

Identifying Antecedents to Learning Effectively with Digital Media: A Student-Centered Approach

Doctoral Thesis
in order to obtain the title of Doctor
from the Faculty of Economics and Social Sciences
at the University of Tübingen

presented by
Molly Hammer, M. Ed.
From Chicago

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ABSTRACT

Digital media is becoming more pervasive in the classroom. Even in Germany that has hesitated compared to other OECD countries to implement technology into the classroom, there is increasingly more pressure to use digital media for teaching and learning processes (Gerick, Eickelmann, & Bos, 2017). This effort to equip schools with digital media such as tablets has emerged despite not knowing how regular digital media use in classrooms affects student learning processes. Although research has attempted to keep up with the pace that digital media has entered classrooms, it has tended to emphasize gains in student achievement (Lai & Bower, 2020), with much less attention paid to the factors that precede student learning processes. To understand how students may learn with digital media in classrooms, recent conceptions of learning have highlighted that students arrive in the classroom with a range of learning skills, beliefs, prior knowledge, and experiences that significantly influence how they interpret their learning environments and acquire new knowledge (Bransford, Brown, & Cocking, 2000). Rather than look at student learning outcomes, this dissertation has aimed to build on previous theories and models about how students learn in classrooms to understand the antecedent factors that precede effective learning processes in classrooms with digital media.

Following the opportunity to learn model (Seidel, 2014), students' previous learning environments, including their families, influence students' individual learning prerequisites, such as students' cognitive and motivational-affective characteristics, which in turn affect students' individual learning processes and subsequently learning outcomes (Seidel, 2014). Therefore, I have investigated (1) how parents' beliefs and behaviors at home affect the development of students' digital media self-efficacy, (2) how students perceive instructional quality in classrooms with digital media depending on their cognitive and motivational-affective characteristics, and (3) how students' perceptions compared in classes with and without digital media as well as in classes where teachers had lower or higher technology innovativeness. These questions were addressed in three empirical studies that used data from a school trial investigating the use of digital media in classrooms.

In Study 1, I investigated how students' family environments and experiences at home shape students' development of digital media self-efficacy. Specifically, using the parent socialization model, one link of the widely used expectancy-value model framework (Eccles et al., 1983), I examined whether parents' behaviors including modeling and provision of digital media mediated the relation between parents' value beliefs regarding digital media and students' digital media self-efficacy ($N = 1,206$ students and their parents). To assess parents'

beliefs and behaviors regarding digital media, a questionnaire was developed. Results showed though parents' value beliefs were related to students' digital media self-efficacy, only parents' provision of smart phones mediated this relation. Findings indicate the importance of parents' beliefs regarding digital media and the need for future research into at home factors that influence students' digital media self-efficacy.

In Study 2 and in Study 3, I investigated students' perceptions of supportive climate and cognitive activation in classes with tablets to understand how the use of tablets may affect how students experience their new learning context and in turn inform students' learning outcomes. In both studies, I used latent profile analysis to first examine whether students could be grouped into distinct profiles based on their subject-specific motivational and cognitive characteristics and whether these profiles differentially predicted students' perceptions. In Study 2, I compared students' profile perceptions of supportive climate in biology classes with (n = 518 students) and without tablets (n = 540 students). After four months of tablet use, the 'struggling' and 'unmotivated' profiles perceived supportive climate significantly more positively than the same profiles in classes that were not given tablets. Building on these findings, in Study 3, I investigated whether there were differences between students' perceptions of supportive climate and cognitive activation in math classes with tablets depending on teachers' beliefs towards using technology (n = 575 students; n = 23 teachers). I found that most students perceived instructional practices more positively in classes where teachers had higher technology innovativeness with the exception of the 'unmotivated' profile that perceived instructional practices more negatively.

The contribution of this dissertation is that students perceive instruction with digital media differently depending on their cognitive and motivational-affective characteristics. Understanding that not all students will perceive and learn with digital media in the same way has important implications for teachers' use of digital media in the classroom as well as researchers investigating how digital media facilitates student learning. Furthermore, students' previous experiences with digital media and characteristics such as digital media self-efficacy can affect how they feel towards and learn with digital media. Moving forward, research exploring how learning with digital media in classrooms takes place should also examine the factors outside the classroom such as students' experiences with digital media at home.

ZUSAMMENFASSUNG

Digitale Medien setzen sich im Klassenzimmer immer stärker durch. Selbst in Deutschland, das im Vergleich zu anderen OECD-Ländern gezögert hat, Technologie im Unterricht zu implementieren, wächst der Druck, digitale Medien für Lehr- und Lernprozesse zu nutzen (Gerick, Eickelmann, & Bos, 2017). Das Bestreben Schulen mit digitalen Medien wie Tablets auszustatten ist entstanden, obwohl nicht bekannt ist, wie sich die regelmäßige Nutzung digitaler Medien im Klassenzimmer auf die Lernprozesse der Schülerinnen und Schüler auswirkt. Obwohl die Forschung versucht hat, mit dem Tempo Schritt zu halten mit dem die digitalen Medien in die Klassenzimmer Einzug gehalten haben, lag der Fokus der Forschung zumeist auf den Leistungssteigerung der Schülerinnen und Schüler (Lai & Bower, 2020), während den Faktoren, die den Lernprozessen der Schülerinnen und Schüler vorausgehen, viel weniger Aufmerksamkeit geschenkt wurde. Um zu verstehen, wie Schüler mit digitalen Medien im Klassenzimmer lernen können, haben jüngste Erkenntnisse hervorgehoben, dass Schüler mit einer Reihe von Lernfähigkeiten, Überzeugungen, Vorkenntnissen und Erfahrungen in den Klassenraum kommen, die die Art und Weise, wie sie ihre Lernumgebung interpretieren und neues Wissen erwerben, maßgeblich beeinflussen (Bransford, Brown, & Cocking, 2000). Anstatt sich mit den Lernergebnissen der Schüler zu befassen, baut diese Dissertation auf vorhergehenden Theorien und Modellen auf wie Schüler im Klassenzimmer mit digitalen Medien lernen, um die vorausgegangenen Faktoren zu verstehen, welche effektiven Lernprozessen in Klassenzimmern vorausgehen.

In Anlehnung an das Modell "opportunity to learn" (Seidel, 2014) beeinflussen die bisherigen Lernumgebungen die individuellen Lernvoraussetzungen der Schüler, wie z.B. die kognitiven und motivational-affektiven Eigenschaften der Schüler, die wiederum die individuellen Lernprozesse und anschließend die Lernergebnisse der Schüler beeinflussen (Seidel, 2014). Daher habe ich untersucht, (1) wie die Überzeugungen und Verhaltensweisen der Eltern zu Hause die Entwicklung der Selbstwirksamkeit der Schülerinnen und Schüler in Bezug auf digitale Medien beeinflussen, (2) wie die Schülerinnen und Schüler die Unterrichtsqualität in Klassenräumen mit digitalen Medien in Abhängigkeit von ihren kognitiven und motivational-affektiven Merkmalen wahrnehmen und (3) wie die Wahrnehmung der Schülerinnen und Schüler im Vergleich zu Klassen mit und ohne digitale Medien sowie zu Klassen, in denen die Lehrerinnen und Lehrer über eine geringere oder höhere technologische Innovationsfähigkeit verfügten. Diese Fragen wurden in drei empirischen

Studien untersucht, die Daten aus einem Schulversuch zur Nutzung digitaler Medien im Klassenzimmer verwendeten.

In Studie 1 untersuchte ich, wie das familiäre Umfeld und die Erfahrungen der Schüler zu Hause die Entwicklung der Selbstwirksamkeit digitaler Medien beeinflussen. Insbesondere untersuchte ich mit Hilfe des „parent socialization model“, einem Bindeglied des weit verbreiteten „expectancy-value model“ (Eccles et al., 1983), ob das Verhalten der Eltern einschließlich der Modellierung und Bereitstellung digitaler Medien die Beziehung zwischen den Wertvorstellungen der Eltern bezüglich digitaler Medien und der Selbstwirksamkeit der Schülerinnen und Schüler in Bezug auf digitale Medien vermittelt (N = 1.206 Schülerinnen und Schüler und ihre Eltern). Um die Überzeugungen und Verhaltensweisen der Eltern in Bezug auf digitale Medien zu beurteilen, wurde ein Fragebogen entwickelt. Die Ergebnisse zeigten, dass die Wertvorstellungen der Eltern zwar mit der Selbstwirksamkeit der Schülerinnen und Schüler in Bezug auf digitale Medien zusammenhängen, jedoch nur die Bereitstellung von Smartphones durch die Eltern diese Beziehung vermittelte. Die Ergebnisse zeigen, wie wichtig die Überzeugungen der Eltern in Bezug auf digitale Medien sind und dass künftige Untersuchungen zu den Faktoren, die die Selbstwirksamkeit der Schülerinnen und Schüler in Bezug auf digitale Medien zu Hause beeinflussen, notwendig sind.

In Studie 2 und in Studie 3 untersuchte ich die Wahrnehmung der Schülerinnen und Schüler in Bezug auf das unterstützende Klima und die kognitive Aktivierung in Klassen mit Tablets, um zu verstehen, wie die Verwendung von Tablets die Art und Weise beeinflussen kann, wie Schülerinnen und Schüler ihren neuen Lernkontext wahrnehmen, und wie diese wiederum die Lernergebnisse der Schülerinnen und Schüler beeinflussen. In beiden Studien verwendete ich eine latente Profilanalyse um zu untersuchen, ob die Schülerinnen und Schüler auf der Grundlage ihrer fachspezifischen motivationalen und kognitiven Merkmale in verschiedene Profile gruppiert werden konnten und ob diese Profile die Wahrnehmungen der Schülerinnen und Schüler unterschiedlich vorhersagten. In Studie 2 verglich ich die Profilwahrnehmungen der Studierenden zum Unterstützungsklima im Biologieunterricht mit (n = 518 Schüler) und ohne Tablets (n = 540 Schüler). Nach vier monatiger Verwendung von Tablets nahmen die Profile "kämpfend" und "unmotiviert" das Unterstützungsklima signifikant positiver wahr als die gleichen Profile in Klassen, die keine Tablets erhielten. Aufbauend auf diesen Ergebnissen untersuchte ich in Studie 3, ob es Unterschiede zwischen der Wahrnehmung des unterstützenden Klimas und der kognitiven Aktivierung durch die Schülerinnen und Schüler im Matheunterricht mit Tablets in Abhängigkeit von den Überzeugungen der Lehrerinnen und Lehrer in Bezug auf den Einsatz von Technologie gab (n = 575 Schülerinnen und Schüler; n =

23 Lehrerinnen und Lehrer). Ich fand heraus, dass die meisten Schülerinnen und Schüler die Unterrichtspraktiken in Klassen, in denen die Lehrerinnen und Lehrer über eine höhere technologische Innovationsfähigkeit verfügten, positiver wahrnahmen, mit Ausnahme des "unmotivierten" Profils, das die Unterrichtspraktiken negativer wahrnahm.

Der Beitrag dieser Dissertation besteht darin, dass Schüler den Unterricht mit digitalen Medien je nach ihren kognitiven und motivational-affektiven Eigenschaften unterschiedlich wahrnehmen. Die Erkenntnis, dass nicht alle Schülerinnen und Schüler digitale Medien in gleicher Weise wahrnehmen und mit ihnen lernen, hat wichtige Auswirkungen auf die Nutzung digitaler Medien durch Lehrerinnen und Lehrer im Unterricht sowie auf Forschung, welche untersucht wie digitale Medien das Lernen der Schülerinnen und Schüler erleichtern. Darüber hinaus können die bisherigen Erfahrungen der Schülerinnen und Schüler mit digitalen Medien und Merkmale wie die Selbstwirksamkeit digitaler Medien beeinflussen, wie sie sich gegenüber digitalen Medien fühlen und mit ihnen lernen. In Zukunft sollte Forschung im Bereich des Lernens mit digitalen Medien auch die Faktoren außerhalb des Klassenzimmers untersuchen, wie z.B. die Erfahrungen der Schülerinnen und Schüler mit digitalen Medien zu Hause.

