comparison approach”. Such an approach simply compares the learning gain of digital games for learning with a non-digital game condition [5]. However, this approach - which only studies the effect of the medium (i.e., a digital game versus a non-digital game environment) - has been criticized, because rather than the medium as such the instructional method mainly influences learning

[9]. Adopting by contrast a “value-added approach” in which the learning gains of children, enrolled in different versions of one educational game, are compared might therefore be better suited to unravel which specific game features foster learning [5], [8]. One game feature that has been suggested to be very effective is adaptivity which refers to the game that adapts to the characteristics and behavior of the learner [10]. In line with [11, pp. 276] we define adaptivity as “the ability of a learning system to diagnose a range of learner variables, and to accommodate a learner’s specific needs by making appropriate adjustments to the learner’s experience with the goal of enhancing learning outcomes”. According to the quality criteria of Caserman et al. [3], adaptive digital games can ensure flow because they keep a balance between a player’s skills and challenge. These games dynamically adapt for example the difficulty level according to the player’s performance in the game. So far, meta-analyses investigating the effect of adaptivity (but not necessarily in games) showed mixed results when comparing a condition in which students learned with an adaptive learning environment (compared to a condition where students were learning with a non-adaptive learning environment or business as usual control group) [13], [14].

2. Theoretical framework

2.1 Operationalizing adaptivity in digital games for learning

Recent technological developments have opened new perspectives for implementing adaptivity in digital games for learning. Given the broad range of possibilities to operationalize adaptivity in these learning systems, there have been several attempts to develop frameworks describing adaptivity for learning (e.g., [11], [15] - [17]). In general, a learning environment, and thus also digital games for learning, can be adapted according to at least the following three dimensions: 1) the learner variables to which the system adapts, 2) the elements of the system that are adapted to the diagnosed learner variables, and 3) the way in which these variables are diagnosed.

A first dimension concerns the learner variables to which the system adapts for [11], also labeled as the “source” of adaptivity [16]. A learning system can account for cognitive (e.g., prior knowledge, meta-cognitive strategies) and noncognitive (e.g., motivation, affect) differences between learners. It has been shown that most current adaptive learning environments focus on only one learner variable, and more particularly on learners’ knowledge of the topic taught [17]. However, a system can be adaptive based on one or multiple learner variables [11], [38].

A second dimension focuses on the elements in the learning environment that are adapted to account for individual differences [11], also labeled as the “target” of adaptivity [16]. These elements might concern the content of the learning environment (e.g., the difficulty and the sequence of learning activities), the mode of representation of information (e.g., audio only vs. audio with image, the colors and lay-out), the support that is provided (e.g., type of feedback, scaffolds, and cues), or learners’ self-representation (which can be modified for example through avatars) [18]. Again, a system can be adaptive based on one or more elements of the learning environments (e.g., both the content and type of feedback can be adapted). It seems that most adaptive systems mainly adapt the content of the learning environment, and more particularly the difficulty of the tasks [17].

A third dimension serves as the “engine” between the source and target of adaptivity. The engine pertains to three aspects: 1) who decides about the diagnosis and/or adjustments, 2) when are the learner variables diagnosed and accordingly when are elements of the learning environment adjusted, and 3) how are these variables diagnosed and accordingly analyzed. First, the decision concerning what the most suitable adjustment of the learning environment should be for the learner can be made by the learner him/herself, the teacher, or the system itself [11]. This issue also has been described as whether the system is learner-, teacher- or

system-controlled [16]. Again, multiple agents can be involved in this diagnosis. Recently, [18] referred to this issue as ‘agency’ and distinguished four categories (i.e., learners have full agency, shared agency between tool and learner, shared agency between tool and teachers, tool has full agency). Second, in terms of when the learner variables are diagnosed, a distinction can be made between ‘static learning environments’ in which the learner variables are diagnosed before entering the learning system and ‘dynamic learning environments’ in which learner variables are assessed during the use of the learning system. In static learning environments, learners will follow a predefined trajectory based on the initial diagnosis. In dynamic learning environments, elements of the learning environment are continuously updated during gameplay. A system that combines a static and dynamic approach to diagnose learner variables is labeled as dual-pathway [16]. In [18] a similar categorization has been proposed to define when learner variables are diagnosed distinguishing: at the start and end points of the activity, at specific milestones during the activity and throughout the activity. Third, different data sources can be used to assess the learner variables to which the system adapts, such as questionnaire data, logdata (e.g., logged events such as task accuracy), physiological responses, and eye-tracking data. According to [17], so far, most adaptations in digital personalized learning environments are program-controlled, the method of adaptation is dynamic, and logdata is used to assess the learner variables.

