Computers and Education Open 2 (2021) 100058

Contents lists available at ScienceDirect

Computers and Education Open

journal homepage: www.sciencedirect.com/journal/computers-and-education-open

A large-scale systematic review relating behaviorism to research of digital technology in primary education

Fabian Gunnars *

Department of Education, Mid Sweden University, Holmgatan 10, Sundsvall 851 70, Sweden

ARTICLE INFO

Keywords:
Elementary education
Evaluation methodologies
Improving classroom teaching
Teaching/learning strategies 21st century abilities

ABSTRACT

Behaviorist methodological considerations in the learning sciences are rare compared to the 20th century. As a result, researchers may be conditioned towards an unbalanced and fragmented evidence base for the improvement of classroom teaching in primary education. The presented systematic literature review relates research of digital technology and learning in primary education to expected learning in primary education. In total, 641 articles published 2011–2020 were included and 2777 were excluded by full-text criteria review using radical behaviorist methodological presuppositions.

Findings show a low but increasing frequency of articles with behaviorist approaches, optimistic expectancy and evidence of learning in primary education through use of digital technology, and a trend for research to emphasize representational functions of digital technology. The relevancy of radical behaviorist methodology is discussed based upon the implications of the findings and other 21st century themes.

1. Introduction

In the learning sciences, behaviorism is considered a well-established approach. As a major part of foundational scientific theorizing, behaviorism dominated many methodological approaches for most of the 20th century [49]. These decades of widespread behaviorist methodological approaches are nowadays regarded by scientists in different light, often dismissed as an important but obsolete part in historical overviews presenting research [48]. The period has even been referred to as the "dark ages" where "nothing worthwhile was discovered" ([5], p. 171) on the motivational influences to learning due to narrow methodological approaches. For example, radical behaviorists reject so-called inner influences often derived from self-reported data without contextual relations [51]. In contrast to these dark ages, studies of digital technology may relate the use of such technology by emphasizing motivational influences and optimistically expect improved learning in primary education [25]. However, there are indications that such improvements might not extend to educational achievement outcomes, despite the widespread use of digital technology [54].

As educational achievement outcomes are a common way for teachers to determine the learning of their students, researchers may need to consider such narrow limitations [43]. This is especially true for research in primary education, as self-assessment may be a difficult task for children [39]. Further, recent technological developments have enabled education policy-making based on highly sought-after large-scale data with bodily and biological conditions [64]. These kinds of conditions for data use could relate an approach to a genetic epistemology. Radical behaviorism presupposes a genetic epistemology [7]. The scientific underutilization of such data may pose an ethical risk of leaving that which might have been scientifically controlled in other hands [52]. In the years 2011–2020, many important and valid literature reviews in the learning sciences have been published (e.g. [17,25, 54,59]) but very few have explicitly had a behavioristic emphasis.

The developments outlined above, combined with large-scale initiatives such as the EU's digital education action plan, clearly indicate the relevancy of deepening our contextual understanding regarding "digital education content and training in digital skills – including digital teaching methods" ([14], p. 10). Thus, this review aims to provide radical behaviorist methodological considerations related to data types and motivational influences to learning in the current literature of digital technology and primary education.

1.1. Relating digital technology in primary education to motivational influences

In an effort to emphasize student-centered learning, many

E-mail address: fabian.gunnars@miun.se.
* ORCID: 0000-0002-9803-3358

https://doi.org/10.1016/j.caeo.2021.100058
Received 10 March 2021; Received in revised form 2 September 2021; Accepted 6 November 2021
Available online 12 November 2021

researchers of digital technology in the learning sciences focus on motivational influences rather than behavior [17,59]. Motivational influences are often thematically related to primary education by the inclusive notions that students "learn better when they are engaged" ([20], *p.* 187) and when teachers "allow the independent work of students" ([19], *p.* 15). By contrast, regulatory behavioral control might reduce the teacher workload but demotivate the students as they become less independent [1,47].

Digital technology has according to Crook and Sutherland [11] previously been identified by researchers of primary education with certain historical contingencies, such as heavy reliance on behaviorist approaches or constructivist research efforts such as LOGOs proposed by Papert [44]. Nowadays the digital can be understood as mainly characterized and identified by a ubiquitous quality [63], providing access to services anytime and anywhere. Such services are enabled by different 21st-century technology, including tablets and smartphone devices due to their lightweight, stationary computers and laptops with internet access, and software that may enable networked outcomes [30,63].

Digital technology may also enable "multiple representations of information, such as pictures, video, and animation" ([43], *p.* 44), providing independent and inclusive accessibility for students [50]. Such findings have commonly been related to special education, where multiple representations have supported students with special needs [26]. Motivational influences for learning appear related to digital technology when student independence is supported inclusively [57]. Motivational influences also seem to benefit cognitive functions for the retention of previous learning [5]. This is indicated by studies that have approached data with methodologies involving complex brain scanning equipment [42]. Assuming digital technology potentially relates to motivational influences, such technology could be expected to reinforce learning in primary education [57]. The potential of digital technology to reinforce learning can be optimistically expected to improve even further as it is "constantly evolving due to the rapid developments in technologies" ([65], *p.* 217).

1.2. Researching expected learning in primary education

Despite the expected learning potential of digital technology [65], an international report by OECD [41] indicates that the widespread use in primary education "has not resulted in progress in relation to students' educational achievement" ([54], p. 116). Many literature reviews have evaluated why this is the case, such as beliefs held by teachers (e.g. [17, 59]).

Researchers of digital technology and learning may approach students' educational achievement in primary education by different methodologies that condition presuppositions for research methods [25]. Broader social approaches are according to Anderson and Shattuck [2] and Michos and Hernández-Leo [33] valid and important but may be methodologically restricted when emphasizing "practical constraints and the specific context" ([2], *p.* 17) such as relating students' educational achievement for the analysis of learning.

The reviews with broader social approaches (e.g. [17,54,59]) emphasizes motivational influences and their expected relation to digital technology and learning in primary education. However, while explicitly deemphasizing behaviorist approaches, Tondeur et al. [59] also explicitly emphasize the need for further "consideration of the school context" ([59], *p.* 567) in addition to the motivational influences.

In a primary educational context, achievement outcomes are commonly distinguished through teaching that does not take motivational influences into account, but rather the behavior that was motivated by such influences [37]. For example, self-assessment may for children be "psychologically difficult to perform and troublesome to communicate" ([39], *p.* 6). Some approaches may better be suited for researchers that emphasize achievement outcomes through contextual relations [51].

The commonly used distinctions of qualitative, quantitative, and mixed methods as seen in the literature review by Spiteri et al. (2020), do not distinguish between self-reported data (e.g. research methods primarily outlining language and beliefs, such as survey questionnaires and interviews), and behavioral data. Even when the distinction is made, broader social approaches may equate behavior to self-reported data through a bi-directional relationship [59].

According to Li et al. (2019), the majority of research on digital technology in the learning sciences "are based on teachers' self-reported data" ([28], *p.* 25). Widespread unbalanced use of research methods aimed at gathering self-reported data may risk a limited and fragmented evidence base [43]. Self-reports are especially restricted when emphasizing behavior [40]. Complimentary approaches for a more balanced use of data may provide valuable contextual findings [11]. In short, there may be benefits to behavioristic approaches that currently are underutilized [6].