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Introduction and Theoretical Framework

1 Introduction and Theoretical Framework

Even before the COVID-19 pandemic that has plagued the world's education systems and has prematurely pushed learning online, there was broad consensus worldwide that students need digital media skills in the present and for the future (e.g., Fishman & Dede, 2016; OECD, 2015; European Commission, 2013). Digital media is a tool that is considered essential not only for improving teaching and learning processes (e.g., Gerjets & Scheiter, 2019) but also for students' future participation in the workplace and in society (e.g., Fraillon, Ainley, Schulz, Friedman, & Duckworth, 2019). Equally important, differential access to opportunities to learn effectively with digital media has increased the achievement gap between students from diverse backgrounds (Fraillon et al., 2019; Warschauer & Matuchniak, 2010). Taken together, there is a substantial need for research that can contribute to understanding how all students can develop digital media skills and effectively learn with digital media.

Background

Given that there is no widely accepted objective measure of digital skills, many labels have been used to describe information and technology skills (Zhong, 2011). Throughout this dissertation, digital media skills refer to the abilities to operate as well as effectively use digital media. Digital media refers to technology such as smart phones or tablets that enable specific forms of information presentation and interaction, such as touch screens and multimodal interactions (for a comprehensive overview of the potential of specific characteristics of digital media in teaching contexts, see Gerjets & Scheiter, 2019). The skills needed to effectively use digital media include *operational skills* which are required to work with hardware and software, *information skills* which are necessary to search, select, and process information, and *strategic skills* which are vital for using digital media for particular personal and professional goals (van Dijk, 2006). Although these are separate sets of skills, information and strategic skills are acquired by learning operational skills, and in turn, highly skilled users are better positioned to benefit from digital media (Hargittai & Shafer, 2006). This definition of digital media skills also builds on the definition of information and computer literacy (ICT) as defined by Senkbeil, Ihme, and Wittwer (2013). It refers to both technological literacy, as in the "functional knowledge of hardware and software" (p. 140) and information literacy, meaning "the ability to use digital media to locate and critically evaluate information and to use it effectively for one's own purposes" (pp. 140-141). This distinction between technical and information literacy is made to indicate the importance of not only the ability to operate digital media as a tool but also the ability to effectively use digital media for goals outside learning. Similar to ICT

literacy, digital media skills are considered necessary for acquiring other competencies and skills needed for participation in modern educational and work settings (Senkbeil et al., 2013). This dissertation uses digital media skills rather than ICT literacy because the measures used throughout the three studies do not emphasize the use of the Internet. Additionally, the measures refer to the specific benefits of digital media (e.g., interactivity, availability of information, multimodality) that are not necessarily characteristic of other forms of technology, such as stationary computers that are confined to one space. For example, tablets in the classroom offer more flexibility for teaching and learning activities than having to relocate to a separate computer lab (Fishman & Dede, 2016). However, there is undoubtedly substantial overlap between information and technical skills that can be gained from a computer or from a device such as a tablet, and the research used in this dissertation draws from studies that have investigated all types of technology used for learning. Digital media skills are used except when specific studies used different terms, and whenever possible, the specific hardware described in previous research is used.

Problem

Despite the importance of digital media skills, recent research has indicated that many students are in fact not developing the necessary technical and information competencies. In order to assess students' current levels of digital competencies, to identify gaps, and to understand the broader contexts behind the development of these skills, the International Computer and Information Literacy Study (ICILS) was developed to measure eighth-grade students' computer and information literacy (Fraillon et al., 2019). Findings from the recent 2018 ICILS indicate that in most countries, the majority of students need support in using computers to complete basic information-gathering and management tasks. Additionally, across the participating countries, 18% of students were found to be working below the lowest level of proficiency, indicating a lack of functional working knowledge of computers as tools. Furthermore, the 2018 ICILS further established that students need to be taught how to use computers effectively and do not develop effective digital literacy skills through exposure to technology alone. Regarding the findings, Dr. Dirk Harstedt, the executive director of the International Association for the Evaluation of Educational Achievement which conducted the study, remarked if a student has not learned these skills at home, it is unlikely that their teacher will be able to fill in the gaps (Klein, 2019). In general, results indicate that worldwide, students are not well prepared for study, work, or life in a digital world (Fraillon et al., 2019).

In addition, the use of digital media such as tablets is thought to increase teaching and learning processes (e.g., Major, Haßler, & Hennessy, 2017; Sung, Chang, & Liu, 2016;

Warschauer, Zheng, Niiya, Cotten, & Farkas, 2010). Yet empirical results on the use of digital media in the classroom are relatively sparse, and previous research that has investigated whether technology in general enhances student learning has shown rather mixed results and large variability (e.g., Escueta, Quan, Nickow, & Oreopoulos, 2017; Petko, Cantieni, & Prasse, 2016; Tamim, Bernard, Borokhovski, Abrami, & Schmid, 2011). Sung et al. (2016) conducted a meta-analysis on studies that investigated learning with mobile devices. Rather than utilizing new technology to enhance higher level tasks such as critical thinking, the authors found that most research has primarily used mobile devices to strengthen engagement or stimulate motivation and secondly to deliver content. In a comparative case study that examined the effects of one-to-one laptop programs in the United States, Warschauer et al. (2010) found mixed results in students' learning and achievement, supporting the idea that technology alone does not improve student outcomes but rather depends on many factors including the technical infrastructure, students' initial levels of digital literacy, and teacher training. In another review using randomized control field trials, Escueta et al. (2017) pointed out that even though education technology can be helpful under some circumstances, such as expanding internet access (e.g., Warschauer et al., 2010), the conditions that lead to enhanced learning are still unclear.

Alternatively, the lack of conclusive empirical evidence may be due in part to the measures used to assess learning with digital media. Petko et al. (2016) explained that the main benefit of educational technology not to be student achievement but a shift towards more student-centered practices. Therefore, successful learning from any technology including digital media may not be fully assessed by traditional measures. Warschauer and Matuchniak (2010) further elaborated, "Measuring outcomes is the most complex aspect of analyzing technology-enhanced learning, in part because the goals of teaching with technology are so diverse, and in part because many of those goals do not have clearly operationalized outcome measures" (p. 201). Similarly, Sung et al. (2016) pointed out that although the research they covered in their meta-analysis on mobile devices designed activities to increase higher level skills such as explorative, communication, and cooperative skills, most studies only measured increases in content knowledge as the dependent variable. In other words, our understanding of how digital media can be used for learning may be incomplete due to a lack of suitable measures that takes into account the other ways digital media may affect learning besides gains in achievement or content knowledge. In their meta-analysis in which they integrate the current state of the art on models of teaching and learning, Seidel and Shavelson (2007) recognized that the effects of teaching on student outcomes were diverse and included changes in students' learning processes and motivational-affective outcomes. Assessing digital media with traditional measures of

achievement or content knowledge gains only explore one aspect of learning with digital media. Taken together, although there may be the potential for digital media to enhance student learning, there is currently a lack of sufficient student outcomes measures available to fully understand how students learn with digital media.

Similarly, Escueta et al. (2017) describe the rate at which new technologies that are aimed at improving education have entered classrooms as a “double-edged sword” (p. 3). Although new technologies offer a great deal of potential for learning, the accelerated speed at which they are being used for this intended purpose has outpaced the ability of researchers to evaluate their use. In the meantime, differential access to new media has exacerbated the already large gaps in achievement across socioeconomic groups (Livingstone & Helpser, 2007; Warschauer & Matuchniak, 2010). Livingstone and Helpser (2007) explained that higher socioeconomic status (SES) households are able to maintain their position of advantage by first gaining access to digital media and then by increasing the quality of that access. Previously, the digital divide primarily referred to differential access to the Internet and physical devices. Now, the digital divide concerns the differential ability to use new media to “critically evaluate information, analyze, and interpret data, attack complex problems, test innovative solutions, manage multifaceted projects, collaborate with others in knowledge information production, and communicate effectively to diverse audiences” (Warschauer & Matuchniak, 2010, p. 213). In sum, Warschauer and Matuchniak have described the skills and competencies that are becoming increasingly important for future employment and participation in modern society. As in many aspects of education, students with more affluent backgrounds, are more likely to have developed digital media skills outside of school and to have benefitted from being able to use digital media for learning more effectively in school. By contrast, students in low SES schools, who are less likely to have developed foundational, prerequisite digital media skills outside of school, are more likely to use digital media for more remedial purposes in school (Warschauer & Matuchniak, 2010). For example, Warschauer (2000) and Warschauer, Knobel, and Stone (2004) found that low SES schools typically focused on activities such as writing newsletters or finding information online to foster basic computer skills, whereas high SES schools were more likely to use computers to develop higher order skills such as analyzing information or critical inquiry. More recently, the ICILS 2018 found that students with higher SES backgrounds had significantly higher computer and information literacy scores than students with lower SES backgrounds and that differences in students’ scores were larger within countries than between countries (Fraillon et al., 2019). For example, in Germany, students from less privileged social backgrounds scored 50 points lower on average than their

counterparts from socioeconomically or culturally more affluent families (e.g., Drossel, Eickelmann, & Vennemann, 2020). At the same time that digital media is being revered and deemed essential for learning, future employment, and participation in society, the digital divide is growing. Whereas students with more affluent backgrounds will develop these skills outside of school, there is a certain urgency for research to investigate how all types of students can develop effective digital media skills.

In their review of the use of tablets in schools, Major et al. (2017) concluded that tablets have significant potential for enhancing learning, but the most important element remains the teacher and their instructional practices. However, recent models of learning have indicated that instructional practices alone do not predict student learning; learning must also be self-directed. Lipowsky, Rakoczy, Pauli, Drollinger-Vetter, Klieme, and Reusser (2009) explained that “learning processes cannot be controlled from the outside; rather, the teacher provides learning opportunities that must be perceived and utilized by the student to be effective” (p. 528). Following this view of learning, instead of a direct link between instructional practices and students’ learning processes, students’ perceptions of their teachers’ instructional practices mediate the effect that an instructional practice will have on student learning (Shuell, 1996). At the same time, a growing body of research that has examined heterogeneity in students’ perceptions has indicated that students’ perceptions of instructional practices within a classroom can differ tremendously. In turn, these differential perceptions have been linked to students’ learning characteristics as well as predictors of achievement gains and motivational development (Göllner et al., 2018). Yet instead of investigating students’ perceptions, research on digital media use in the classroom has largely explored the relevant teaching characteristics that determine how teachers integrate technology into the classroom (e.g., Scherer, Siddiq, & Tondeur, 2019). Much less research has focused on students and how they perceive instruction with digital media.

The solution proposed by this dissertation

In sum, not only is effectively using digital media considered as a tool for learning but effectively using digital media can be considered its own essential skill for future participation in the workplace and in society (Fraillon et al., 2019). However, international assessments such as the 2018 ICILS (Fraillon et al., 2019) and empirical evidence summarized in meta-analytic reviews by Sung et al. (2016) instead indicate that students are not developing the necessary competencies nor is digital media being effectively leveraged to enhance teaching and learning processes. Current research on how students learn with digital media has fallen behind the rate at which it has entered the classroom (Escueta et al., 2017). Yet as research on digital media

attempts to catch up, it has emphasized gains in student achievement (e.g., Bower & Lai, 2020) or in content knowledge (e.g., Sung et al., 2016). Efforts to investigate how digital media facilitates student learning have therefore focused too much on the cognitive outcomes without enough attention to the processes preceding or underlying student learning.