In sum, adaptivity implemented in digital games for learning can vary on each of these three dimensions and the effectiveness of digital games might depend on the operationalization of this adaptivity.

2.2 Current limitations in research on the effectiveness of adaptive digital games for learning

Despite the general assumption that instruction accounting for learner differences is more effective than one-size fits all instruction [10], research evidence supporting this assumption is obscure due to several limitations of the studies relating to 1) individual differences, 2) the conditions being compared, 3) the operationalization of adaptivity, and 4) the outcomes that are assessed.

First, most studies look at the group effect of digital game-based learning, although interventions might not be as effective for all learners [19]. It can be assumed that the extent to which learners take advantage of a game differs based on background, cognitive, or noncognitive factors [21]. However, the role of learner variables has hardly been studied when determining the effectiveness of adaptive digital games for learning, with some exceptions observing larger learning gains for children with lower cognitive abilities [22] and for high anxious learners [23].

Second, in terms of the design of the study, only few studies compared the effectiveness of an adaptive digital game to a nonadaptive digital game [12], [19]. Rather, most effectiveness studies are characterized by a control condition with pen-and-paper, a non-game control condition, or even do not use a control condition, impeding a straightforward interpretation of the results in terms of the effectiveness of the adaptivity implemented in the game [12], [20].

Third, in terms of the intervention, studies have rarely defined how adaptivity is operationalized in their study impeding a profound understanding of its effectiveness [17]. Furthermore, seldomly a manipulation check is utilized in which authors confirm that the adaptivity works as designed [24].

Fourth, in terms of the measured learning outcomes, studies investigating the effectiveness of adaptive digital games for learning often did so in a "narrow sense", as they focused only on immediate cognitive effects (i.e., assessing whether trained skills were gained immediately after gameplay). The need for a broader and more considerate investigation of the effectiveness of games is also echoed in a recent meta-analysis of [26]. Furthermore, limitations related to the learning outcomes do not only relate to the type of learning outcomes that are assessed (i.e.,

mainly cognitive and skills similar to the ones being trained in the game), but also to the time of assessment [6]. Only rarely transfer and retention effects are examined [6], [19]. Furthermore, the type of data sources that are used to assess the effectiveness of adaptive digital games for learning have often been restricted to outcomes on non-standardized tests for cognitive outcomes (which can inflate effect sizes) and self-reports for noncognitive outcomes [4], [26].

2.3 Research objectives of the current study

Given the limitations in existing research, it is important to advocate for a broader framework that can advance the quality of effectiveness research on adaptive digital games for learning. In this paper we focus on effectiveness studies which have the goal to “assess whether a given intervention produces positive impact of the type desired and predicted, most commonly involving real-world impact” [27, p. 29]. This means that so-called feasibility or mechanistic studies which aim to evaluate the reliability and external validity of input data, inference mechanism or adaptation decisions of the adaptive system are not in the scope of this study [27], [28]. The current study is characterized by two research objectives. First, we will develop a new conceptual framework that accounts for a broad evaluation of the effectiveness of adaptive digital games, integrating insights from different theoretical frameworks concerning learner differences, adaptivity, and measured learning outcomes. Second, we will apply this framework to describe recent research in the domain of evaluating the effectiveness of adaptive digital games for learning compared to digital nonadaptive games.

3. Toward a framework analyzing research on the effectiveness of adaptive digital games

The first objective of the current study is to develop a generic conceptual framework that accounts for a broad evaluation of adaptive digital games. Figure 1 depicts the generic conceptual framework and is inspired by different theoretical frameworks that respectively take into consideration 1) differences between learners when evaluating the effectiveness of an intervention, 2) differences in operationalization of adaptivity in a learning environment, and 3) differences in learning outcomes and how they can be assessed.

First, column 1 and column 2 in Figure 1 are based on the Opportunity-Propensity framework of [29]. This is an inspiring theoretical framework to consider individual differences in the effectiveness of adaptive digital games. The Opportunity-Propensity framework stipulates that learners are more likely to realize their potential for learning if they are provided opportunities to learn [30]. These *opportunities* are characteristics of the learning environment, such as, for instance, adaptive digital games. Furthermore, the framework also acknowledges that even when children are offered the same opportunities to learn (e.g., being provided with the same adaptive digital game), the extent to which they take advantage of these opportunities varies as a consequence of differences in antecedent and propensity factors [21]. Factors such as socioeconomic status (SES), parental educational expectations are considered as *antecedent factors* because “they operate earlier in time and explain the emergence of opportunities and propensities [29, pp. 602]. These *propensity factors* “are any factors that relate to the ability or willingness to learn content once it has been exposed or presented in particular contexts” [29, pp. 601) and, thus, includes learners’ cognitive (e.g., prior knowledge) and noncognitive factors (e.g., motivation, self-efficacy). Consequently, the evaluation of learners’ opportunities to learn, through the use of adaptive digital games, is inherently connected with learners’ antecedent and propensity factors.