1.3. Contextually relating behavioral outcomes

There are many behavioristic approaches, which generally are considered as well-established for emphasizing expected learning from contextually related outcomes [49]. Relating context from a radical behaviorist approach conditions research methods to a strictly defined event of behavior (e.g. actions, conduct, demeanor, doings, mannerisms) that according to radical behaviorist presuppositions can be described without reference to feelings, thoughts, opinions, attitudes, theories, or political tendencies [53]. Knowledge is from a radical behaviorist approach considered as learned from such an event by observable effects in the future related "upon other behavior" ([52], *p.* 410).

The radical behaviorist view of knowledge relates to a genetic epistemology, characterized by a physiological process that originates and develops in the contextually related human being [7]. Radical behaviorism is according to Carrara [7] incompatible with the neobehaviorism of theorizers such as Carnap, Schlick, or Tolman and Hull, as they heavily emphasize mathematical equations and deductive logic. Such emphasis on mathematical equations and deductive logic "when it's not needed is not science but *scientism*" ([56], *p.* 28).

As opposed to the broader social approaches, behaviorism determines learning by narrow measures and comparison of contextually related outcomes and observable parts [11]. This results in a narrow and distinct view of teachers in primary education, in which their profession relies on consequent and sequential educational reinforcement of students' motivational influences by "approval or other social reinforcers explicitly contingent upon scholastic behavior" ([52], *p.* 405).

While a behavioristic analysis prima facie may appear archaic and perhaps even unhelpful for broader social approaches [5], recent technological developments might indicate the opposite. According to Williamson [64], new data-driven technologies that sometimes solely depend upon large-scale quantities of biometrical data with bodily and biological conditions are currently sought after by educational policy-makers and governance. Such conditions for use of data could relate an approach to a genetic epistemology. Similar to technological advances in the past, observable events shift "with every discovery of a technique for making private events public. Behavior which is of such small magnitude that it is not ordinarily observed may be amplified" ([52], *p.* 282).

A radical behaviorist approach may not guarantee findings of all the valid and important levels of complexity in primary education. However, limiting the scope to behavior may provide "sequential construction involving simpler task constituents" ([11], *p.* 13). Such a narrow behaviorist scope may in part be required for the scientific rigor of broader social approaches [7].

The development of digital technology originally drew heavily on the behaviorist approaches [11]. The bodily and biological conditions of recent technological developments [64], might from a radical behaviorist genetic epistemology indicate an amplified complex shift from the levels of biological, chemical and physical to the observable cultural level [7,52]. This may in part indicate the relevancy of radical behaviorist methodology for research that relates digital technology to learning in primary education.

1.4. Research questions

This review aims to provide radical behaviorist methodological considerations related to data types and motivational influences to learning in the current literature of digital technology and primary education.

RQ1: What data types do studies that relate digital technology to primary education depend on, according to radical behaviorist methodological presuppositions?
RQ2: How do studies of digital technology thematically relate motivational influences to expected learning in primary education?
RQ3: What outcomes have been reported by studies that relate digital technology to primary education and learning with behavioristic conditions?

2. Methodological approach

This is a systematic review. The approach is considered scientifically valuable due to the high requirements of explicit details throughout [23]. To a certain extent, explicit details ensure the removal of bias, as steps of the process easily can be retraced. Systematic literature reviews are also considered appropriate for methodological considerations, relevant to the aim of this review [23]. The protocol for systematic reviews and meta-analyzes as described by the 17-item checklist of the PRISMA-P statement [34] was followed and interpreted in the spirit of guiding advice to navigate the reporting of the review.

2.1. Planning and search strategy

Some concepts discussed in this review are broad and often relate to historical contingencies not necessarily defined in the previous sections of this review. The wide and changing nature of the research fields provides substantial challenges to provide a comprehensive overview that is balanced in complexity yet adheres to the goal of a systematic review to "detect as much of the relevant literature as possible" ([23], *p*. 2). This may be true for most fields that relate to technology, but especially true for digital technology [65]. Thus, the inclusion criteria for the reviewed literature are wide and correspond to the aim and RQs outlined in the previous section of this review:

- Data detailing students or in-service teachers in primary education must be present.
- Digital technology and ubiquitous aspects must be related to learning in primary education.
- Expected learning in primary education must be discussed.
- Text need to be in English.

As planning for an appropriate search strategy, a prototype study was conducted from January to March 2020 with complex search strings related to concepts that were historically contingent on digital technology, yielding 215 record inclusions from the Web of Science database. The records were deemed as unreliable when reading the selected full-texts. For example, the ubiquitous quality of digital technology was sometimes referred to with other historically contingent names than the digital, and broader social approaches often referred to the concept of behavior differently. The unreliable results of the prototype study indicated a need for simple search strings, rather than complex search strings.

Another issue of the prototype study was the dependency on the title, abstract, and keyword for inclusion eligibility assessment. Certain articles distinguish data as self-reported or behavioral in the abstract section, but a majority solely present studies as either qualitative or quantitative. As a result, articles may contain data types omitted elsewhere, rendering the methodological distinctions of qualitative or quantitative as unhelpful to the aim of this review. Thus, an extensive search that included a full-text screening process from the start was required.

Only records identified by Scopus as articles were sought after. While conference papers and other publication types are of high value to a research field, they generally do not have as a strict peer-review process as journal articles. Further, they are often developed into journal articles at a later stage, which in effect would provide duplicate result inclusion without benefits to this review. To generate as a complete view of the relevant articles as possible, the search engine Scopus was chosen for its ability to include article results at a substantially higher level than other popular search engines [61]. The subject areas "MEDI", "BUSI", "BIOC" were excluded at this stage.

The extensive search was conducted with the simple search string: "primary AND (school OR education* OR learning) AND (digital OR technology)". Publication years included 2011–2020 in full, yielding 4203 non-duplicate results for full-text eligibility assessment.

2.2. Text mining open-code paper selection process

Large-scale data quantities were automatically processed and manually open-coded through text analytics and basic data mining, with the mixed-model qualitative analytic research software QDA Miner 6.0 [27]. Additionally, QDA Miner was used for what Kelleher et al. [21] refer to as machine learning algorithms, forming naïve Bayes network models and predictions. Such models are appropriate for text analytics, as "naïve Bayes models are often successful in this domain" ([21], *p*. 262).

Due to unreasonable accessibility requirements or low demand, any full-texts not retrieved after scripted DOI clean-up and manual CrossRef lookup or Google Scholar searches were excluded. After 786 articles were excluded due to unavailable full-texts, 3418 full-text documents were compiled into the software, and connected to publication year meta-data provided by SCOPUS search results.

Then, each reference section at the end of articles was manually removed to provide more accurate text mining. Following this, words, paragraphs, or sentences marked as quotations were automatically generated according to basic search expressions such as "data", "survey" and "higher education OR graduate". These quotations were used to manually code text in the full-text, title, or keywords with clear indications that the article did not satisfy at least one of the inclusion criteria.