Building on recent conceptualizations of learning and applying them to learning with digital media, students arrive in the classroom with different learning characteristics (e.g., skills, abilities, and prior knowledge) and experiences that affect how they interpret their learning environments and in turn learn (Bransford, Brown, & Cocking, 2000). In particular, research using large-scale assessments such as the ICILS (Fraillon et al., 2019) and PISA (Zhong, 2011) have indicated that students use technology more often outside the classroom than inside, and students' home access to digital devices and years of experience using digital devices was found to be related to students' digital competences (Fraillon et al., 2019). Subsequently, at-home factors and parents may play a larger role in shaping students' digital media skills and should be investigated further to more fully understand the different experiences with digital media students bring to the classroom. Additionally, decades of educational research and extensively used pedagogical psychological models have indicated the importance of students' learning prerequisites such as their individual cognitive and motivational affective characteristics in determining how students learn (Cronbach & Snow, 1969; Seidel, 2014; Snow, Corno, & Jackson, 1996). Considering learning with digital media, besides instructional practices with digital media, student characteristics may determine whether students learn effectively with digital media. Taken together, to understand how learning with digital media takes place, greater attention should be paid to the factors that precede student learning processes, including students' home environments and students' motivational and cognitive characteristics.

In the first place, previous research has indicated that students' digital media self-efficacy is an important precursor to students' motivation to use digital media for learning and digital media competences (e.g., Aesaert & van Braak, 2014; Moos & Azevedo, 2009; Tsai & Tsai, 2003). Previous research has shown parent and at-home factors are related to students' digital media self-efficacy (e.g., Aesaert & van Braak, 2014; Zhong, 2011). Therefore, in the first study we use the parent socialization model, one link of the expectancy-value model framework (Eccles et al., 1983), to examine how students' digital media self-efficacy may be related to parents' beliefs and behaviors at home involving digital media.

In the second and third studies, we focus on students' perceptions of instructional quality with digital media and how they differ and are shaped by students' learning characteristics. Specifically, in the second study, we investigate student perceptions of supportive climate in

classes with and without tablets and differences in perceptions are examined in relation to students' cognitive (e.g., general cognitive ability and prior content knowledge) and motivational-affective (e.g., interest and self-concept) characteristics. Building on the second study, the third study more closely examines student perceptions of supportive climate as well as cognitive activation in classes with tablets and investigates how student perceptions depend on students' characteristics and teachers' beliefs towards using technology. Student perceptions of cognitive activation and supportive climate are valid indicators of teachers' cognitively activating and instructionally supportive practices, are closely tied to initiating and maintaining students' learning processes, and have been found to be predictors of achievement gains as well as motivation development (e.g., Kunter, Klusmann, Baumert, Richter, Voss, & Hachfeld, 2013).

Across the three studies, the aim is to understand the factors at the student level that affect how students learn with digital media. In this way, the three studies were designed to complement existing research on the factors that predicts teachers' integration of technology into teaching and learning activities. Additionally, all three studies build on previous empirical findings regarding the role of parents as well as the importance of student characteristics and student perceptions to understand how students learn with digital media. Across the studies, the consistent backdrop is that students arrive in the classroom with different characteristics and experiences that affect how they perceive and learn with digital media. In order to understand how students' home experiences and learning characteristics precipitate how students learn with digital media, the three studies use a student-centered approach. By that I mean, we assume that the students investigated in each study are not drawn from a homogenous population, and differences in home environments and student learning characteristics represent important distinctions for how they learn with digital media. Rather than focusing on student learning outcomes, the aim of this dissertation is to look at the preceding factors underlying student learning processes with digital media. Looking at the preceding factors may lead to a better understanding of how student learning with digital media takes places, or currently, why it is not taking place for many students.

Before I introduce the outlined studies, I present the theoretical background and the state of the research concerning (a) how parents and home environments shape students' digital media self-efficacy, and (b) the relationships between student characteristics, students' perceptions of instruction with digital media, and student learning outcomes. First, I describe two theoretical frameworks that identify the importance of students' family backgrounds and individual learning characteristics in understanding student learning and student learning with

digital media (Chapter 1.1). Next, I discuss how parents' beliefs and behaviors relate to students' self-concepts including digital media self-efficacy (Chapter 1.3) and how students' learning characteristics and perceptions of instruction with digital media can shape student learning with digital media (Chapter 1.4). Finally, I present the study outline (Chapter 1.5).

1.1 Identifying the antecedents of student learning with digital media

Digital media such as tablets have entered classrooms faster than researchers can investigate the actual effects of tablet use on teaching and learning processes. Although research in this field continues to grow, much of this research has emphasized gains in achievement or content knowledge (e.g., Lai & Bower, 2020; Sung et al., 2016), with much less attention paid to the processes that precede or underlie student learning as well as how the students themselves perceive learning with digital media.

The opportunity to learn model, also known as the supply-use model, offers a framework that can be applied to understand the complex interplay of teaching and learning processes that occur within classrooms and lead to diverse student learning outcomes (Seidel, 2014). In the opportunity to learn model, teaching is defined as designing learning environments with the aim of providing optimal opportunities for students to carry out their learning activities effectively (Seidel, 2014). Rather than assuming a direct link between teaching practices and student learning outcomes, under this model, the effects of teaching practices on students' learning outcomes are mediated by individual learning processes and moderated by individual learning prerequisites (Brühweiler & Blatchford, 2011). In other words, besides how teachers implement digital media in the classroom, students may carry out learning activities with digital media differently depending on their individual learning prerequisites, and this in turn can lead to different learning outcomes. Before students arrive in the classroom, their individual learning prerequisites are shaped by their previous learning environments including their family backgrounds.

Inherent to this conception of learning is that students are active participants in the construction of their knowledge and acquisition of skills rather than only the recipients of teacher-directed knowledge (Klieme et al., 2009). Bransford et al. (2000) explain that students may construct new knowledge and develop new understandings based on what they already know and believe. Thus, the role of the teacher is to help students build on what they already know in order to construct new knowledge. According to this constructivist point of view, students arrive in formal education settings with a range of prior knowledge, skills, beliefs, and

concepts that significantly influence how they interpret their learning environments as well as how they acquire new knowledge (Bransford et al., 2000).

The opportunity to learn model is the result of decades of educational research and the integration of a number of approaches and viable models for understanding teaching and learning in classrooms (Seidel, 2014). To understand how the model was developed, Seidel (2014) describes two paradigms that traditionally have been used to study how teaching processes affect student learning processes and can lead to differential effects on cognitive, motivational-affective, and meta-cognitive aspects of learning. The structural paradigm breaks teaching down into components and tests the effects of these components on student learning outcomes and has provided the basis for educational effectiveness research. The approach here is to investigate whether the theoretically assumed structures can be empirically supported and whether the postulated learning effects occur. Focusing more on the learning side, the process paradigm can be used to test whether the processes considered theoretically relevant for learning were addressed by teaching activities and had observable effects on learning outcomes. One example of the use of this paradigm is the cognitive learning process model of teaching and learning developed in the meta-analysis by Seidel and Shavelson (2007). Using this model, teaching activities that have been identified in previous models as being effective were further characterized as being more or less proximal to executive learning processes. Understanding how distinct paradigms and teaching and learning models have evolved as empirical research grows highlights that teaching and learning are complex processes that cannot be explained by a single psychological theory. The benefit to using the opportunity to learn model is that it integrates several theories and empirical research findings into a single common model and represents the progression up to the current state of the art on research on teaching and learning (Seidel, 2014).

A model that is grounded in theory and empirical research is particularly useful considering it was previously assumed that the current generation of students who have grown up surrounded by digital media would naturally learn from digital media (e.g., Prensky, 2001). Prensky (2001) further argued that digital natives would learn in fundamentally different ways than the previous generations, and traditional teaching methods would no longer be effective. Although many educational researchers have strongly rejected this view (e.g., Bennett, Maton, & Kervin, 2008; Helpser & Eynon, 2010; Thompson, 2013), the myth that young people today are digital natives and therefore digital experts has been hard to dispel. Particularly in Germany, there was some controversy over whether schools should teach the use of digital media or whether students acquired these skills outside of school anyways (Eickelmann & Gerick, 2020).

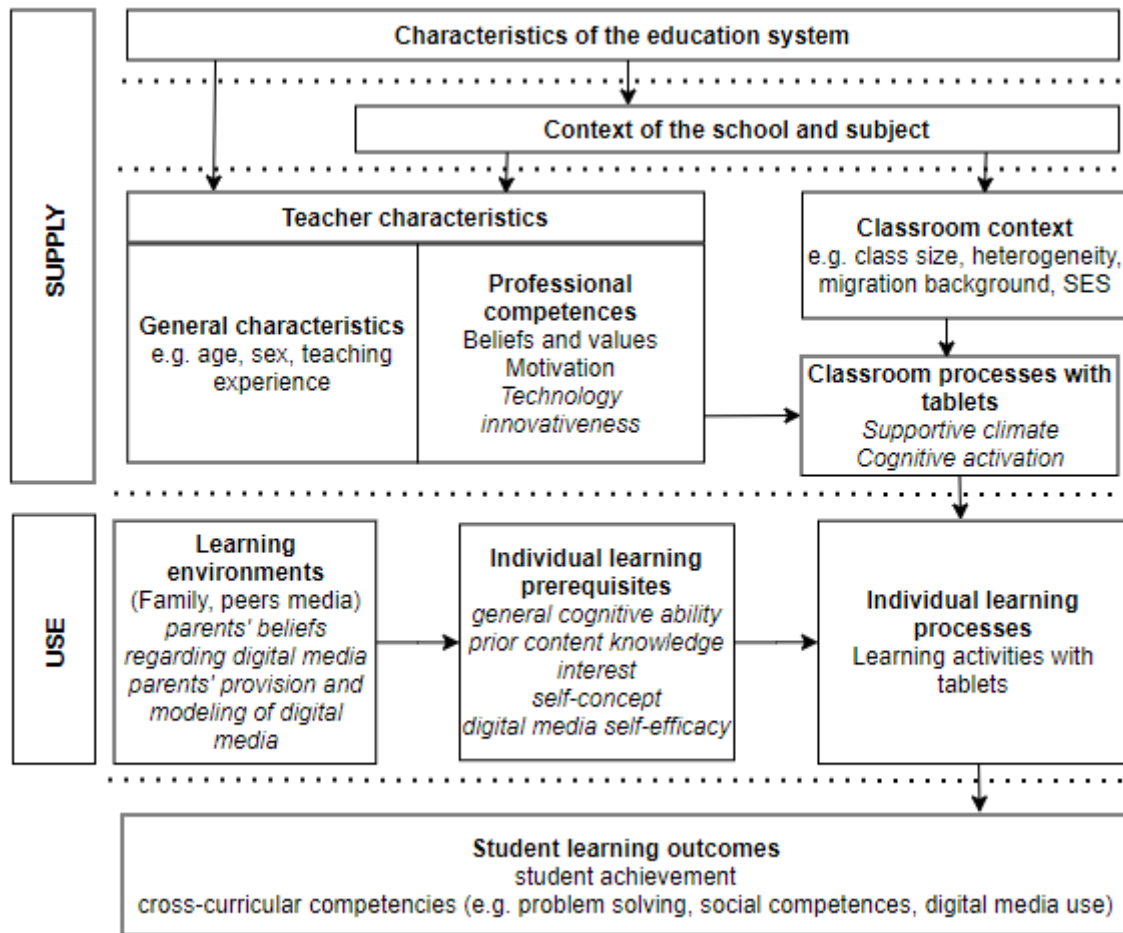
Furthermore, generalizing about the ways in which an entire generation of students learn fails to recognize the cognitive differences in young people and variation within age groups (Bennett et al., 2008).