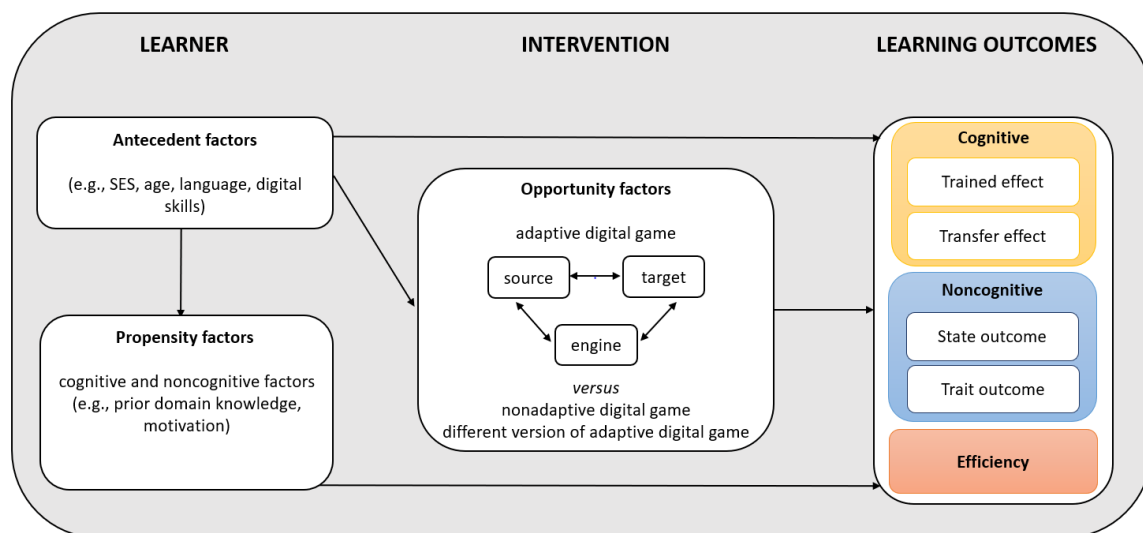


Figure 1. Framework for analyzing research on the effectiveness of adaptive digital games

Second, to further operationalize learners' opportunity factors, distinct frameworks describing adaptivity in learning systems [10], [11], [15]-[18] have inspired the operationalization of adaptivity in our new conceptual framework. Column 2 in Figure 1 presents the distinction between the "source" of adaptivity, the "target" of adaptivity and the "engine" that serves between the source and the target (see section 1.1). The source refers to the learner variables to which the digital game adapts and includes cognitive (e.g., pre-existing skills) and noncognitive (e.g., interest) learner variables. The target touches upon the elements in the digital game that are adapted, such as the content, mode of representation, and support. The engine between the source and target of adaptivity involves who is involved in the diagnosis of learner variables and the subsequent adjustments (i.e., learner, teacher, game), when learner variables are diagnosed (i.e., before entering the digital game and/or during gameplay), and which data sources are used to assess these learner variables (e.g., self-reports, logdata, physiological data). Furthermore, to enable a straightforward interpretation of the effectiveness of the adaptivity itself [5], the framework proposes to compare the effects of an adaptive version of a digital game with a nonadaptive version of the same digital game. Alternatively, two adaptive versions of the same digital game can be compared.

Third, the dimensions in our conceptual framework regarding the learning outcomes (i.e. column 3 in Figure 1) are largely inspired by a conceptual framework for assessing the effectiveness of digital game-based learning [4]. These scholars operationalized effectiveness in the context of digital game-based learning in terms of cognitive, noncognitive and efficiency outcomes. In terms of cognitive outcomes they further distinguish between improved performance on the skills that are trained in the game as well transfer of these skills in other contexts. Also in terms of noncognitive outcomes, one can distinguish between state outcomes that might fluctuate during game play as a result of being involved in the game (e.g., situational interest, flow experience) and trait outcomes that are more stable and relate to the broader domain to which the skills trained in the game belong (e.g., motivation or attitudes towards a subject). Finally, efficiency outcomes include time management: "if a game helps in reducing the time needed to teach a certain subject matter, resulting in similar learning outcomes, it is considered as effective" [4, p. 34]. Especially in the case of educational games, the balance between gaming and learning should be monitored. For example, if it takes two hours to learn something that needs five minutes with a text book the game might not be good (depending on the goals of the educators) [3]. Learning outcomes can be assessed during the intervention, immediately after the intervention or delayed. Furthermore, different data sources (e.g., tests, questionnaires, observations, interviews) can be used to determine cognitive, noncognitive and

efficiency learning outcomes [31], [33]. Thanks to developments in statistical modeling, increasingly valid and reliable educational assessments are available to be used in intervention studies to capture more complex performances [34]. Learning outcomes can be measured during the intervention, immediately after the intervention and delayed after the intervention.