With some exceptions, as part of the paper selection process were retraced, sampled, and iterated later during analysis, articles were excluded in the following order, included in Fig. 1: 385 were excluded due to not being written in English (notably, 50 of these were marked as English in Scopus), 1986 were excluded due to in-service teachers or students not being mentioned or related to learning in primary education, 167 were excluded as they used secondary data only, such as reviews and editorials, and 239 were excluded due to the technology discussed not aligning with the definition of digital used in this review. This rendered 641 articles to be included for analysis. None of the excluded articles affected the presented findings from the analysis, as the findings was separated from the screening process at a later stage. For publication year data relating the screening process, see Table 1.

2.3. Variable considerations for analysis

This review includes large-scale data quantities for statistical analysis of included articles. For this review to answer its research questions in part with statistical analysis, it requires construction of quantifiable variables in included articles based upon a qualitative evaluation of how the included articles relate to digital technology and learning. For

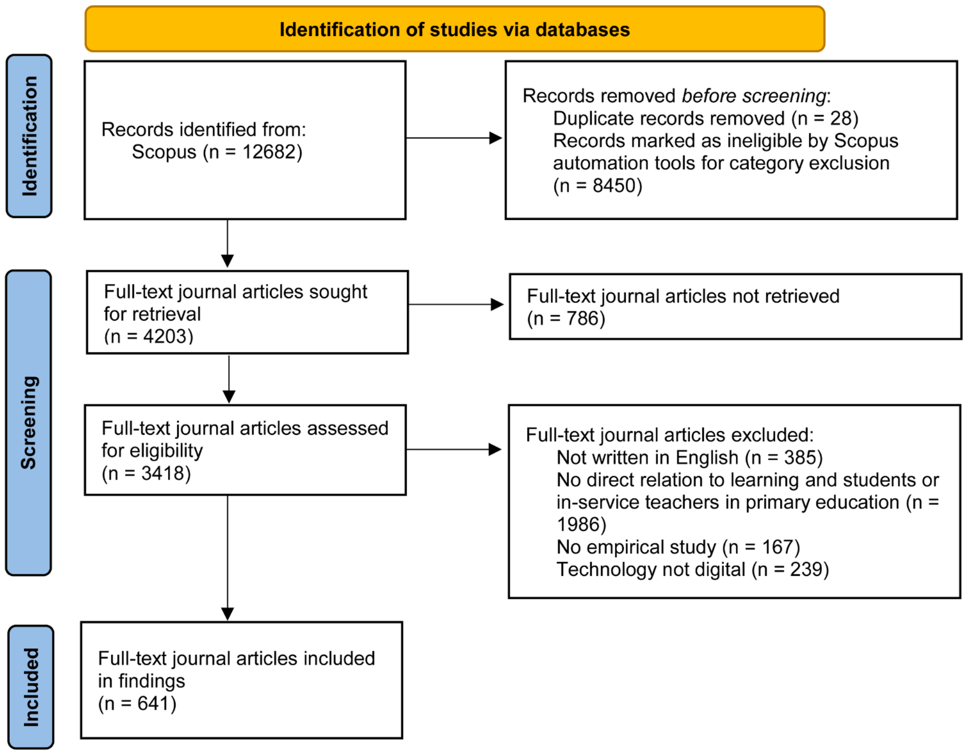

Fig. 1. PRISMA flowchart of the paper selection process.

Table 1
Publication year of the articles from the screening process.

PUBLISHED YEAR	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	TOTAL
INCL N =	41	41	44	40	42	48	58	75	110	142	641
=	1,0%	1,0%	1,0%	1,0%	1,0%	1,1% 1,4%		1,8%	2,6%	3,4%	15,2%
EXCL N=	189	199	270	268	315	345	341	356	540	739	3562
% EXCL	4,5%	4,7%	6,4%	6,4%	7,5%	8,2%	8,1%	8,5%	12,8%	17,6%	84,8%

example, articles might relate digital technology and the expected learning to themes of improved educational achievement of students and/or motivational influences. Included articles might analyze data from research methods such as self-reports from blogs. In this review, binary variables were coded according to details similar or identical to these examples. When the coding was complete, Statistical Package for the Social Sciences (SPSS) 25 was used for statistical computations, as QDA Miner does not provide such functions.

The data types were conditioned by two measures. The first measure was the data collection techniques, according to trustworthiness criteria adapted to studies of naturalistic inquiries, such as the collection of participant-generated artifacts, screen recordings, and questionnaires [10,38]. The second evaluated how the analysis was presented, measured according to the radical behaviorist presuppositions for distinguishing self-reports from behavior. The measures were later combined to outline data types, such as behavioral observation detailing mannerisms of students, or self-reported observation from classroom observations detailing beliefs based upon speech and language.

This evaluation is relevant to the aim of this review to provide radical behaviorist methodological considerations related to data types and motivational influences to learning in the current literature of digital technology and primary education. However, a potential risk for behaviorist bias is duly noted as it might have affected the interpretations, compared to broader approaches.

2.4. Text mining open code analysis and variable construction

Working on top of the guiding statistics and thematic estimations from the paper selection process outlined in Section 2.2, additional words, paragraphs, or sentences marked as quotations were automatically generated. These additional quotations were generated by basic search expressions and advanced fuzzy string search expressions related to the binary variables outlined above. These quotations were used as guidance when reading the texts by providing specific word counts for each document, or color-markings in the text used as thematic estimations.

Binary variables were then constructed by a general inductive approach [55,58]. Inductivism may be considered the preferential use for the radical behaviorist perspective [7]. The binary variable construction concerned the manual assigning of open codes to manually marked text chunks in conjunction with related sections such as paragraphs in proximity or title and keywords, to carefully evaluate variable relevance to assigned document. The same manually assigned codes were iteratively used as basic machine-learned fuzzy string search expressions according to limiting scripts, providing further guiding estimations of thematically color-marked text. Further additions and iterations to the paper selection process outlined above were also made at this stage. For an overview of the text mining process, see Fig. 2.

Given the large-scale data set, the process required extensive human, manual measures to ensure methodological rigor and variable reliability. Despite thorough efforts of (a) sampling any automatic process for validity, and (b) multiple retracing of every analysis step, results may