Considering more evidence-based research, Lai and Bower (2020) conducted a tertiary review of educational technology that analysed 73 systematic literature reviews including meta-analyses. Of these 73 reviews papers, 65 (89%) focused on examining learning outcomes. Although, the authors found that these review papers generally found benefits and improvements with using educational technology across technologies, disciplines, and educational levels, the authors noted some of the reviews only reported that there was an improvement in learning rather than the use of technology resulted in better outcomes than when technology was not used. Concluding their review, the authors reasoned “The use of educational technology is a complex phenomenon, which requires a focus on much more than learning outcomes to understand fully” (p. 254). To that end, the opportunity to learn model offers a framework integrating both the structural and process paradigms to fully understand the complex phenomenon of teaching and learning with digital media.

Altogether, the model captures how teaching and learning processes are constrained by contextual factors on the level of the education system, particular school context, and specific classroom situation, as well as on the individual student level by students’ previous learning experiences and learning prerequisites (as represented in Figure 1.1). Considering the expansiveness of the model, it is best used to identify relevant factors at each level and from there determine individual research approaches (Seidel, 2014). In particular, on the student level the model identifies the relevant factors that affect individual learning processes. However, it is quite clear how the opportunity to learn model could also be used to identify the relevant factors at the level of the education system (e.g., policies concerning digital media use) and particular school context (e.g., the technical infrastructure and level of IT support) that affect how students learn in classrooms with digital media as well. Focusing on the student level, investigating the contextual and preceding factors that influence students’ learning processes in the classroom can help to more fully understand how students learn with digital media.

Figure 1.1

An Adapted Opportunity to Learn Model Applied to Learning with Digital Media (Brühweiler & Blatchford, 2011)

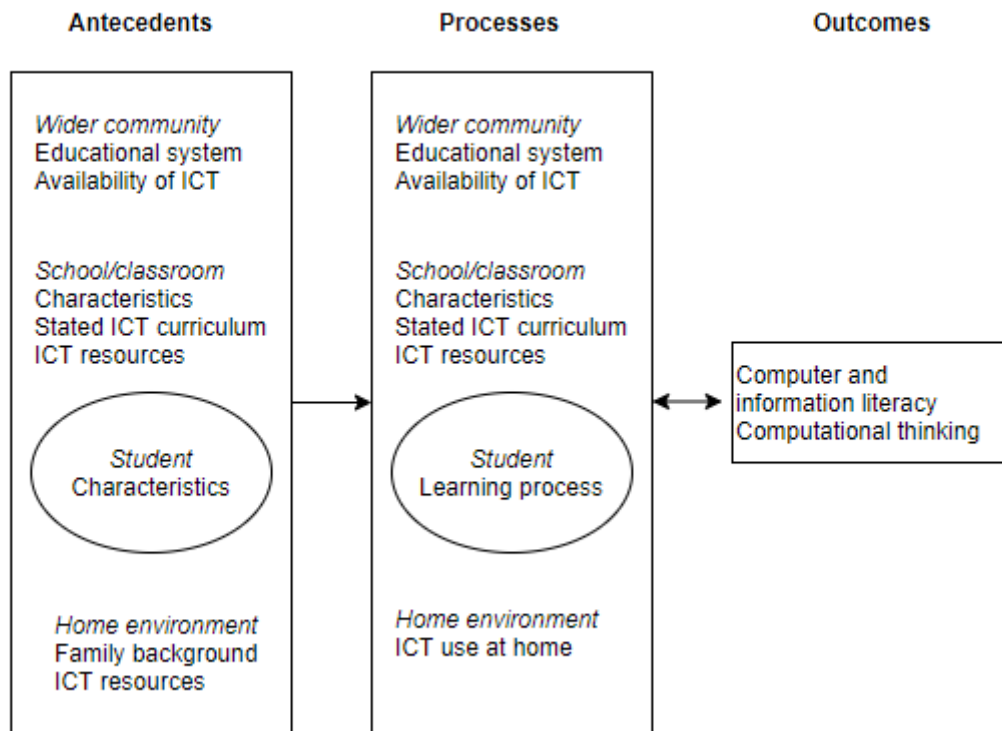


Although the opportunity to learn model has not yet been applied to learning with digital media to the best of my knowledge, the contextual framework of the ICILS 2018 has recognized similar variables situated on multiple levels of education systems to provide the basis for understanding variation in students' information and technical competences (as represented in Figure 1.2). In addition to measuring eighth-grade students' computational and information literacy (CIL) and computational thinking (CT), the ICILS 2018 also includes questionnaire data on students' and teachers' use of computers and other digital devices as well as their attitudes towards the use of digital technologies. Inherent to the framework is that CIL and CT learning occurs in overlapping contexts of in-school and out-of-school learning. Additionally, the framework specifies the temporal status of contextual factors in the learning process. Under their conceptual framework, contextual factors are considered either antecedents or processes. At the student level, antecedent factors include ICT experience as well as variables from the home environment, in particular parent socioeconomic status and home ICT resources. These

factors are considered to precede students' learning processes, which in turn directly influence CIL and CT learning (Fraillon et al., 2019).

Figure 1.2

The Contextual Framework of the ICILS 2018 (Fraillon, Ainley, Schulz, Friedman, & Duckworth, 2019, p. 7)



1.2 The Role of Parents in Shaping Students' Digital Media Self-Efficacy

Increasingly more research is exploring how digital media can be used for teaching and has investigated how teachers shape digital media use through classroom instruction. However, students arrive in the classroom with different experiences, skills, and beliefs (Bransford et al., 2000) including the extent to which they have been exposed to and have used digital media. Besides teachers in the classroom, parents at home may also play a pivotal role in shaping students' beliefs about digital media, and these beliefs are in turn important precursors to students' use of digital media for learning. Previous research has shown parent and at-home factors are related to students' digital media self-efficacy (e.g., Aesaert & van Braak, 2014; Zhong, 2011); however, the mechanisms that underlie these relations are less clear. To explain how parental and at home factors affect how students develop digital media self-efficacy, I will first describe how expectancy-value theory presents a framework for understanding the contextual factors that promote adolescents' self-concepts. I then describe how the parent

socialization model, one link in the expectancy-value theory framework, can be used to explore how parents' beliefs and behaviors involving digital media may affect students' development of digital media self-efficacy. I conclude by discussing the importance of digital media self-efficacy for learning and effectively using digital media.

1.2.1 The expectancy-value model framework and students' self-concepts

The expectancy-value model framework from Eccles and colleagues (1983) is used to understand the precursors to adolescents' achievement-related choices and engagement. In the words of Jacobs and Eccles (2000), the model suggests "the key determinants of choice are the relative value and perceived probability of success of each available option. Expectancies and values are assumed to directly influence performance and task choice and to be influenced by task-specific beliefs such as self-perceptions of competence" (p. 406). Following the model, children are influenced by the beliefs and the behaviors of their socializers as well as their previous achievement-related experiences to form their self-beliefs. In turn, these self-beliefs ultimately lead to future expectancies of success and task values that guide their task choices and performance in adolescence (Jacobs & Eccles, 2000). In particular, parents' values have been found to play a key role in socializing children's self-perceptions and activity choices (Eccles et al., 1983). Expectancies for success refer to children's beliefs about how well they will do on upcoming tasks in the immediate or long-term future, whereas task values can be understood as the difference between "Can I do this task?" and "Do I want to do this task?" (Jacobs & Eccles, 2000, p. 408). This distinction is made to highlight that the desirability or attractiveness of a task influences the motivation to complete the task. Applying this model to students' development of digital media skills, when children perceive themselves to be competent in the use of digital media, they are likely to value using digital media, want to use digital media, and perform well when using digital media.

Eccles et al. (1983) outlined four motivational components of task value: attainment value, intrinsic value, utility value, and cost. Attainment value is understood as the personal importance of doing well on a task, intrinsic value is the enjoyment a person gets from doing the task, and utility value is how well the task relates to current and future goals. In contrast, cost is understood as the negative aspects of engaging in the task, such as performance anxiety or fear of failure as well as the effort that is needed to succeed and the opportunities that are lost from not choosing another task. The distinct task values tend to play different roles as students move from primary to secondary school. For example, whereas children may engage in a task because of the intrinsic value (i.e., they find the task interesting), they are likely to continue engaging in the task during adolescence because of the perceived utility value (i.e.,

they find the task to be useful). Children's task values are also important because they are positively related to children's competence and expectancy beliefs. Jacobs and Eccles (2000) explained that children who do not feel competent when engaging in an activity are not likely to want to continue to be involved in that activity and therefore miss out on developing positive experiences.

Regarding the practical implications of the expectancy-value model framework, considerable research has investigated the decline in students' perceived task values of math and science from primary to secondary school to understand and address the lack of students studying STEM subjects in high school and at universities (e.g., Gaspard, Häfner, Parrisius, Trautwein, & Nagengast, 2016; Häfner et al., 2017; Häfner et al., 2018). Through this body of research, it has been widely documented that children's perceived task values with respect to math and science are important predictors of students' achievement-related choices and engagement in adolescence. To this end, extensive research has focused on understanding how children's subject-specific task values are formed based on mechanisms outlined in the expectancy-value model to find solutions that keep adolescents interested in pursuing math and science courses of study and careers. In particular, Häfner et al. (2017) developed two interventions aimed at improving students' motivation in math and specifically intended to help families with lower motivational resources. If parents believe a specific subject does not hold much value, their children are at risk to develop low values for the subject as well (e.g., Simpkins, Fredricks, & Eccles, 2012). Häfner et al. (2017) found that especially students whose parents reported lower math utility values benefited from the interventions and reported higher utility and attainments values five months after the intervention. Altogether, this highlights that families shape the environments students grow up in and emphasizes the decisive role parents play in influencing their children's values.

While the expectancy-value model has not been used to understand students' engagement or choices in their use of digital media, it allows a blueprint for (a) understanding the importance of students' subject-specific self-beliefs as predictors of future achievement-related choices and engagement in digital media, (b) understanding the variables and underlying mechanisms that can explain students' development of self-beliefs regarding the use of digital media, and (c) in particular, highlights the role of parents in shaping children's self-beliefs and achievement-related choices through a variety of child-specific beliefs and activity-specific behaviors. Importantly, regarding the use of digital media, international large-scale assessments including ICILS 2018 (Fraillon et al., 2019) and PISA 2003 and 2006 (Zhong, 2011) have found students more often use digital media outside of school than in school. This suggests that to understand

how students develop self-beliefs with respect to digital media, looking at their experiences outside of school may be particularly beneficial. Although many experiences, such as school and organized activities, and different socializers, including teachers and peers, provide contexts in which children's values are shaped, parents have been identified as playing a pivotal role (Eccles et al., 1983). As children's first socializers, parents provide experiences that influence their children in ways that have immediate and long-term consequences by setting in motion processes that shape their children's developmental trajectories across time (Simpkins, Fredricks, & Eccles, 2015).

1.2.2 The parent socialization model: How parents' beliefs and behaviors shape children's digital media self-efficacy

The parent socialization model set forth by Eccles et al. (1983), also known as the family socialization model (e.g., Simpkins et al., 2015), illustrates how parents shape children's motivational beliefs and choices through their own beliefs and behaviors. Specifically, the model proposes that parents' beliefs influence parents' behaviors which in turn affect children's outcomes including self-perceptions, subjective task values, future goals, expectancies, and performance (Jacobs & Eccles, 2000). Typically, research using the parent socialization model has shown when parents have positive beliefs about a school subject such as math, they pass these beliefs onto their children through their behavior, such as encouraging their children to like math or performing math activities together (Simpkins, Fredricks, & Eccles, 2012). Besides academic subjects, these studies have also explored leisure domains such as sports and music (Simpkins et al., 2012). Specifically, Simpkins et al. (2012) found mothers' behavior mediated the link between mothers' and adolescents' beliefs in sports, music, and math, but not in reading. Applying the parent socialization model to students' development of digital media beliefs, parenting behaviors involving digital media are hypothesized to mediate the link between parents' and students' beliefs with respect to digital media.