4. Applying the framework on recent studies investigating the effectiveness of adaptive digital games

The second objective of the current study is to apply the newly developed framework to recent studies in the domain of effectiveness of digital adaptive games for learning. Therefore, a literature search was conducted in the database Web of Science using the following search string: “Abstract or Title = adaptive digital game” with a restriction in publication date between 01/01/2019 - 29/10/2023). Importantly, the reason for the rather narrow time frame is that the literature search was mainly intended as a check of the completeness of the different dimensions of the framework and to illustrate how the newly developed framework can be used for discussing the design of intervention studies investigating adaptive digital games. The goal of the literature search was not to generate a comprehensive overview of previous research that investigated the effectiveness of adaptive educational games. The search resulted in 72 records which we extracted to a separate file. All records (including title, authors, abstract) were reviewed on their eligibility. The following inclusion criteria were used: 1) intervention study that was conducted in a classroom context in K-12 education, 2) the effectiveness of the adaptive digital game was investigated in terms of learning outcomes (cognitive, noncognitive, and/or efficiency), 3) a value-added design approach was adopted (i.e., the effectiveness of the adaptive digital game was compared with the effectiveness of a nonadaptive version of the same digital game or different forms of adaptivity in the same digital game were compared). In total, six studies met the inclusion criteria (see Table 1). In the following section, each of the studies are described in terms of our proposed conceptual framework (see Figure 1).

Table 1. Overview of studies investigating the effectiveness of adaptive digital educational games in the last four years.

Reference	Learner	Adaptivity	Learning outcomes
[19]	-AF: / -PF: prior knowledge	-S: task accuracy (early numerical ability) -T: task difficulty -E: system, dynamic assessment, IRT analysis based on logdata	-C (trained + transfer effect) -NC (trait effect) -Ef
[31]	-AF: / -PF: /	-S: task accuracy (early numerical ability) -T: task difficulty -E: system, dynamic assessment, IRT analysis based on logdata	-Ef
[24]	-AF: / -PF: /	-S: estimation ability -T: estimation accuracy threshold -E: system, dynamic, logdata	-NC (state effect)
[36]	-AF: age -PF: /	-S: task accuracy (executive skills) -T: task difficulty -E: system, dynamic, logdata	-C (transfer effect)
[20]	-AF: home language, SES -PF: prior knowledge	-S: task accuracy (early reading ability) -T: number of tasks -E: system, dynamic, logdata	-C (trained + transfer effect) -NC (trait effect)
[35]	-AF: / -PF: /	-S: game progress, answer results (physics) -T: number of scaffolds (i.e. answers, explanations) presented -E: system, dynamic, logdata	-C (trained) -NC (transfer)

Noot: AF = antecedent factors, PF = propensity factors, S = source, T = target, E = engine, C = cognitive, NC = noncognitive, Ef = efficiency

4.1 The effectiveness of an adaptive digital educational game for the training of early numerical abilities in terms of cognitive, noncognitive and efficiency outcomes

This study concerns the effectiveness of an adaptive digital game for learning early math skills (Number Sense Game, NSG¹). Children ($N = 84$, age range 6-7 years) in first grade of primary education were randomly assigned to a condition in which children trained early numerical skills with an adaptive version of the NSG, or to a condition in which they trained with a nonadaptive version of the same game. The training took place over a period of three weeks resulting in six training sessions in total.

In terms of source of adaptivity, the adaptive version of the NSG adapts for children's cognitive variables and more specifically their ability as continuously measured based on the individual performance during gameplay. The target of adaptivity was the difficulty of the task which was determined based on the performance of the children through psychometric modeling techniques (i.e., Item Response Theory, IRT). The engine of adaptivity was inspired by the Elo-rating system [37], a rating of the learners' ability was constantly updated and adjusted after each item response during game play. The adaptivity can be described as system-adaptivity as it was the tool itself which diagnosed the learners and subsequently decided about the next task. In the nonadaptive version of the NSG, the levels were presented with theoretically-assumed increased difficulty, however children could always proceed to the next level regardless of their performance.

In terms of measurement, near (number line estimation and digit comparison) and far (math ability) transfer outcomes were assessed with standardized tests before, immediately after the intervention, and delayed after two weeks. Math anxiety was assessed with a questionnaire administered one-on-one before and two weeks after the intervention. Efficiency outcomes were operationalized based on pretest-posttest outcomes and registering the training time needed to achieve particular learning gains. It was also examined whether the effect of the intervention was moderated by the children's prior knowledge.