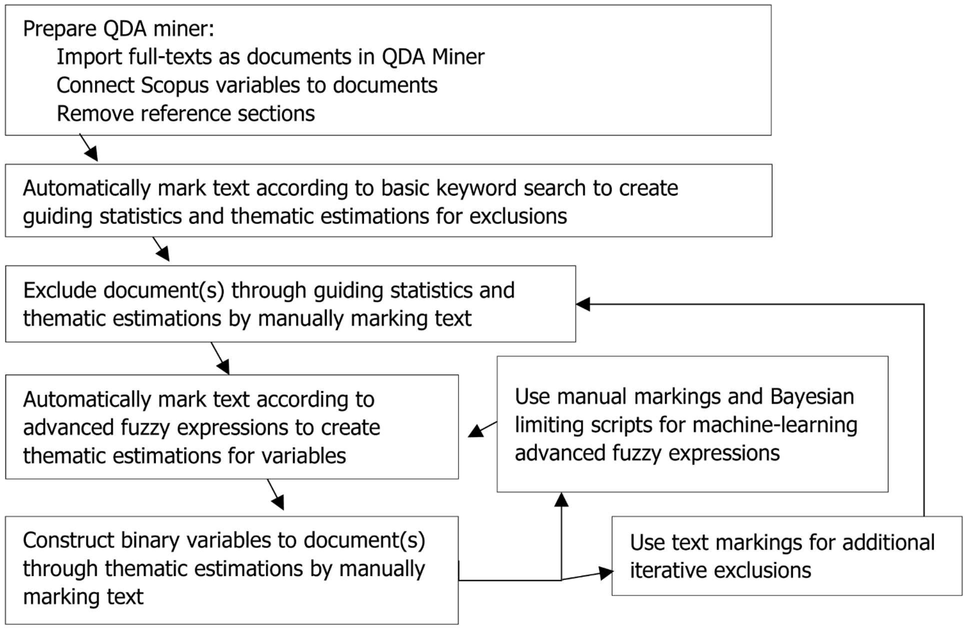

Fig. 2. flowchart of the text mining process for paper selection iteration, analysis, and variable construction.

have been affected by the limitations of the researcher. However, compared and tested against the prototype study which solely relied on titles, keywords, and abstracts, variable validity was extensively improved, as many articles would have been excluded due to omitted details.

3. Findings

As both qualitative and quantitative analysis were used for the review of included articles, findings below are not only presented through statistical computations but also with direct quotes as examples.

Five general categories emerged from the findings that address the first RQ of this review. These categories were conditioned on the radical behaviorist presuppositions of this review that distinguishes data types according to the measures of data collection techniques and distinguishing use of data for either behavior or belief in the analysis. The articles that include more behavioral data types than self-reported data types (e.g., 2 behavioral data types and 1 self-reported data type), or solely behavioral data types (e.g., 1 behavioral data type and no self-reported data types), were categorized as behavioral studies as they majorly depend on this data type in the analysis (see categories 4–5 in Table 2). Of the selected 641 articles of this review, 20,1% were behavioral studies.

3.1. Unbalanced distribution of data types

While much important work is being done outlining beliefs of in-service teachers and students, adding valid complexity to the field, findings demonstrate a skewed ratio to the distribution of these methodological approaches: 61,6% of the selected articles majorly depend on self-reported data (see data types 1,2 in Table 2). Even if behavioral data may not guarantee specific outcomes of a study, articles with behavioral data might compensate to the ratio, thus increasing the chances of relating or deepening knowledge of contextual constituents.

Table 2
Data type categories of the included articles.

DATA TYPE	SELF-REPORTED DEPENDENT STUDIES			BEHAVIORAL STUDIES	
	Only SelfrDa (1)	Mostly SelfrDa (2)	Balance (3)	Mostly BehavDa (4)	Only BehavDa (5)
ARTICLE N = TOTAL PERCENT	339 52,9%	56 8,7%	117 18,3%	47 7,3%	82 12,8%
CUMULATIVE PERCENT	52,9	61,6	79,9	87,2	100

The distribution of data types across 2011–2020 has fluctuated, most notable during 2014–2016 and 2018–2020 (see Fig. 3 which is adjusted for category comparison of publication year distribution according to light and dark colors). Compared to 2011–2014, the percentage distribution of published behavioral studies during 2015–2020 increased. This is a promising trend, as these behavioral studies might expand our knowledge about behavior that requires 21st-century skills. As it stands, “little is known about the effects of these skills on children’s cognitive development” ([3], *p.* 1). Currently, such skills seem to emerge and develop outside of primary schools, with examples such as the introduction of tablets to primary education classrooms that “has been so rapid and very much a grassroots development that was not centrally planned” ([9], *p.* 1052). This seems to be a reappearing object of study, as similar calls for research has been made in 2011, emphasizing that “teaching activities in high performing schools needs further analysis and represents an opportunity to focus policy design on the quality of the use of ICT” ([13], *p.* 1367).

3.2. Relating digital technology to primary education according to analyzed data type

The second RQ of this review is concerned with the way studies of digital technology thematically relate motivational influences to expected learning in primary education. These ways are outlined and discussed below.

Generally, articles with self-reported dependent studies had a positive statistically significant correlation ($r = 167, p < 0.01$) to themes that concerned student or in-service teacher equity of outcome related to digital technology and primary education. For example, a well-established concern is the digital divide, which outlines issues such as wealth and its effects on digital technology use [22]. Equity oriented articles also highlighted digital technology through special education-related issues such as activities “bearing in mind ADHD

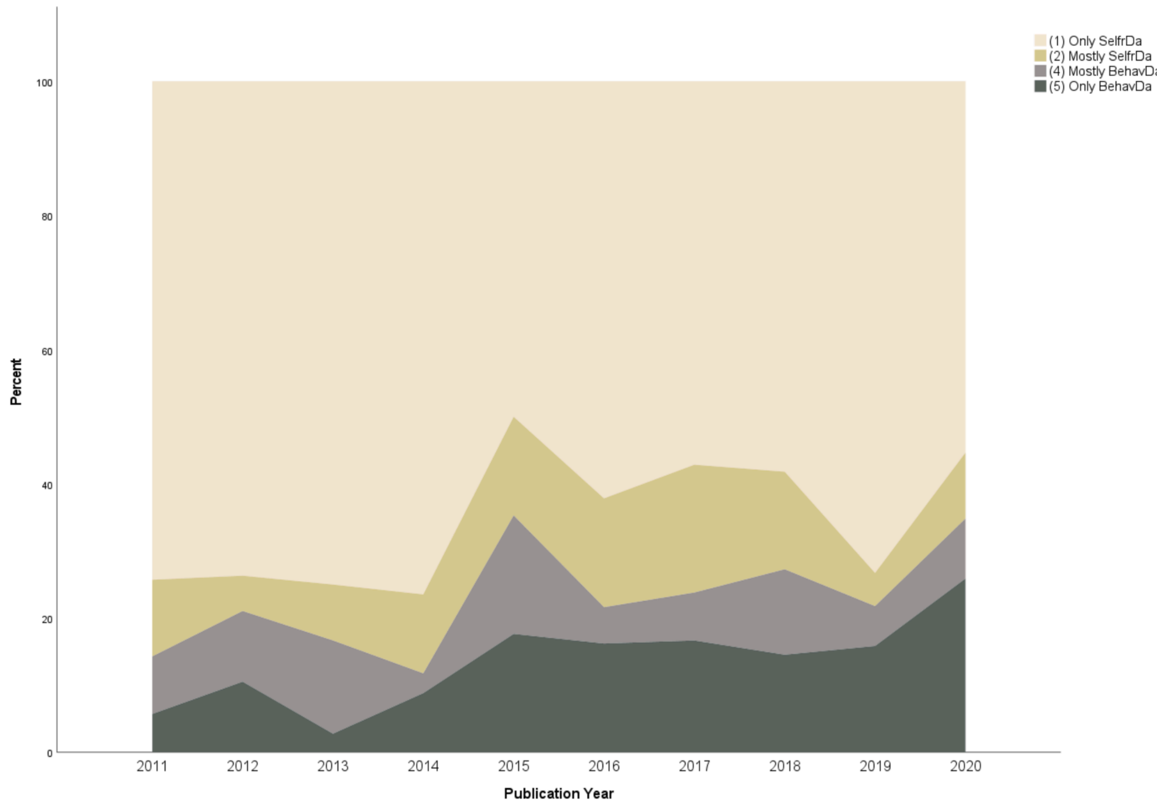

Fig. 3. comparison of publication year distribution according to dependence on different data types. The figure is adjusted as stacked by percent, with articles that analyze a balanced amount of data types removed. Darker colors show behavioral studies.

students' specific learning difficulties along with their learning styles" [29] or "use of constructivist learning integrating technology [that] allowed children in special education to be more active in defining their own learning goals" ([24], p. 801).