Many studies have pointed out the importance of students' socioeconomic backgrounds when investigating variation in students' digital media skills (e.g., Livingston & Helpser, 2007). Children and adolescents depend on the income and education level of their parents, and lower income parents may face barriers such as the cost of digital devices and lack of experience regarding digital media skills (Livingston & Helpser, 2007). In particular, Vekiri (2010) found students from higher SES families were more likely to positively value ICT, whereas students from lower SES families had fewer chances to develop ICT competences and showed lower ICT self-efficacy. Additionally, Clark, Demont-Heinrich, and Webber (2005) showed that parents with higher incomes demonstrated higher levels of ICT access and ICT skills and tended

to perceive that their children needed advanced ICT skills for success, whereas parents with lower incomes regarded ICTs as entertainment and wanted to minimize their children's screen use. However, Simpkins et al. (2015) suggested socioeconomic backgrounds may not be sufficient to understand why some children develop skills and others do not. The authors explained that not all adolescents from families with many resources participate in organized activities, such as sports or music classes, even though they are likely to have the resources to support participation (Simpkins, Ripke, Huston, & Eccles, 2005). Alternatively, some children and adolescents in families with very limited resources participate in organized activities (Simpkins, Davis-Kean, & Eccles, 2005). At the same time, it is well acknowledged that "mere access" to digital media is insufficient to foster effective use of digital media (Livingston & Helpser, 2007). To better understand the variation in children's outcomes, parents' beliefs and behaviors can further explain how students develop self-perceptions and competences beyond the effects of SES (Simpkins et al., 2015).

In line with most social cognitive theories of behavior, Eccles et al. (1983) assume that beliefs cause behaviors. With respect to parenting, parents have general beliefs about the world as well as child specific beliefs, and these combined beliefs influence their parenting behaviors (Jacobs & Eccles, 2000). Returning to the discussion of task values, the expectancy-value model assumes that parents as well as students have distinct value beliefs (Eccles et al., 1983). In another example aimed at addressing secondary students' loss of interest in math and science, Harackiewicz, Rozek, Hulleman and Hyde (2012) tested an intervention intended to influence students' math and science utility values by targeting parents' math and science utility values. Parents were sent two brochures outlining the utility value of STEM topics. The reasoning behind the brochures was to demonstrate to parents the importance of math and science, prompting them to discuss the importance of these topics with their children and encourage them to pursue math and science courses. The authors found that students whose parents received the intervention enrolled in significantly more math and science courses than students whose parents were in the control group. In this way, parents' beliefs (e.g., math and science utility values) affected their parenting behaviors, (e.g., encouragement), which in turn affected their children's outcomes.

Furthermore, Jacobs and Eccles (2000) explain that parents provide their children with opportunities and experiences that support the development of certain competences. When children are young, parents are responsible for initially getting their children involved in certain activities, such as by buying equipment or lessons, and spending time with them to help them develop their skills. These initial experiences may prompt children to continue spending time

on these activities as they become adolescents and make their own decisions. In this way, the behaviors parents engage in when their children are young affect the choices their children make in adolescence. Exposure to certain activities such as the use of digital media affects preference and skill acquisition, and therefore perceived competence. Besides providing certain experiences, parents can also model involvement in valued activities. Jacobs and Eccles (2000) explained that parents display behaviors that children may later copy and adopt as part of their own behavior. They further elaborated “The ways in which parents spend their time, the choices they make between available activities, and the sense of self-competence that they project send strong messages to their children about activities that are valued and about acceptable ways to spend time” (p. 419). Parents’ roles may shift from providing exposure, opportunities, and role modeling to providing encouragement and guidance as children construct their own values and make their own choices.

According to the parent socialization model (Eccles et al., 1983), parents’ beliefs influence their behaviors which in turn help shape students’ self-beliefs. Parents’ beliefs include the extent to which parents personally value certain activities. In relation to digital media, when parents enjoy using digital media (intrinsic value), find digital media useful (utility value), or consider using digital media to be important for one’s self (attainment value), their parenting practices involving digital media may in turn endorse the use of digital media. By contrast, when parents perceive using digital media to be exhausting or distressing (emotional cost) or come at the expense of other, more enriching activities (opportunity cost), their parenting practices may go against the use of digital media. Subsequently, parent specific behaviors such as the provision of specific experiences (e.g., lessons or equipment) and their modeling of involvement in valued activities can affect the extent to which children value and engage with different activities (Jacobs & Eccles, 2000). If parents provide their children with smart phones, tablets, and computers or laptops at an earlier age, their children have more opportunities to spend time with these devices which may in turn influence how they perceive their ability to use digital media. Additionally, when parents choose to spend their own time using digital media and convey self-competence using these devices, they may send the message that using digital media is a valued activity and an acceptable way to spend time, thus prompting their children to value and use digital media. Taken together, children may gain more experience successfully using digital media and develop digital media self-efficacy. In turn, digital media self-efficacy can be considered an important precursor to how effectively students learn and work with digital media.

1.2.3 Digital media self-efficacy and effectively learning with digital media

In reviewing the literature since Bandura (1977) first theorized about the power of self-efficacy beliefs, Usher and Pajares (2008) found in line with Bandura's hypothesis, mastery experienced consistently predicted students' self-efficacy beliefs and were critical determinants of motivation and behavior across academic domains. Furthermore, Schunk and Pajares (2008) found that students who were confident in their academic capabilities, subsequently monitored their work more effectively, were more efficient in addressing problems, showed more persistence, and were ultimately more successful in school. Understanding the role that teachers, peers, and parents play in the creation and development of students' self-efficacy helps to inform practices aimed at fostering and nurturing these self-beliefs (Usher & Pajares, 2008).

Building off previous research regarding self-efficacy, digital media self-efficacy can be understood as the extent to which a student believes he or she can successfully operate digital media (Bong & Skaavali, 2003). In line with Bandura (1977) and Usher and Pajares (2008), it is likely to be largely formed by students' prior experiences with using digital devices successfully or not. In turn, students who believe that they are capable and that they can and will perform well when using digital media are more likely to put forth effort in this endeavor and persevere in the face of difficulties. This is evident in Tsai and Tsai (2003) which found students with high self-efficacy in using the internet had better information-searching strategies and performance in web-based learning tasks than students with low internet self-efficacy. Compared to students with high internet self-efficacy, students with low internet self-efficacy lacked the confidence in their ability to use the internet to try new approaches for searching for information and solving problems themselves. In another example, Rohtagi, Scherer, and Hatlevik (2016) found that students' use of ICT for recreational purposes was the dominant predictor of students' self-efficacy beliefs, which in turn predicted students' computer and information literacy achievement. The authors explained that students' prior use of ICT created positive mastery experiences in using ICT, leading to positive self-efficacy beliefs, and ultimately resulting in improved ICT performance. In other words, students' ICT self-efficacy explained the effect of students' use of ICT on their computer and information literacy. Additionally, Lee and Wu (2017) found students with better attitudes towards computers and more confidence in completing high-level ICT tasks had higher engagement in online reading activities and in turn higher reading literacy. The authors proposed though reading performance may not be the goal when students work with computers, their attitude and confidence towards computers and ICT tasks led them to be more engaged in online reading activities, accumulate

online reading experience, and ultimately enhance students' reading performance in print texts, as measured by PISA.

Taken together, students' self-efficacy beliefs with respect to using the Internet and various technologies influence students' computer and information literacies (e.g., Rohtagi et al., 2016; Tsai & Tsai, 2003) and facilitate achievement in domains such as reading (e.g., Lee & Wu, 2017). Furthermore, in line with previous research regarding self-efficacy beliefs, students' experience using technologies help students to develop ICT self-efficacy beliefs (e.g., Rohtagi et al., 2016). Students' digital media self-efficacy may also be associated with the positive effects of self-efficacy beliefs found in Schunk and Pajares (2008), such as addressing problems in digital media related tasks more efficiently or showing more persistence when problems arise when using digital media. Altogether, investigating digital media self-efficacy can be considered an important precursor to effectively learning with digital media.

1.3 Student Characteristics and Student Perceptions of Instruction with Digital Media: The Power of Perceptions

Prior to the emergence of digital media in the classroom, researchers in the field of educational effectiveness have sought to understand what contributes to the kind of high quality instruction that fosters student learning (Kunter et al., 2013) and have investigated the effects of specific instructional practices on student learning growth (Seidel & Shavelson, 2007). Through this body of research, instructional practices that promote cognitive activation and provide a supportive classroom climate have consistently been shown to be essential components of instructional quality (e.g., Klieme, Pauli, & Reusser, 2009; Pianta & Hamre, 2009). The degree of cognitive activation and individual learning support have been found to be essential in initiating and maintaining insightful learning processes (Kunter et al., 2013). Notably, research has shown that cognitively activating instruction and personal instructional support affects not only students' achievement gains (e.g., Kunter et al., 2013) but also their motivation development (e.g., Wagner, Göllner, Werth, Voss, Schmitz, & Trautwein, 2016). With respect to research on digital media use in the classroom, it is largely driven by trying to understand how digital media may facilitate student learning (Scherer, 2020). Therefore, investigating students' perceptions of a supportive climate and cognitive activation in classes with digital media can illustrate how digital media can be used to enhance the established instructional practices shown to facilitate insightful student learning processes.

In the following, I first describe cognitive activation and supportive climate and how they may be affected by digital media. I then outline previous research that has shown student ratings

of cognitive activation and supportive climate are valid and reliable indicators, predict student learning outcomes, and are situated from the perspective of the learner. Subsequently, I describe the added value of investigating students' individual perceptions by demonstrating the relation to students' learning characteristics and individual learning outcomes. Lastly, I discuss the advantages of person-centered approaches to examine students' individual perceptions and learning characteristics and how this can help to understand how different students learn with digital media.

1.3.1 Investigating cognitive activation and supportive climate as components of instructional quality

Klieme et al. (2009) describe cognitive activation as an observable pedagogical practice or pattern that “encourages students to engage in (co)-constructive and reflective higher-level thinking and thus to develop an elaborated, content-related knowledge base” (p. 141). Teachers must challenge students by giving them tasks and asking them questions that engage them in higher levels of thinking while prompting them to build on what they already know. Key features include challenging tasks, the activation of prior knowledge, content-related discourse, and participation practices. Furthermore, a supportive classroom climate is characterized by “supportive teacher-student relationships, positive and constructive teacher feedback, a positive approach to students' errors and misconceptions, individual learner support, and caring teacher behavior,” (Klieme et al., 2009, p. 141). Teachers provide individual learning support by continuously monitoring individual students' learning processes to provide feedback and adaptive instruction while respecting their autonomy (Baumert et al., 2010). Extensive research has shown that cognitively activating instruction has positive effects on student achievement and supportive climate has positive effects on student motivation (Baumert et al., 2010; Kunter et al., 2013). However, there is a lack of research investigating how the use of digital media may affect students' perceptions of the extent of cognitively activating and instructionally supportive practices.