In terms of cognitive outcomes, children showed improved scores on all trained skills (i.e., digit comparison, number line estimation) from pre- to posttest, with no observed differences between the adaptive and nonadaptive condition immediately after the intervention. Second, no differences were observed regarding transfer skills between the adaptive and nonadaptive condition on mathematical competence. Third, delayed posttest results showed significant improvements compared to the pretest in all conditions. However, no differences between the conditions immediately after the intervention and delayed after a few weeks were observed. Fourth, regarding the effects in terms of individual differences, children with high/low prior knowledge or children with different SES backgrounds equally benefited from the adaptive or nonadaptive condition. In terms of noncognitive outcomes, the results revealed that children's math anxiety scores decreased from pre- to posttest, but no differences between the adaptive

¹ Developed by De Smet, Elen, Luwel, Onghena, Reynvoet, Torbeyns, Van Dooren & Verschaffel (GOA)

and nonadaptive condition were determined. In terms of efficiency outcomes, the results indicated that children assigned to the adaptive condition needed significantly less time compared to the nonadaptive condition to achieve the same learning goals. Interestingly, for number line estimation tasks, a significant interaction between prior knowledge (score on number line estimation task) and condition was obtained; children with high prior knowledge benefited more from the adaptive game condition, in the sense that they needed less time to obtain the learning goals compared to children with high prior knowledge in the nonadaptive condition. By contrast, children with low prior knowledge needed significantly more time in the adaptive condition to reach the learning goals compared to children with low prior knowledge in the nonadaptive condition.

4.2 The effect of adaptivity in digital learning technologies. Modelling learning efficiency using data from an educational game

This study concerns the same data collection as the study described in 4.1. Information about the target group, number of participants and adaptivity can be found in 4.1. This study attempts to empirically validate the beneficial impact of an adaptive digital game by analyzing logdata from the Number Sense Game (NSG), an educational game that trains early numerical skills. This study differs from the one presented in 4.1 as a more fine-grained operationalization of learning efficiency was obtained by using logdata collected during gameplay.

In terms of outcomes, this study only investigates the effect of the adaptivity in terms of learning efficiency. Therefore, a longitudinal random IRT model was used to model and compare children's progress within and across sessions between the adaptive and nonadaptive version of the game.

The results showed that the students made progress both in the nonadaptive and the adaptive version of the NSG, but that the adaptive version stimulated learning more. The implemented adaptivity increased learning efficiency across (i.e., the extent to which a student on average improved from one session to the next sessions), but not within a game-playing session (i.e., the extent to which a student on average improved within a session). The higher learning efficiency in the adaptive version, however, did not lead to higher estimated abilities at the last response of the last session (i.e., final skills). This observation corresponded to the findings described in 4.1, which were based on a pre-posttest analysis, and provided evidence that, when not improving cognitive or noncognitive outcomes, adaptivity in educational games can foster learning efficiency.

4.3 The strength and direction of the difficulty adaptation affect situational interest in game-based learning

This within-subject study investigated the effect of adaptivity on children's situational interest in a digital game called Number Trace learning game. In total, 167 children (age $M = 11.61$ years) practiced fraction understanding with the game for four 45 min sessions during two weeks. Each child was alternately assigned a basic non-adaptive level and then an adaptive level. The adaptive level was based on the student's result in the basic non-adaptive level.

The source of adaptivity in the game was the learners' cognitive ability. More specifically, the adaptivity was based on the learners' estimation accuracy in the preceding nonadaptive basic game level. The target of adaptivity was the fraction magnitude estimation accuracy threshold required for an answer to be considered as correct. Based on the learner's estimation accuracy, the direction (upwards or downward) and strength of the difficulty adaptation was adjusted in the adaptive game level. Regarding the engine, the game system only was responsible for the diagnosis of learner variables and the presentation of the next tasks. Learners were diagnosed during gameplay based on the logdata.

The study focuses on the effectiveness of the adaptive game in terms of noncognitive outcomes. Regarding noncognitive outcomes, first, situational interest was measured as the

researchers were interested in the in-game effect. Situational interest was measured during gameplay after each of the game levels with one question which could be answered by students on a 5-point Likert scale. A second noncognitive outcome was perceived difficulty, another in-game effect that was measured. Immediately after finishing the game levels perceived difficulty was assessed on a 9-point Likert scale. In addition, task correctness was measured during gameplay and used as manipulation check.