A positive statistically significant amount ($r = 232$, $p < 0.01$) of articles with behavioral studies thematically related educational achievement of its students to digital technology, clearly showing a consensus to the relevance of behavioral data types that emphasize contextual outcomes in the research field when relating students' educational achievement to learning. For example, some studies that rely on self-reported data conclude with mentions that "the results should be read with caution, since the assessment of the program has been carried out through a self-report test and not with real observations of actual behavior" ([15], p. 14), and conclusions may only reflect belief when "limited with self-reported data" ([32], *p.* 3429).

Behavioral studies also emphasized themes of multiple representations of digital technology a positive statistically significant amount ($r = 144$, $p < 0.01$). This result was contrary to some of the assumptions of this review, as discussions of multiple representations arguably benefit by themes of potential related to digital technology, yet articles that depend on self-reported data omit them to a greater extent than behavioral studies.

The focus of preferences to use technology rather than learning outcomes methodologically connects themes of potential, instead of actual use based on the school curriculum. Articles with self-reported dependent studies more frequently discussed themes related to the reformation of expected learning in primary education than other articles. A majority of these articles did this by surveys of in-service teacher preferences to use digital technology in primary education, presupposing potential benefits of digital technology in primary education. However, while the articles that discussed themes of reformation were more frequent in certain types of studies, this was not to a statistically significant extent.

3.3. Relating digital technology to primary education according to the year of publication

As both teachers and students adapt to technological developments, ways of relating digital technology to primary education in the included scientific literature that analyzes in-service teachers and students may change as the years go on. Thus, to further address the second RQ of this review, publication year data is valuable to analyze. According to simple regression analysis and publication year percentage distribution comparison, 2011–2020 have shown three major changes among the variables of this review. Other themes remained relatively stable across the years and data types. It must be noted, however, that 2017–2020 had higher publication rates than previous years, which may affect the presented findings below.

The first change concerns a declining trend of articles with themes of expected outcomes regarding the instrumental value of digital technology for teachers, showing a coefficient of -1629 and an adjusted R^2 of 0,003, std. deviation of 0,459. The second trend outlines a declining number of articles emphasizing digital technology and its ability to increase student motivation for learning, showing a coefficient of -1498 and an adjusted R^2 of 0,002, std. deviation of 0,499. These two trends may either indicate some novelty effects of introduced digital technology being worn off or a consensus of such themes as valid.

Finally, simple regression analysis also shows a major increasing trend during 2011–2020 of articles emphasizing multiple representation qualities of digital technology in primary education, showing a coefficient of 4976 and an adjusted R^2 of 0,036, std. deviation of 0,484. This could indicate a thematic research area that arguably illustrates the effects of digital technology developments, along with clear examples of potential use. While the statistical values for this increasing trend may have been affected by skewed publication rates, publication year percentage distribution also showed a similar major increase that confirm the trend (for a comparative example, see Fig 4 illustrating the

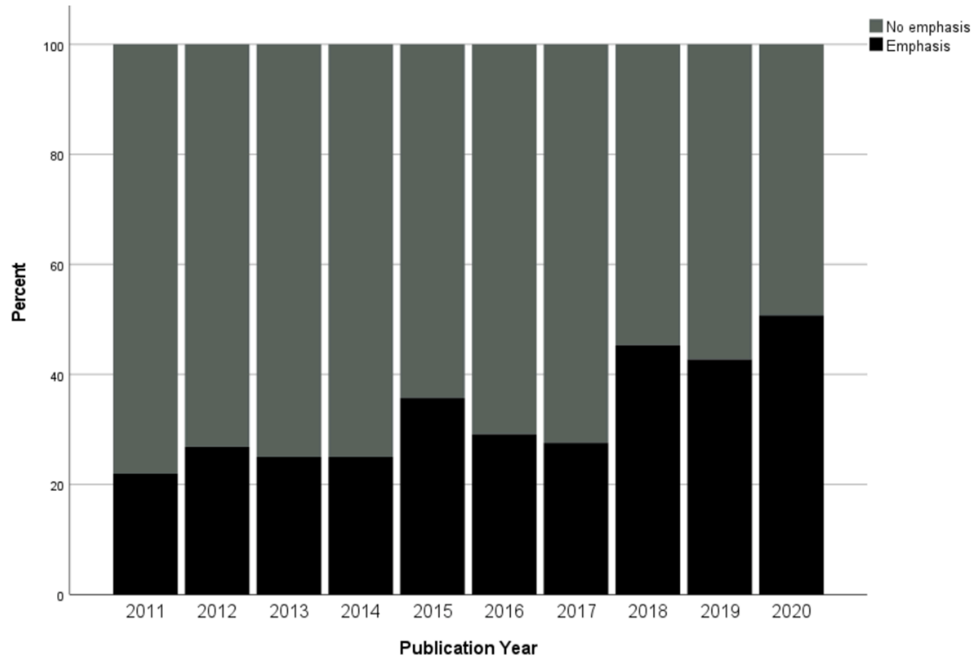

Fig. 4. comparison of publication year distribution of articles emphasizing multiple representation qualities of digital technology in primary education. The figure is adjusted as stacked by percent.

percentage distribution of each publication year).

3.4. Behavioral studies and learning outcomes

Evaluating expected learning outcomes from digital technology in primary education can be done by different methodological approaches, as previously discussed in this review. According to the measures conditioned on the radical behaviorist presuppositions outlined in the previous sections of this review, 129 articles were categorized as behavioral studies. Below, findings are presented that address the third RQ of this review, which concern outcomes that have been reported by studies that relate digital technology to primary education and learning with behavioristic conditions.

In general, the behavioral studies reported beneficial outcomes of digital technology in primary education in terms of student achievement, student scholastic behavior, or teacher classroom management as defined by each article. Compared to other curriculum subjects or domains, mathematics was overrepresented. In Table 3, behavioral studies were categorized according to the primary education curriculum domain and confirmed outcomes from findings of the studies.

The behavioral studies published 2011–2020 can be regarded to show optimistic findings of progress in relation to students learning outcomes in primary education through the use of digital technology. The articles also report potential disadvantages with similar conclusions as self-reported dependent studies. Disadvantages include increased "unintentional information management demands" ([12], *p.* 2275) for teachers, "extraneous cognitive load placed on the learners" ([8], *p.* 2), and the high market price of certain devices [46,62].