Given the potential of digital media in teaching and learning, the use of digital media in classrooms may offer the most promise or the most damage to students' perceptions of cognitively activating processes. On the one hand, teachers are limited by the availability of the applications that are currently on the market (Ward, Finley, Keil, & Clay, 2013). Depending on the subject and domain, there may already be applications with cognitively stimulating designs and content. However, even content-specific applications are not necessarily designed for educational purposes (Ward et al., 2013), potentially placing an additional burden on teachers to create novel lessons without a previously developed curriculum. Additionally, realistic and

dynamic visual displays in particular can distract students from paying attention to the relevant information (Renkl & Scheiter, 2015), further placing more stress on the teacher to redirect students to engage in higher level thinking. Furthermore, cognitive activation requires a “certain quality” of interaction and participation between teacher and students (Klieme et al., 2009, p. 140). These pedagogical practices can be hard to replicate, even with personalized learning or intelligent software. Cognitive activation requires teachers to trigger students’ cognitive processes by integrating students’ previous knowledge with the current task and challenging students’ beliefs so the students can evaluate the validity of their own solutions (Lipowsky et al., 2009). To do so, teachers must provide individual questions and feedback which might not be imitated by just any software, and teachers might not be trained to trigger cognitive processes alongside digital learning. Finally, whereas technology offers immediate access to information, the sheer ease and availability of so much information may promote “mile wide, inch deep” thinking and a resistance to information that requires more effort (Giedd, 2013).

Digital media may also support teacher-student relationships and facilitate opportunities for teachers to offer more individual support to students while allowing them to retain their autonomy. In turn, students may perceive that instruction with digital media provides more instructional support and a supportive classroom climate. Digital media can provide opportunities for teachers to offer ongoing feedback as well as to collect cumulative assessment data (Goodwin, 2012). Communicating online can enhance students’ willingness to ask for help from their teacher because of a greater sense of anonymity and a decrease in feelings of intimidation that may occur in a social environment (Bures, Abrami, & Amundsen, 2000). In a study of a one-to-one laptop school, Lei (2010) found that social-communication technologies provided students more opportunities to ask questions, especially for students who were too shy to ask questions in the classroom, and students reported that it was more convenient to email their teachers to ask questions or to set up an appointment. Conversely, in a study investigating primary students’ use of iPads, Falloon (2014) raised the issue that although students may appear to be engaged in learning with an applications, recordings of their activities revealed that many were actually skimming the information or had converted the learning task into a game. This indicates the additional challenges that teachers may have in monitoring the depth of students’ learning and identifying learning difficulties, which can in turn prevent teachers from offering appropriate support.

1.3.2 The benefits to using student ratings of supportive climate and cognitive activation

To assess cognitive activation and supportive climate, student ratings have been widely used and have been found to be valid and reliable indicators (e.g., Fauth, Decristan, Rieser, Klieme, & Büttner, 2014; Lüdtke, Robitzsch, Trautwein, & Kunter, 2009; Wagner et al., 2016; Wagner, Göllner, Helmke, Trautwein, & Lüdtke, 2013) as well as predictors of achievement and motivation (e.g., Göllner, Wagner, Eccles, & Trautwein, 2018; Wagner et al., 2016; Kunter et al., 2013; Wagner et al., 2013). Generally, student ratings allow to gain unique insight into the educational setting and are more cost effective, less labor-intensive, and more easily obtained than reports from teachers or external reviewers (Lüdtke et al., 2009). Student ratings are not merely the result of a single or limited number of observations but rather reflect students' every day, firsthand experiences in classrooms and have been found to provide reliable assessments of instructional practices (Lüdtke et al., 2009). Besides practical considerations, student ratings can be considered the most appropriate source of data for assessing the educational setting as Lüdtke et al., (2009) explained "a given student's behavior can be assumed to be more affected by his or her interpretation of the classroom context than by any objective indicator of that context" (p. 120). Asking students about their firsthand classroom experiences naturally situates their experiences from the perspective of the learner. Accordingly, students may be more suited to determine the affordances and constraints of learning activities (Wallace, Kelcey, & Ruzek, 2016).

In particular, regarding aspects of cognitive activation, Kunter and Baumert (2006) suggested that student ratings provide the best information regarding whether tasks and interactions are suitable for and agreeable to students. In comparison to the teacher ratings, the authors found that teachers did not seem to be sensitive to whether the tempo they set was too fast for their students. Additionally, the authors found comparing the teacher ratings and the external ratings by trained raters of the cognitive demands required to complete homework tasks, the teachers were not able to gauge the cognitive challenge of the assigned tasks. Student ratings also provide valuable insight for assessing the quality of student-teacher interactions. In another study comparing teacher and student ratings, Aldrup, Klusmann, Lüdtke, Göllner, and Trautwein (2018) found the teacher ratings of social support were mostly independent of what their students perceived and were unrelated to student development. By contrast, students were found to be particularly sensitive to the social support they perceived, and students' individual ratings of social support were linked to all student outcomes including achievement and self-esteem. Aldrup et al. (2018) further commented that student perceptions were found to reflect

observable differences in whether students perceived their teachers were responding to their personal and learning needs. Additionally, with respect to mathematics instruction, Kunter et al. (2013) found that students' perceptions of cognitive activation predicted greater achievement gains and students' perceptions of supportive climate predicted motivation development. Altogether, investigating students' perceptions of cognitive activation and supportive climate offers unique and meaningful insight into what happens in the classroom from the perspective of the learner. Given these advantages, investigating student perceptions in classes with digital media offers a promising but so far underutilized approach for understanding how digital media affects student learning.

1.3.3 Using student perceptions as a pathway for understanding how students learn with digital media

In addition to being valid and reliable indicators as well as predictors of student achievement and motivation, student perceptions of supportive climate and cognitive activation can be considered an intermediary between instructional practices and student learning (Göllner et al., 2018). Lipowsky et al. (2009) explained, "learning processes cannot be controlled from the outside; rather, the teacher provides learning opportunities that must be perceived and utilized by the student to be effective" (p. 528). In this way, students' perceptions of their teachers' instructional practices mediate the effect that an instructional practice will have on student learning (Shuell, 1996). If students' perceptions do not match the intention behind the instructional practice, then the instructional practice is not likely to reach its goal (Doyle, 1977).

Schenke (2018) further explained that student perceptions of their classroom interactions play an important role in understanding how students learn. According to social-cognitive theory (Bandura, 1986), students are active in interpreting their classroom environment and form perceptions on the basis of their interactions with and in that environment. In turn, student perceptions of that environment shape their behavior and subsequent learning outcomes. In this way, how students perceive the instructional environment may be regarded as more important for determining what the student will learn than the actions of the teacher (Shuell, 1996). This is also in line with the idea of the *functional significance* of an environment as presented by Ryan and Grolnick (1986). This idea suggests that the meaning the individual assigns to an environment is more important than the environment itself for understanding students' behaviors.

To demonstrate how students' perceptions of instructional practices mediate how students learn, Schenke (2018) examined whether student perceptions of the quality of classroom interactions explained the association between observed instructional practices by trained raters

and students' mathematics achievement and effort. She found that observed emotional support was significantly associated with students' perceptions of emotional and instructional support, and students' individual perceptions of emotional support and instructional support were significantly linked to their self-reported effort. Specifically, a 1-unit increase in students' perceptions of emotional support was associated with a 0.60-unit increase in elementary school students' self-reported effort and a 0.26-unit increase in middle school students' self-reported effort. Additionally, a 1-unit increase in students' perceptions of instructional support was associated with a 0.60-unit increase in elementary school students' self-reported effort and a 0.26-unit increase in middle school students' self-reported effort. Whereas students' perceptions did not appear to mediate the effect of the observed instructional practices on students' mathematics achievement, students' perceptions predicted their mathematics achievement as well as their self-reported effort. Notably, Schenke (2018) pointed out the timeframes of the observations of instructional practices and the timeframe when the students rated their perceptions varied and not all the constructs measuring students' perceptions aligned with the observed dimensions. Furthermore, although individual-level perceptions were important for understanding student outcomes, the statistical models used in the study were only able to investigate mediation at the classroom-level. Regardless, Schenke (2018) suggested that students' perceptions of instructional support may provide a pathway for understanding students' achievement and learning-related behavior. Considering the potential for understanding how instructions "gets" into students (Schenke, 2018, p. 47), the study laid the groundwork for using student perceptions to understand how instructional practices with digital media may affect student learning outcomes.

In sum, cognitively activating and instructionally supportive practices have been found to support students' learning processes and to result in achievement gains and motivation development (Kunter et al., 2013). The ways that teachers cognitively activate students by giving them tasks and lines of questions, activating prior knowledge, and challenging students to engage in higher level thinking has been found to result in achievement gains (Aldrup et al., 2018; Kunter et al., 2013; Schenke, 2018). Furthermore, the extent to which teachers provide a supportive classroom climate by offering constructive feedback and creating an environment where students feel safe making mistakes has been shown to lead to motivation development (Kunter et al., 2013), effort (Schenke, 2018), and self-esteem (Aldrup et al., 2018). In order to assess cognitive activation and supportive climate, student ratings have been found to be valid and reliable indicators as well as to provide valuable insight from the perspective of the learner (Kunter & Baumert, 2006; Wallace et al., 2016). In addition, student perceptions of cognitive

activation and a supportive climate can be considered an intermediary between instructional practices and student learning (Göllner et al., 2018). Even if teachers provide cognitively activating or instructionally supportive instruction, if students do not perceive the instruction in this way, then the intended effects and benefits of these instructional practices will not take place. Taken together, investigating students' perceptions of cognitively activating and supportive classroom climate practices in classes with digital media can indicate how the use of digital media can affect students' learning processes and in turn student achievement and motivation.

1.3.4 The added value of investigating individual student perceptions and students' characteristics

Yet, within classrooms, students' perceptions can differ tremendously (Göllner et al., 2018). Individual differences in students' perceptions have previously been considered to be the result of measurement error or have been dismissed as being the result of rating tendencies (Göllner et al., 2018; Lüdtke et al., 2009). However, students' idiosyncratic perceptions can indicate meaningful differences in how students perceive instructional practices (Aldrup et al., 2018; Göllner et al., 2018; Seidel, 2006) and in turn learning outcomes (e.g., Aldrup et al., 2018; Jurik et al., 2014). Considering analyses at the individual student level, Scherer, Nilsen, and Jansen (2016) examined individual perceptions of supportive climate and cognitive activation using PISA 2012 data from three countries. Rather than using only confirmatory factor analysis, different latent variable modeling approaches were used to describe students' individual perceptions with respect to their factor structure, measurement invariance, and relations to achievement, self-concept, and motivation in mathematics. The four approaches varied by allowing for item cross-loadings or not and differentiating between specific and general factors or not. In all four modeling approaches, significant relations were found between individual student perceptions and math achievement, self-concept, and motivation. Individual variation at the student level could not be attributed to measurement error or disagreement but was rather found to be due to students' individual differences.

Given the practical advantages of using student ratings, they are often used to evaluate teachers, particularly in the United States (Schweig, 2014). However, some studies have found student ratings of aspects of instructional support and cognitive activation to differ from classroom observations or teacher reports (Kunter & Baumert, 2006), calling into question the validity of student ratings. However, Kunter and Baumert (2006) pointed out that low levels of agreement can reflect perspective-specific validities that tap into different aspects of the classroom environment. Increasingly more research has reported that individual student

perceptions provide useful information about students' individual experiences in their classroom learning environments, not necessarily to evaluate teachers (Göllner, Fauth, & Wagner, 2020). As pointed out, although there are many advantages to using student ratings to assess instructional practices, aggregating them at the class level can mask meaningful information. Schweig (2014) explained that three classrooms can arrive at the same aggregate score with very different distributions of individual scores. In one classroom, all students may give the same rating, reflecting perfect consensus. However, in another classroom, half of the students may give the instructional practice the highest rating and the other half the lowest rating but still result in the same score as the first classroom. In the last classroom, there can be a mix of high and low ratings that cancel each other out but still result in the same mean score as the first and second classrooms. Göllner et al. (2018) explained that individual student perceptions of instructional quality are composed of both common opinions shared by all students in a classroom and an idiosyncratic component that reflects students' non-shared perceptions. However, the idiosyncratic component is often ignored (Aldrup et al., 2018), although such information has been found to offer valuable insight. When examining how student perceptions mediate the effect of instructional practices on student learning outcomes, Schenke (2018) found that individual-level effects were stronger than the effects of classroom aggregates of students' perceptions on outcomes. Additionally, Aldrup et al. (2018) found the students' idiosyncratic perceptions of social support were closely linked to their outcomes, whereas at the class level, the relations were more heterogeneous.