The task correctness measure and perceived difficulty measure were only used as a manipulation check, i.e. to see whether the strength and direction of adaptation affected children's task correctness and perceived difficulty, which was indeed the case. In terms of noncognitive outcomes, the results indicated that only downwards adaptivity (i.e., decreasing difficulty of items) had a positive effect on children's situational interest while upwards adaptivity (i.e., increasing difficulty of items) significantly decreased children's situational interest.

4.4 The effect of adaptive difficulty adjustment on the effectiveness of a game to develop executive function skills for learners of different ages

The goal of this study was to investigate the effect of adaptivity on learners' executive function skills. A randomized control design was adopted with 101 students ranging between 10 and 17 years old (age $M = 12.13$). The Alien game was used during the intervention which aims to increase learners' executive function skills of shifting. Learners were randomly assigned to the experimental condition where they were expected to play an adaptive version of the Alien game, or to the control condition where they were expected to play a nonadaptive version of the Alien game.

The source of adaptivity in the game was the students' performance in executive skills. This was measured based on the players' performance. The target of adaptivity was the difficulty adjustment of the tasks students were presented with during gameplay. The engine of adaptivity concerned difficulty adjustment of the game which changed after three consecutive correct responses or after each incorrect response.

A pre- and posttest measuring learners' executive functions (EF) skills was administered with a standardized test (i.e., the Dimensional change card sorting task). Alongside, students' actions within the game were logged such as their accuracy, missed responses, and difficulty adjustments by the adaptive game.

The results showed that in the adaptive and nonadaptive conditions learners' EF skills significantly improved from pretest to posttest, independent of the condition they were assigned to. Furthermore, a significant difference by age was observed. More specifically, learners of 15 years or older performed better on the EF test compared to younger groups of players. Additional analyses showed a trend that the effectiveness of the adaptive games on EF skills may be moderated by observing that learners benefited more from playing the adaptive version of the game compared to the nonadaptive version of the game.

4.5 The effectiveness of adaptive versus non-adaptive learning with digital educational games

The aim of this study was to investigate the effectiveness of an adaptive game to promote early reading skills. The study includes children of the third grade of Kindergarten ($N=191$). The effect of an adaptive version of the Reading Game (RG) compared to a nonadaptive version of the RG and an active control group, on young children's cognitive and noncognitive learning outcomes was investigated. Participating classes were randomly assigned to either an experimental or control condition and subjects in the experimental condition were randomized within the adaptive and nonadaptive game condition. In the active control condition children received similar tasks as in the RG, but these tasks were not embedded in a digital game, and thus, there was no feedback or attractive narrative and all children received the same number

and difficulty of exercises. The intervention lasted four weeks, with two 30-minute sessions a week.

The source of adaptivity in the RG adapts for cognitive variables and more specifically the ability of the learner to read. Second, the ability of the learner is measured continuously based on the learner's performance during gameplay. Inspired by the Elo-rating system [32], the ability or rating for the players was constantly updated and adjusted after each item response. Psychometric modeling techniques (i.e., IRT) were adopted to determine the difficulty of the tasks based on the performance of the students [37]. Third, the adaptive learning environments adjusted the number of tasks based on the learner's ability during gameplay. In the nonadaptive version of the RG, the levels were presented with increased difficulty level as in the original RG.

Pre and post near (phonological awareness, letter knowledge) and far transfer skills (reading ability) were indexed. Concerning noncognitive factors, children's interest in reading and self-concept were assessed. Prior knowledge, home language and SES were taken into account to investigate how these variables moderated the effectiveness of the intervention.

Regarding the results, first, on all near transfer skills, children showed improved scores from pretest to posttest. Concerning the differences between the adaptive, nonadaptive and active control conditions, no differences between the conditions were observed immediately after the intervention. Second, regarding far transfer, we observed no differences between the adaptive, nonadaptive and active control condition on general mathematical competence or reading fluency. No significant interaction effects of condition and prior knowledge, condition and home language and condition and SES were observed indicating that none of these factors moderated the cognitive outcomes of the intervention. Regarding interest in reading and self-concept towards reading, no differences were observed between the adaptive, nonadaptive and active control condition. Consequently, children's noncognitive outcomes were not affected by the adaptive RG.

4.6 Adaptive scaffolding and engagement in digital game-based learning

The aim of this paper was to investigate the effect of adaptive scaffolding on students' learning performance and engagement. In total, 61 students from a Taiwan secondary school (mean age = 13) participated in the study. The students were randomly assigned to an adaptive scaffolding group or a non-adaptive scaffolding group. The digital learning game 'summon of magiccrystal' was used about six hours during two weeks to enhance students' knowledge about Newton's laws (physics). To answer the research questions, a pre- posttest intervention study design was used.