Based on other outcomes of the behavioral studies, the potential benefits or at least necessity for use of digital technology seem to be much greater than the disadvantages, if related to the correct context. More studies seem to focus on promising areas such as using multiple representations to monitor students' cognitive development and real-time activity information for assessment and classroom management [18,36]. The emerging field relating to this particular use of digital technology is commonly referred to as learning analytics [35], which seem to enable effective use of behavioral data for educational purposes.

Table 3
Behavioral studies confirmed outcomes according to curriculum domain.

CURRICULUM DOMAIN	Neutral	Worse	Benefit Outcome	Beneficial Management	TOTAL
Art	0	0	1	0	1
Digital Literacy	2	3	5	1	11
Generic Assessment	0	0	1	5	6
Generic Logic Construct	3	0	12	3	18
Generic Skill Construct	0	2	3	0	5
Generic Social Construct	1	1	6	0	8
Geography	1	0	0	0	1
Literacy	3	1	12	2	18
Literacy, Mathematics and Science	0	1	1	0	2
Mathematics	8	1	25	4	38
Mathematics and Generic Social Construct	0	0	1	1	2
Mathematics and Science	2	0	14	1	17
Music	0	0	2	0	2
TOTAL	20	9	83	17	129

3.5. Answers to the RQs

RQ1 concerned what data types studies that relate digital technology to primary education depend on, according to radical behaviorist methodological presuppositions. This review has outlined five data type categories that to a varying degree distinguish studies that rely on self-reported data from studies that rely on behavioral data. It further connected the categories to publication year data.

RQ2 concerned how studies of digital technology thematically relate motivational influences to expected learning in primary education. This review discussed the statistical significance of themes such as educational achievements of students related to digital technology, multiple representations of digital technology, and equity of outcome related to digital technology. It further connected the data type categories from RQ1 to these themes, and simple regression analysis based on publication year data were performed.

RQ3 concerned the outcomes that have been reported by studies that relate digital technology to primary education and learning with behavioristic conditions. This review analyzed general learning outcome findings of articles categorized as behavioral studies and connected them to primary school curriculum.

4. Discussion

4.1. Implications for research and practice

Alongside the radical behaviorist methodological presuppositions of this review ([7,52], 1974), the trend of increased articles with themes of multiple representations might explain the increasing percentage distributed frequency of behavioral studies, as they both relate a genetic epistemology.

Contrary to the international report by OECD [41], a majority of the behavioral studies included in this review showed optimistic learning outcomes in primary education through the use of digital technology. However, it is important to note the low frequency of confirmatory studies or published studies that failed to produce significant results. While the research field that studies digital technology in primary education has advanced contextual knowledge about behavior a great amount in 2014–2020, such emphasis is still underutilized compared to the advances in technology.

Combined with the declining trend of studies that emphasize motivational influences, considerations above confirm that in part, the findings of this review indicate that there is relevancy of radical behaviorist methodology in the learning sciences. As indicated by the findings, such methodology might prove useful to research on 21st-century technology themes. In short, such themes include:

- Further development of digital technology that teachers can use which would "allow the collection of data generated by the activity (e.g., multimodal interactions, learning analytics), their dynamic processing, and their use to support and enhance the embodied learning and teaching processes" ([16], *p*. 17).
- Increased awareness of the perceived value of technology that is not digital is currently "fading in today's educational environment" ([60], *p*. 273). Consequently, students today are born and grown up with rapidly developing changes that condition technological and social demands on student behavior [31].
- Clarification to what kind of responsibility educational institutions have when managing the transitional character of technological developments "as mediator between students and technologies, from the perspective of teaching students about the best use of these tools". ([45], p. 423). For example, 21st-century skills such as digital literacy conditioned by multiple representations might be beneficial to promote from early childhood [4].

4.2. Limits and threats to validity

Findings with statistical significance do not guarantee value. While significant, some of the findings of this review were arguably not very strong. Even the strong findings will most likely correct in the near future due to skewed publication rates. Based on the data in this review, the variables analyzed will still yield strong findings after such corrections, but further research with aspects not considered in this review is required to draw any conclusions at this stage. For example, comprehensive bibliometric reviews might give insight into the high publication rates of 2017–2020.

While this review emphasized the behaviorist approach, it cannot function in a vacuum. In other words, if the skewed ratio were to point in the other direction, the radical behaviorist methodological considerations of this literature review would be redundant. Reiterating the validity and importance of other approaches, this review has due to narrow scope omitted valuable findings from social themes, which instead can be found in other reviews (e.g. [17,25,54,59]). This review has also adhered to relatively simple variables and statistical computations. While this may have prevented invalid coding or fatal mistakes in data analysis, omitted valuable aspects considered more complex, such as the social themes, or further in-depth statistical computations, might have brought more nuance to the reader.

5. Conclusion

This review provided radical behaviorist methodological considerations related to data types and motivational influences to learning in the current literature of digital technology and primary education. Findings revealed an unbalanced and skewed ratio illustrating a high frequency and percentage distribution of self-reported dependent studies, clearly detailing a need for more behavioral studies as compensatory balance. Promising indications seen in 2015–2020 dictate a correction to this trend, which if continued may result in a better methodological balance in the research field.

Digital technology affects many professions to a large extent [30,63]. Current technological developments have shown attempts for making education policy intensively data-led, solely based upon large-scale data with bodily and biological conditions [64]. According to the findings of this review, this can also be seen in the research field that relates digital technology with primary education, where the bodily and biological data increasingly are studied through different uses of multiple representations. Such use of data relates a genetic epistemology with compatible methodological conditions to radical behaviorism.

Behaviorist approaches are often dismissed as blunt tools effective at influencing independent schoolwork of students by regulatory behavioral control [1,47,48]. As a result, many researchers in the field have in the years 2011–2020 emphasized motivational influences [17, 59]. Such approaches have their merits, but the findings of this review indicate that more studies with methodological presuppositions conditioned by behaviorist approaches are needed for deepening our contextual knowledge of contextual constituents.

Any set of agreed methodological approaches that generate research "does not prove its value unless the research is valueable" [51]. Behaviorism could function as an instrument for regulated control and may, therefore, merit critique about unethical implications when adopting these instruments as a researcher in the learning sciences [5]. However, refusing to adopt the same methods as a researcher to avoid misuse of power "is merely to leave control in other hands" ([52], *p*. 437). Therefore, it is important for educational institutions to initiate change rather than reacting to it, as these rapid technological developments are "something we can no longer avoid" ([45], *p*. 422). One way to initiate such a change is to do research with a radical behaviorist methodological approach.

Declaration of Competing Interest

None.

Changes after transfer to open-access

There were some indications from the transfer offered by the co-editor that my submission may have been perceived as more focused on machine-learning than intended. I have therefore reduced this emphasis in the abstract, and removed this part from the highlights. I have also corrected a counting mistake in the abstract.

Other than the abstract and highlights, the submission is identical to the one I made for Computers & Education.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.caeo.2021.100058.