Besides measurement error, Schweig (2014) explained that the lack of consensus in student ratings can arise for substantive reasons such as the existence of sub climates or microclimates, referring to groups of students within the same classroom who perceive instruction in different ways. Some evidence indicates this may be a result of teachers having different expectations of students and treating students accordingly (e.g., Lüdtke, Trautwein, Kunter, & Baumert, 2006). However, increasingly more research has indicated that students can perceive the same instructional practice in different ways, and these differences have been linked to students' learning characteristics (Seidel, 2006). For example, Seidel (2006) used latent class analysis to group secondary education physics students from 82 classrooms into five homogenous profiles based on their cognitive and motivational-affective characteristics, and these characteristics systematically affected how students perceived their learning environment. Specifically, Seidel (2006) found students with overall positive characteristics and students with low general cognitive ability but high interest and self-concept were most likely to perceive a class as more supportive than students with overall negative characteristics or students who underestimated

their ability. Further research has shown students' profile membership is also related to cognitive and motivational outcomes. After identifying the same student profiles as Seidel (2006), Jurik, Gröschner, and Seidel (2014) found secondary education physics students with 'strong' and 'overestimating' profiles, reported higher cognitive learning activity and intrinsic learning motivation, whereas students with 'underestimating' and 'struggling' profiles reported lower cognitive learning activity and intrinsic learning motivation compared with the classroom mean.

Similarly, in another study using latent profile analysis, Lazarides and Ittel (2012) found secondary education math students could be grouped into four distinct patterns of perceived quality of instruction. Students who had a high probability of belonging to the 'high quality pattern' and perceiving high levels of cognitive activation and supportive climate reported significantly higher math interest than any other subgroups, whereas students with a high probability of belonging to a 'low quality pattern' showed significantly lower self-concept in math than students from any other subgroup. Overall, Lazarides and Ittel (2012) suggested that the existence of the distinct patterns in students' perceived instructional quality and their relations to students' math self-concept and interest indicate that students process their learning environments in different ways based on background characteristics, and these individual perceptions matter for learning success. Notably, Lazarides and Ittel (2012) discussed how the relationship between student perceptions of instructional quality and learning outcomes (i.e., math interest and math self-concept) cannot be determined. Whereas they suggested that students' math self-concept and interest differed depending on students perceived instructional quality, they acknowledged that the effect could work in the other direction. In this case, instead of student outcomes, self-concept and interest could very well be considered student characteristics that shape how students perceive their learning environments.

Regarding research using student perceptions of instructional quality, Göllner et al. (2018) explained research that has explored students' idiosyncratic perceptions and the relation of these perception to students' learning processes is quite rare. The authors explained that most research either looks at students' individual perceptions and their relation to academic outcome variables or aggregates students' individual perceptions at the class level to describe instructional quality. To address the lack of research looking at students' idiosyncratic perceptions of instructional quality, Göllner et al. (2018) compared two groups of students with a different or the same math teacher in Grades 9 and 10 in order to differentiate between students' rating tendencies and dyadic student-teacher effects. Whereas the authors found many of the individual differences in student ratings were teacher-independent and could be attributed to rating tendencies, this

depended on which aspect of instructional quality was rated. They found the highest rating tendencies for students' general impressions of their teachers and their teachers' methods of preventing students from disrupting classroom activities. Lower rating tendencies were found for perceived structure and support, and no effects of rating tendencies were found for comprehensibility. Additionally, students' idiosyncratic perceptions were associated with student learning outcomes. Irrespective of any teacher, students with higher math achievement, a better math grade, more math enjoyment, and greater experienced competences in math had more positive perceptions of their teachers' instructional practices in general. Furthermore, Göllner et al. (2018) showed students' perceptions of instructional quality reflected dyadic effects between individual students and teachers depending on the instructional quality measure. Overall, this research shows individual perceptions of instructional practices are valid in that they are linked to student learning outcomes. Both rating tendencies and dyadic effects can impact students' perceptions depending on the construct being measured, but rating tendencies and dyadic effects should not be dismissed. Dyadic effects reflect the quality of the relationship between a student and teacher, and this is important for student learning outcomes. Rating tendencies are also linked to individual student learning outcomes and are associated with student characteristics such as math competence and enjoyment. Altogether, individual ratings provide important information about how individual students view their classroom experiences.

Taken together, asking students about their perceptions of cognitive activation and supportive climate may be more appropriate than other measures such as teacher ratings or external reviews because student ratings are situated from the perspective of the learner, and individual student ratings are often associated with student outcomes (e.g., Aldrup et al., 2018; Schenke, 2018). Furthermore, student perceptions of cognitive activation and supportive climate may be more telling at the individual rather than the classroom level. Göllner et al., (2018) explained "Whereas a teacher's ability to prevent disruption is more relevant for the class as a whole, students' idiosyncratic perceptions of their teacher's sensitivity might be more relevant for understanding individual students' learning within the classroom" (p. 711). Regarding the present dissertation, if the goal is to understand how students learn with digital media in the classroom, averaging across differences in students' perceptions can mask the effectiveness of cognitively activating and instructionally supportive practices with digital media for different types of students.

Considering differences in students' perceptions, in a series of three studies Fauth et al. (2019) examined the stability of students' instructional quality ratings across time and across

classes. Across the three studies, instructional quality, including aspects of cognitive activation and supportive climate, were measured using student ratings. Based on these findings, Fauth et al. (2019) asserted “student characteristics should not only be understood as a product of teaching quality but also an antecedent of it” (p. 16). Whereas previous models have shown teacher characteristics predict teaching quality which predicts student learning outcomes, Fauth et al. (2019) contended that in addition to teacher characteristics, student characteristics shape teaching quality and how it is measured. Therefore, the importance of student characteristics with respect to differences in instructional quality cannot be understated.

In sum, extensive research has shown that students’ perceptions are valid and reliable indicators of supportive climate and cognitive activation. In addition, students’ perceptions of cognitive activation and supportive climate have been found to be powerful predictors of student achievement and motivation, indicating the importance and value of student perceptions. Increasingly more research has examined how students’ perceptions can differ tremendously within classrooms. Such research has shown that students’ idiosyncratic perceptions are not the result of measurement error but are instead evidence that students experience the classroom in very different ways, and this has serious implications for how much they gain from classroom instruction. From a practical point of view, using student ratings offers a cost effective and less labor-intensive way to collect data on a large number of students. Whereas other measures such as videos or log files offer considerable advantages for investigating what students are actually doing in classrooms with digital media, they may be limited in exploring large samples and scalability due to cost and data privacy concerns. Moving forward, research on digital media use in the classroom can benefit from taking students’ idiosyncratic perceptions into account. To understand differences in students’ perceptions, more research is examining the link between students’ learning characteristics and students’ perceptions. In particular, increasingly more research has used person-centered approaches to investigate the interplay of student characteristics and the relation to student learning.

1.3.5 The advantages to using a person-centered approach

Using a person-centered approach allows to focus on individuals and their individual perceptions and is particularly suited for investigating the complexity of student learning that involves many factors and their interrelations (von Eye & Bogat, 2006). Whereas a more traditional variable-centered approach assumes a sample comes from a homogenous population, the objective in a person-centered approach is to identify the unobserved subpopulations composed of similar individuals (Wang & Wang, 2012). A variable-centered approach represents “a synthesis (or averaged estimate) of the relationships observed in every individual

from the sample under study, without systematically considering the possibility that these relationships may meaningfully differ in subgroups of participants” (Morin, Morizot, Boudrias, & Madore, 2011, p. 59). By contrast, a person-centered approach is based on the proposition that distinct subgroups may exist, and if so, aggregate-level parameters may contradict parameters for groups or individuals (von Eye & Bogat, 2006). Von Eye and Bogat (2006) further explained three criteria for using a person-centered approach: (a) a sample is analyzed under the assumption that it was drawn from more than one population, (b) attempts are made to establish the external validity of the groupings, and (c) the groups are interpreted on the basis of theory. Subgroups may exist a priori or can be identified using methods such as latent class analysis or latent profile analysis, both of which group individuals into distinctive classes or profiles based on their responses to a set of observed variables (von Eye & Bogat, 2006). Using these methods, individuals are allocated into groups to minimize the within-group variation, or equivalently, to maximize the between-group variation (Magidson & Vermunt, 2002).

Furthermore, a person-centered approach is particularly suited for examining the complex organization of multiple characteristics within students (Bergman, Magnusson, & El-Khoury, 2003). When considering what shapes students’ perceptions, increasingly more research has looked beyond the effect of single characteristics and has examined the interplay of multiple student characteristics (e.g., Huber & Seidel, 2018; Lau & Roeser, 2008; Schenke, Ruzek, Lam, Karabenick, & Eccles, 2017). Returning to Seidel’s (2006) study which used latent class analysis to group students into distinct profiles based on cognitive as well as motivational-affective characteristics, four characteristics were used as profile indicators: general cognitive ability, prior content knowledge in physics, physics self-concept, and physics interest. According to Huber and Seidel (2018), general cognitive ability has been cited as the most predictive factor in students’ success (e.g., Dearyl, Strand, Smith, & Fernandez, 2007). With regard to prior content knowledge, students with low math achievement as measured by PISA, were less likely overall to have positive perceptions of their math teacher (Göllner et al., 2018). Additionally, students with high prior content knowledge in physics, as measured by the TIMSS, were more likely to engage in interactions with teachers, suggesting they may have stronger student-teacher relationships (Jurik et al., 2014). Considering self-concept, students with a high self-concept of ability more frequently engaged in interactions with teachers and received more supportive teacher feedback (Pielmeier, Huber, & Seidel, 2018), implying they would tend to perceive a more supportive classroom climate. Also considering interest, Lazarides and Ittel (2012) found students’ who were more likely to perceive high levels of cognitive activation and supportive climate reported higher math self-interest and self-concept.

However, Seidel (2006) identified a student profile showing high general cognitive ability and high prior content knowledge of physics, but low self-concept of ability and an intermediate level of interest. She referred to this profile as the ‘underestimating profile’ and 29% of the students could be grouped into this profile. Additionally, she identified another profile showing low general cognitive ability yet rather high self-concept and interest and referred to this profile as the ‘overestimating’ profile, accounting for 16% of the sample. Seidel found students who could be described by the ‘overestimating’ profile perceived the learning environment as more supportive than those who fit the ‘underestimating’ profile. These profiles demonstrate the importance of not only looking at students’ cognitive abilities but seeing them in combination with affective and motivational aspects. Rather than analyzing individual variables, the methodological approach allowed to analyze individual students, which in turn provided more nuanced insight about close to half of the sample (Seidel, 2006).

Although latent variable mixture modeling approaches have been criticized for groupings that reflect low, medium, and high levels of the construct under study, using these methods can also lead to the identification of qualitatively different subgroups with multidimensional indicators (Bray & Dziak, 2020). Additionally, these approaches may lead to the reconciliation of contradictory findings by showing that different theoretical models apply to different subgroups of students (e.g., Hickendorff, Edelsbrunner, McMullen, Schneider, & Trezise, 2017). The ‘underestimating’ and ‘overestimating’ profiles identified in Seidel (2006) can be described as inconsistent for having non-uniform characteristics and conflicting information about students’ achievement and other cognitive or motivational characteristics (Südkamp, Praetorius, & Spinath, 2017). Unlike students with consistent profiles, such as high levels of cognitive abilities along with high levels of learning motivation, students with inconsistent profiles are harder for teachers to identify and thus harder to offer their support (Südkamp et al., 2017). Whereas previous research investigating learning with technology has shown rather mixed results and large variability (e.g., Tamin et al., 2011), it is possible that some subgroups of students responded more positively to the use of technology than others. However, the existence of incoherent profiles suggests that multiple characteristics would be needed to more fully understand the differences in subgroups in instruction with digital media.