The source of adaptivity is the ability level of the student concerning the learning content. The diagnosis of learner variables and adjustments were done by the system. Learner variables were diagnosed during gameplay and logdata (i.e. progress data and answer results) were used to assess students' ability. The target of adaptivity was that scaffolds (e.g. explaining relevant concepts, clarifying a task, or prompting learners to further consider a problem), were shown only when the system estimated that the student would need the scaffolds. Students in the nonadaptive condition received all pre-planned scaffolds in a fixed order.

Students' near transfer skills were assessed before and immediately after the intervention with a non-standardized test (i.e. 30 items measuring conceptual understanding of physics). Furthermore, students' engagement was measured through four subscales immediately after the intervention with a questionnaire that was based on a validated instrument.

The results indicated that students in the adaptive game condition performed better at posttest compared to students from the nonadaptive game condition. Also students' engagement showed to be significantly higher on three out of four scales of the instrument measuring engagement. Finally, no moderation effect was observed of level of engagement on the relation between types of scaffolding and performance.

5. Discussion and concluding thoughts

The aim of the study was twofold. First, we aimed to develop a new conceptual framework that accounts for a broad evaluation of the effectiveness of adaptive digital games, integrating insights from different theoretical frameworks concerning learner differences, adaptivity, and measured learning outcomes. Second, our goal was to investigate whether this framework can be used for analyzing previous literature about the effectiveness of adaptive digital games for learning. Based on this mapping, we can infer what current gaps and challenges are regarding 1) differences between learners when evaluating the effectiveness of an intervention, 2) differences in operationalization of adaptivity in a learning environment, and 3) differences in type of learning outcomes and when and how they can be assessed.

First, three (out of six) studies examined whether there was a moderating effect of individual differences on the effectiveness of the adaptive digital educational game. Propensity factors such as prior knowledge were investigated in the studies [19] and [20]. Antecedent factors such as home language, SES and age were examined in the studies [20] and [36]. Given the limited number of studies that took into account differences between learners when evaluating the effectiveness of an adaptive digital game, it seems that much insight can be gained by taking into account both propensity (e.g., prior knowledge, executive functions, motivation, anxiety) and antecedent (e.g., gender, SES, age) factors in future studies.

Second, in terms of tool adaptivity, there was little variety in how the adaptivity in the digital game was operationalized. Regarding the source, all studies adapted to cognitive learner variables (such as math skills, executive function skills or reading skills). The target of adaptivity was in most cases the difficulty of the tasks that changed. While in some studies the difficulty could only be adjusted upwards (e.g., [19]), in other studies also downwards adaptivity was possible (e.g., [24]). In one study, the number of tasks learners were presented changed based on their ability [20]. In the study of [35], the target was the scaffolds that were given based on the system's estimation whether the student needed help, clarification or prompts to encourage students to do an action [35]. Regarding the engine, the diagnosis of learner variables and assignment of follow-up tasks was in each study conducted by the algorithm underlying the game. In each study included in the review, learner variables were diagnosed during gameplay only and learner variables were assessed based on logdata. To further expand our knowledge about the effectiveness of adaptive games, two recommendations can be given. First, the operationalization of adaptivity in previous studies did not differ a lot. Future studies can focus on more variety in source (e.g., also taking into account noncognitive learner variables) and target (e.g., adjust the feedback or instruction) of adaptivity. Furthermore, often only one (small) aspect changes based on one learner variable. There is a need for more larger adaptations in educational games, but obviously this requires more innovation in technologies. In terms of engine, we observed similar results as [17] that studies investigate mostly dynamic adaptive learning environments where the ability of the learner is constantly updated during the intervention. Second, we did not identify any paper that compared different forms of adaptivity. In the future, we encourage researchers to expand the value-added approach by, for instance, comparing two conditions (e.g., adaptation based on a single cognitive factor such as knowledge versus multiple factors such as knowledge and metacognition). Third, recent research acknowledges the importance of the role of the teacher to strengthen personalization above the tool-adaptivity [39]. Next to the adaptivity that is implemented in the digital game, the teacher can act as an additional source of personalization [17]. Similar to the adaptivity underlying digital games, this personalization might vary in terms of the source and target of the personalization as well as the way in which the learner variables are diagnosed by the teacher [15]. For example, studies experimentally investigating how the data provided on a teacher dashboard can better support specific learners could be an avenue for future research. Teachers may additionally adapt their instruction to students' needs,

for instance, by providing additional instruction based on the data that are generated by the adaptive digital game (e.g., by the teacher dashboard) [17], [25]. In the five studies we discussed, the games were all implemented in isolation to enable researchers to derive the effectiveness of the digital tool itself.