References

[1] Allodi MW. A critical review of ideology, policy and circumstances in the swedish context related to inclusive education organisational climate and students' wellbeing (editor). In: Dovigo F, editor. Special educational needs and inclusive practices. Sense Publishers; 2017. p. 97–116.
[2] Anderson T, Shattuck J. Design-Based Research: a decade of progress in education research? Educ Res 2012;41(1):16–25. https://doi.org/10.3102/0013189X11428813.
[3] Arfé B, Vardanega T, Ronconi L. The effects of coding on children's planning and inhibition skills. Comput Educ 2020;148. https://doi.org/10.1016/j.compedu.2020.103807.
[4] Banzato M, Coin F. Self-efficacy in multimodal narrative educational activities: explorative study in a multicultural and multilingual Italian primary school. Media Commun 2019;7(2):148–59. https://doi.org/10.17645/mac.v7i2.1922.
[5] Barrett LF. How emotions are made: the secret life of the brain. Houghton Mifflin Harcourt; 2017.
[6] Bosseldal I. Vart tog behaviorismen vägen?: Social responsivitet mellan barn och vuxen, hund och människa. Lund University, Faculty of Social Sciences; 2019.
[7] Carrara K. Radical behaviorism and cultural analysis. Springer; 2018 (M. charles nicholl, trans.).
[8] Chiu TKF, Jong MSY, Mok IAC. Does learner expertise matter when designing emotional multimedia for learners of primary school mathematics? Educ Technol Res Dev 2020;68(5):2305. https://doi.org/10.1007/s11423-020-09775-4.
[9] Clarke L, Abbott L. Young pupils', their teacher's and classroom assistants' experiences of iPads in a northern ireland school: "Four and five years old, who would have thought they could do that? Br J Educ Technol 2016;47(6):1051–64. https://doi.org/10.1111/bjet.12266.
[10] Cohen L, Manion L, Morrison K. Research methods in education. 8th ed. Routledge; 2018.
[11] Crook C, Sutherland R, Duval E, Sharples M, Sutherland R. Technology and theories of learning (editors). Technology enhanced learning: research themes. Springer; 2017. p. 11–27. https://doi.org/10.1007/978-3-319-02600-8_2.
[12] Diekema AR, Olsen MW. Teacher personal information management (PIM) practices: finding, keeping, and re-finding information. J Assoc Inf Sci Technol 2014;65(11):2261–77. https://doi.org/10.1002/asi.23117.
[13] Enrique Hinostroza J, Labbé C, Brun M, Matamala C. Teaching and learning activities in Chilean classrooms: is ICT making a difference? Comput Educ 2011;57(1):1358–67. https://doi.org/10.1016/j.compedu.2011.01.019.
[14] European Union. Digital education action plan (2021-2027). European Union; 2020. https://ec.europa.eu/education/education-in-the-eu/digital-education-action-plan_en.
[15] Fernández-Montalvo J, Peñalva A, Irazabal I, López-Goñi JJ. Effectiveness of a digital literacy programme for primary education students. Cult Educ 2017;29(1):1–30. https://doi.org/10.1080/11356405.2016.1269501.
[16] Georgiou Y, Ioannou A, Ioannou M. Investigating immersion and learning in a low-embodied versus high-embodied digital educational game: lessons learned from an implementation in an authentic school classroom. Multimodal Technol Interact 2019;3(4). https://doi.org/10.3390/mti3040068.
[17] Granić A, Marangunić N. Technology acceptance model in educational context: a systematic literature review. Br J Educ Technol 2019;50(5):2572–93. https://doi.org/10.1111/bjet.12864.
[18] Hui YK, Mai B, Qian S, Kwok LF. Cultivating better learning attitudes: a preliminary longitudinal study. Open Learn 2018;33(2):155–70. https://doi.org/10.1080/02680513.2018.1454830.
[19] Joo-Nagata J, Abad FM, Giner JGB, García-Peñalvo FJ. Augmented reality and pedestrian navigation through its implementation in m-learning and e-learning: evaluation of an educational program in chile. Comput Educ 2017;111:1–17. https://doi.org/10.1016/j.compedu.2017.04.003.
[20] Julià C, Antolí JÒ. Spatial ability learning through educational robotics. Int J Technol Des Educ 2016;26(2):185–203. https://doi.org/10.1007/s10798-015-9307-2.
[21] Kelleher JD, Mac Namee B, D'Arcy A. Fundamentals of machine learning for predictive data analytics: algorithms, worked examples, and case studies. 2nd ed. Cambridge: The MIT Press; 2020.
[22] Kilic C, Sancar-Tokmak H. Digital story-based problem solving applications: preservice primary teachers' experiences and future integration plans. Aust J Teach Educ 2017;42(12):21–41. https://doi.org/10.14221/ajte.2017v42n12.2.
[23] Kitchenham B. *Procedures for performing systematic reviews* (0400011T.1 nicta technical report. Keele University; 2004. p. 1–26.
[24] Kleemans T, Segers E, Droop M, Wentink H. Webquests in special primary education: learning in a web-based environment. Br J Educ Technol 2011;42(5):801–10. https://doi.org/10.1111/j.1467-8535.2010.01099.x.
[25] Lai JW, Bower M. How is the use of technology in education evaluated? A systematic review. Comput Educ 2019;133:27–42. https://doi.org/10.1016/j.compedu.2019.01.010.
[26] Lewandowski L, Wood W, Miller AL, Luiselli JK, Fischer AJ. Technological applications for individuals with learning disabilities and ADHD. Computer-Assisted and web-based innovations in psychology, special education, and health. Academic Press; 2016. p. 61–94.
[27] Lewis RB, Maas SM. QDA Miner 2.0: mixed-model qualitative data analysis software. Field Methods 2007;19(1):87–108. https://doi.org/10.1177/1525822X06296589.
[28] Li G, Sun Z, Jee Y. The more technology the better? A comparison of teacher-student interaction in high and low technology use elementary EFL classrooms in china. System 2019;84:24–40. https://doi.org/10.1016/j.system.2019.05.003.
[29] Liontou T. Foreign language learning for children with ADHD: evidence from a technology-enhanced learning environment. Eur J Spec Needs Educ 2019;34(2):220–35. https://doi.org/10.1080/08856257.2019.1581403.
[30] Littlejohn A, Jaldemark J, Vrieling-Teunter E, Nijland F, Littlejohn A, Jaldermark J, Vrieling-Teunter E, Nijland F. Networked professional learning: an introduction. Networked professional learning. Springer; 2019. p. 1–14.
[31] Liu ZY, Shaikh ZA, Gazizova F. Using the concept of game-based learning in education. Int J Emerg Technol Learn 2020;15(14):53–64. https://doi.org/10.3991/ijet.v15i14.14675.
[32] Mazman Akar SG. Does it matter being innovative: teachers' technology acceptance. Educ Inform Technol 2019;24(6):3415–32. https://doi.org/10.1007/s10639-019-09933-z.
[33] Michos K, Hernández-Leo D. Supporting awareness in communities of learning design practice. Comput Human Behav 2018;85:255–70. https://doi.org/10.1016/j.chb.2018.04.008.
[34] Moher D, Shamseer L, Clarke M, Ghersi D, Liberati A, Petticrew M, Shekelle P, Stewart LA, Group PP. Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. Syst Rev 2015;4(1):1. https://doi.org/10.1186/2046-4053-4-1.
[35] Molenaar I, Horvers A, Baker RS. What can moment-by-moment learning curves tell about students' self-regulated learning? Learn Instr 2019;72. https://doi.org/10.1016/j.learninstruc.2019.05.003.
[36] Molnár G, Csapó B. Making the psychological dimension of learning visible: using technology-based assessment to monitor students' cognitive development. Front Psychol 2019;(JUN):10. https://doi.org/10.3389/fpsyg.2019.01368.
[37] Mølstad CE, Petterson D, Prøitz TS, Normand R, Liu, M, Carvalho LM, Oliveira DA, LeVasseur L. Soft infusion: constructing 'teachers' in the pisa sphere. Education policies and the restructuring of the educational profession. Springer; 2018. p. 13–26. https://doi.org/10.1007/978-981-10-8279-5.
[38] Muñoz-Cristóbal JA, Jorrín-Abellan IM, Asensio-Peréz JI, Martínez-Monés A, Prieto LP, Dimitriadis Y. Supporting teacher orchestration in ubiquitous learning environments: a study in primary education. IEEE Trans Learn Technol 2015;8(1):83–97. https://doi.org/10.1109/TLT.2014.2370634.
[39] Nieto-Márquez NL, Baldominos A, Pérez-Nieto MÁ. Digital teaching materials and their relationship with the metacognitive skills of students in primary education. Education Sciences 2020;10(4). https://doi.org/10.3390/educsci10040113.
[40] Noroozi O, Alikhani I, Järvelä S, Kirschner PA, Juuso I, Seppänen T. Multimodal data to design visual learning analytics for understanding regulation of learning. Comput Hum Behav 2019;100:298–304. https://doi.org/10.1016/j.chb.2018.12.019.
[41] OECD. Pisa 2012 results in focus. what 15-year-olds know and what they can do with what they know. OECD; 2014.
[42] Olmos E, Cavalcanti JF, Soler JL, Contero M, Alcañiz M, Yu S, Ally M, Tsinakos A. Mobile virtual reality: a promising technology to change the way we learn and teach. Mobile and ubiquitous learning: an international handbook. Springer; 2017. p. 95–106. https://doi.org/10.1007/978-981-10-6144-8.
[43] Outhwaite LA, Gulliford A, Pitchford NJ. Closing the gap: efficacy of a tablet intervention to support the development of early mathematical skills in UK primary school children. Comput Educ 2017;108:43–58. https://doi.org/10.1016/j.compedu.2017.01.011.
[44] Papert S. Mindstorms: children, computers, and powerful ideas. Basic Books; 1980.
[45] Pischetola M. Teachers and technologies in brazilian schools: a study from the perspective of media ecology. Ital J Sociol Educ 2019;11(2):411–27. https://doi.org/10.14658/pupj-ijse-2019-2-20.
[46] Ricoy MC, Sánchez-Martínez C. Tablet use in primary education. Technol Pedag Educ 2019;28(3):301–16. https://doi.org/10.1080/1475939X.2019.1608291.
[47] Roth G, Vansteenkiste M, Ryan RM. Integrative emotion regulation: process and development from a self-determination theory perspective. Dev Psychopathol 2019;31:945–56. https://doi.org/10.1017/S0954579419000403.
[48] Saari A. Out of the box: behaviourism and the mangle of practice. Discourse Stud Cult Pol Educ 2019;40(1):109–21. https://doi.org/10.1080/01596306.2018.1549707.
[49] Sawyer RK, R. K. Sawyer. The new science of learning (editor). The cambridge handbook of the learning sciences. 2nd ed. Cambridge University Press; 2014. p. 1–20.
[50] Sigafoos J, van der Meer L, Schlosser RW, Lancioni EG, O'Reilly M, Green VA, Luiselli JK, Fischer AJ. Augmentative and alternative communication (AAC) in intellectual and developmental disabilities (editors). Computer-assisted and web-based innovations in psychology, special education, and health. Academic Press; 2016. p. 255–85.
[51] Skinner BF. Are theories of learning necessary? Psychol Rev 1950;57(4):193. https://doi.org/10.1037/h0054367.
[52] Skinner BF. Science and human behavior. The Macmillan Company; 1953.
[53] Skinner BF. About behaviorism. Knopf; 1974.
[54] Spiteri M, Chang Rundgren SN. Literature review on the factors affecting primary teachers' use of digital technology. Technol Knowl Learn 2020;25(1):115–28. https://doi.org/10.1007/s10758-018-9376-x.

[55] Sundgren M. Blurring time and place in higher education with bring your own device applications: a literature review. Educ Inform Technol 2017;22(6): 3081–119. https://doi.org/10.1007/s10639-017-9576-3.
[56] Taleb NN. Skin in the game: hidden asymmetries in daily life. Random House; 2018.
[57] Tesolin A, Tsinakos A, Shengquan Y, Mohamed A, Avgoustos T. Opening real doors: strategies for using mobile augmented reality to create inclusive distance education for learners with different-abilities. Mobile and ubiquitous learning: an international handbook. Springer; 2018. p. 59–80. https://doi.org/10.1007/978-981-10-6144-8.
[58] Thomas DR. A general inductive approach for analyzing qualitative evaluation data. Am J Eval 2006;27(2):237–46. https://doi.org/10.1177/1098214005283748.
[59] Tondeur J, van Braak J, Ertmer PA, Ottenbreit-Leftwich A. Understanding the relationship between teachers' pedagogical beliefs and technology use in education: a systematic review of qualitative evidence. Educ Technol Res Dev 2017;65(3):555–75. https://doi.org/10.1007/s11423-016-9481-2.
[60] Vanderschantz N, Hinze A. Computer what's your favourite colour?" Children's information-seeking strategies in the classroom. Proc Assoc Inform Sci Technol 2019;56(1):265–75. https://doi.org/10.1002/pra2.21.
[61] Visser M, van Eck NJ, Waltman L. Large-scale comparison of bibliographic data sources: Scopus, web of science, dimensions, crossref, and microsoft academic. Quantitative Science Studies 2021;2(1):20–41. https://doi.org/10.1162/qss_a_00112.
[62] Walsh V, Farren M. Teacher attitudes regarding barriers to meaningfully implementing iPads in a primary school setting. Comput Sch 2018;35(2):152–70. https://doi.org/10.1080/07380569.2018.1462674.
[63] Wang Q, Shengquan Y, Mohamed A, Avgoustos T. Core technologies in mobile learning. Mobile and ubiquitous learning: an international handbook. Springer; 2018. p. 127–39. https://doi.org/10.1007/978-981-10-6144-8.
[64] Williamson B. Digital policy sociology: software and science in data-intensive precision education. Crit Stud Educ 2019:1–17. https://doi.org/10.1080/17508487.2019.1691030.
[65] Zbick J, Vogel B, Spikol D, Jansen M, Milrad M, Ayala AP. Toward an adaptive and adaptable architecture to support ubiquitous learning activities (editor). Mobile, ubiquitous, and pervasive learning: fundaments, applications, and trends. Springer; 2016. p. 193–222. https://doi.org/10.1007/978-3-319-26518-6.