Third, a range of learning outcomes were considered in previous studies. The effectiveness of the adaptivity was investigated in terms of cognitive (i.e., [19], [20], [36], [35]), noncognitive (i.e., [19], [20], [24], [36]) and efficiency outcomes (i.e., [19], [31]). Studies [19] and [20] not only measures near transfer skills (i.e., achieving the learning goals of the game), but also includes tests measuring far transfer (i.e., meaning that the effect of the training is assessed only in terms of learners' progress on the trained skills). Regarding noncognitive outcomes, both in-game effects as well as transfer effects were measured. For example, [24] measured in-game effects by assessing situational interest during gameplay. [19] assessed whether playing a game that trained early numerical skills led to a decrease in math anxiety which can be considered a far transfer noncognitive learning outcome as playing the game may have an effect on perceptions on learning a specific subject. Compared to the critique raised in previous studies that evaluations are often limited to investigating near transfer cognitive outcomes, it seems that there is a shift towards broader evaluations. In terms of when and how the learning outcomes were measured, learning outcomes were assessed during gameplay in three studies, immediately after the intervention in four studies and delayed in one study. The number of studies investigating the effectiveness of adaptive games in the long term still seems limited but nevertheless crucial to gain insight into the sustainability of the intervention effects [40]. In contrast, it seems that the number of studies that are investigating children's cognitive and noncognitive factors during the intervention is increasing. Benefits are that this data can give a more fine-grained idea about how children's knowledge and skills develop [41]. Finally, different data sources were used to assess different types of learning outcomes: logdata (i.e., [24], [31], [36]), questionnaire (i.e., [19], [20], [24], [35]), test (i.e., [19], [20], [36], [35]). To obtain a more complete picture of how children's noncognitive factors vary between conditions and from pre- to posttest, the additional use of unobtrusive (e.g., physiological) measures during gameplay may be an interesting avenue for further investigation [42], [43].

The study showed that there are still a number of methodological, pedagogical and conceptual challenges for a sound evaluation of adaptive digital games. In terms of methodological challenges, until today only few research investigated the effectiveness of adaptivity in an adequate way. In the future, the framework may be used to consider the appropriateness of the design of the studies investigating the effectiveness of adaptive games. We encourage researcher to conduct (quasi-)experimental research comparing adaptive with non-adaptive game conditions (or another adaptive game condition). One difficulty may be that differences between adaptive and nonadaptive versions of the same game are currently subtle and therefore rather difficult to observe differences in learning outcomes between conditions. Therefore, one promising avenue is to increasingly use logdata, eye tracking data, or psychophysiological data because these can offer precise measurement [28]. In terms of pedagogical challenges, close collaborations between instructional designers and game developers are required to assure that the adaptivity addresses propensity factors that have been shown to be important for learning. One avenue for future research is to investigate the relation between learning goals and type of adaptivity. For example, different types of adaptation may be differently valuable for different learning content. A static learning environment may provide adequate support for the acquisition of straightforward procedural knowledge, while more challenging cognitive skills or knowledge, such as overcoming the natural number bias, may demand a more complex adaptation. Another pedagogical challenge is when implementing adaptivity in educational games that by adjusting the difficulty of learning contents or adjusting the sequence of learning events, these measures interfere with games' storylines, potentially breaking the narrative [3]. Concerning conceptual challenges, we encourage researchers to

describe the adaptivity in the game based on the different dimensions of adaptivity proposed in the framework. This way, the results of studies can be interpreted in view of the degree of adaptivity within the game.

In sum, the proposed conceptual framework offers a number of advantages. First, it provides terminology that allows for discussion about the effectiveness of adaptive digital games for learning. The framework unpacks relevant but complex concepts such as learner variables, adaptivity and learning outcomes which can help to discuss the effectiveness of adaptive games in a nuanced way. Second, the framework can help to compare and summarize findings across studies regarding the effectiveness of adaptive digital games, as well as to interpret mixed findings as reported in previous reviews and meta-analyses [12], [14]. Third, the framework is valuable to uncover current gaps in educational research (see suggestions in previous sections). Fourth, the framework can offer terminology to describe the design of intervention studies. This would be particularly useful in terms of pre-registration of studies which has been increasingly encouraged in recent years. Fifth, the framework can support teachers and practitioners to evaluate the usefulness of adaptive tools for their classroom practice. Teachers can analyze adaptive tools they consider to implement in their practice based on the adaptivity subcategories target, source and engine. Finally, the framework pushes forward theory with respect to investigating the effectiveness of adaptive digital games by integrating different theories (Opportunity-Propensity framework, different conceptualizations of adaptivity, and educational evaluation frameworks to assess game effectiveness) into one conceptual framework.

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Conflicts of interest

The authors declare that they have no conflict of interest. All authors agree with the content of the manuscript and authorship order. This submission represents our own work. This manuscript has not been published and is not under consideration for publication elsewhere.

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