With respect to the context of ICT, person-centered approaches have been rarely used (Scherer, Rohtagi, & Hatlevik, 2017). Rather, research on students’ use of ICT typically has examined how ICT use and academic achievement are related and has identified the importance of students’ background and cultural capital for exploiting the available technologies (Scherer et al., 2017). However, previous research has suggested that within samples, there are different

subgroups of students who use ICT outside of the classroom in distinct ways and that this has implications for how they learn with ICT inside the classroom. For example, using only the Norwegian data from the 2013 ICILS, Scherer et al. (2017) used latent profile analysis and found two distinct subgroups of students that differed greatly in the extent to which they used ICT outside of school. The authors suggested that the existence of profiles indicates that even when students were given the same opportunities to access digital technology in Norway, they did not exploit these opportunities to the same degree. In turn, this suggests that when students in the same classroom are provided with the same opportunities to use ICT for learning, individual students may make use of digital technologies in different ways.

With respect to the practical implications, Scherer et al. (2017) proposed rather than reporting on the average ICT use for an entire sample, distinguishing between subgroups provides a more differentiated view on students' ICT use and its relation to further constructs. In turn, this differentiated view on students' use of ICT can help teachers to understand and acknowledge the diversity in students' experiences with ICT and not enforce a uniform and ideal type of user profile during instruction as well as provide teachers with valuable information about students' potential need for support. Acknowledging the different patterns in students' ICT use can also help teachers to identify opportunities students could use to enhance their digital competences as well as potential risks such as frequent ICT use outside of school (Scherer et al., 2017). For example, in another study using latent profile analysis, Salmela-Aro, Muokta, Alho, Hakkarainen, and Lonka (2016) found that sixth grade students in Finland could be categorized into distinct profiles based on school engagement and school burnout measures. The authors found almost half of the students could be grouped into profiles displaying varying patterns of cynicism towards school. Examining the relations between profiles and students' use of socio-digital technologies, the students belonging to the high cynicism profile, characterized by high levels of burnout, exhaustion, and feelings of inadequacy, reported they would be more academically engaged and hardworking if there was greater use of ICT in schools. The authors suggested this subgroup of students may have felt cynicism towards school because of the gap between their personal use of socio-digital technologies and the lack of socio-digital technologies in school practices.

In sum, a person-centered approach is particularly suited for studying students' individual characteristics and their relation to student perceptions of cognitive activation and supportive climate in classes with digital media. Using a person-centered approach allows to investigate multiple characteristics within individuals, which can be particularly useful for investigating the interplay of student characteristics. One example is latent profile analysis that allows to

investigate how distinct groups of students depending on the interplay of cognitive and motivational affective characteristics may differentially perceive instruction with digital media. These differential perspectives can offer unique insight into how different types of students perceive the addition of digital media to well-known components of instructional quality as well as links to student learning outcomes. Emerging research has already identified distinct profiles of digital media use in students outside of school, which has important implications for how students may learn with digital media inside school (e.g., Scherer et al., 2017; Salmela-Aro et al., 2016).

Conclusion

Taken together, when not using student ratings for assessing teachers, individual student ratings are appropriate for understanding how digital media use in the classroom affects student learning from the perspective of the learner, in view of the idea that student perceptions mediate the effect an instructional practice will have on student learning (e.g., Shuell, 1996). Specifically, investigating student perceptions of cognitive activation and supportive climate in classes with digital media can indicate how students perceive the addition of digital media to established instructional practices that have been shown to incite meaningful learning processes and lead to achievement gains and motivation development (Kunter et al., 2013). At the same time, the use of individual student ratings, which has strong ties to students' motivational-affective and cognitive characteristics, offers a way to better understand the differential effects digital media use may have on different kinds of students.

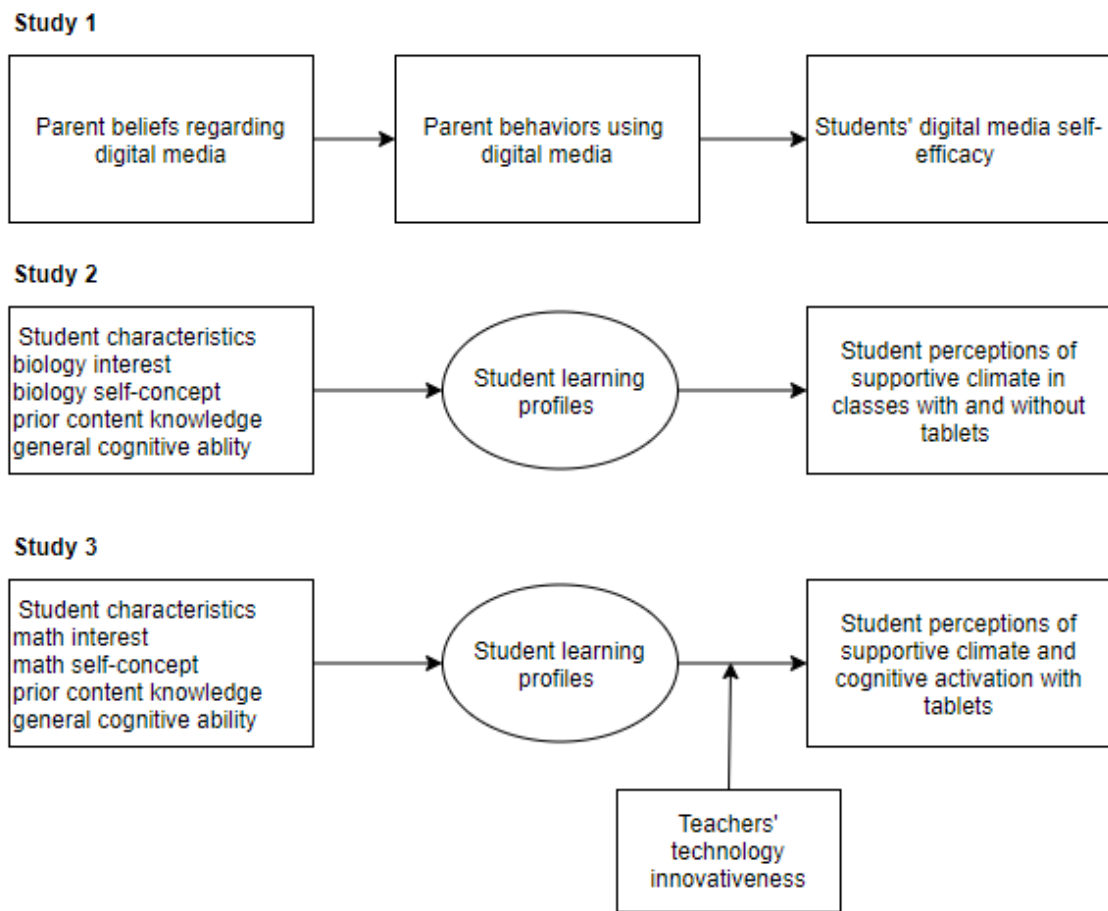
Or to put it quite simply: When considering how students learn with digital media, of course what matters is what teachers do with digital media in the classroom. However, if the aim is to understand how what teachers do with digital media affects student learning outcomes, it is also important to consider how students perceive teachers' instructional practices with digital media. If students do not recognize an instructional practice as emotionally supportive or if they do not feel that they have the opportunity to explain their own ideas, then the intended benefits of these practices will not take place for these students. The goal of using digital media in classrooms can be considered twofold: (a) to facilitate student learning in ways not possible without digital media; and (b) to give students opportunities to gain exposure and comfort in using digital media and develop effective digital media skills, not necessarily just for learning reading, math, and science skills.

1.4 Outline of the Studies

The present dissertation was designed to address two major research questions. First, how do parents' beliefs and behaviors regarding digital media shape students' digital media self-

efficacy? Second, what factors determine how students perceive instruction with digital media? Based on the opportunity to learn model, students' home environments and their family backgrounds as well as students' individual learning prerequisites affect how students learn in the classroom. By identifying and exploring these antecedent factors at the student level, I aimed to address gaps in the current state of the research on student learning with digital media.

Figure 1.3 shows the conceptual diagrams of the three studies conducted for this dissertation. For all three studies, the data were drawn from the *tabletBW* project. *TabletBW* is a school trial stemming from a school initiative funded by the Ministry of Education, Culture, Youth and Sports of Baden-Württemberg, with the aim of supporting schools in the effective use of digital media for teaching. Accompanying the school trial is a multi-cohort, longitudinal study investigating whether and under what conditions digital media enable successful teaching and learning processes in the classroom. Academic track schools across the state applied to participate and were randomly assigned to tablet and control conditions, and schools then decided which two classes from each school would participate. Schools in the tablet condition were equipped with tablets for each student. Under the conditions of the initiative set out by the Ministry, the teachers in tablet classes were asked to integrate tablets into their daily classroom practices, however, they were not enrolled in professional development programs or instructed how to use tablets in their classes. The participants included students and teachers who have taken part in questionnaires and tests at four time points over the course of three years from Grade 7 to (planned) Grade 9. Parents were informed and asked to sign consent forms for their children to participate in the study, and ethical approval was obtained from the Ministry.

Figure 1.3*Conceptual Diagrams of the Three Studies Included in the Dissertation*

In particular, the first study investigated how students' family environments shape students' development of digital media self-efficacy, which in turn may affect students' individual learning processes with digital media. Specifically, using the parent socialization model, one link of the widely used expectancy-value model framework (Eccles et al., 1983), the first study examined whether parents' behaviors towards digital media would explain by way of mediation the effect of parents' task-value beliefs regarding digital media on students' digital media self-efficacy. To assess parents' beliefs and behaviors regarding digital media, a questionnaire was developed. Parents were separately asked to participate in the questionnaire when they were asked to sign consent forms for their children to participate in the study. Only parents who agreed to participate were sent a questionnaire with the identification code of their child which was then used to match the parent questionnaires with the student questionnaires ($N = 1,206$ students and their parents).

In the second and third studies, building on extensive theory and empirical findings regarding students' perceptions of instructional quality, students' perceptions of supportive climate and cognitive activation in classes with tablets were investigated to understand how the addition of tablets may affect how students experience their new learning context and in turn inform students' learning outcomes. Both papers used latent profile analysis to first examine whether students could be grouped into distinct profiles based on their subject-specific motivational and cognitive characteristics and whether these profiles differentially predicted students' perceptions. The second paper first investigated whether students' learning characteristics could be used to differentially predict how students perceived supportive climate in classes with and without tablets. The sample included the first cohort of 1,058 biology students from 56 classes in 28 schools of the school initiative. Half of the classes received personal tablets and acted as the tablet group ($n = 518$ students) while the other half did not receive tablets and represented the control group ($n = 540$ students). After identifying and showing the predictive validity of the profiles, students' profile-specific perceptions were compared in classes with and without tablets four months after the students in the tablet group received their personal tablets. Additionally, students' profile-specific perceptions were compared over time within the tablet classes and within the control classes.

Building on these findings, the third study investigated whether teachers' use of tablets moderated the relationship between students' learning characteristics and students' perceptions of supportive climate as well as cognitive activation in classes with tablets. Another study from the *tabletBW* project showed teachers' technology innovativeness largely determined the instructional quality of lessons as rated by external reviewers (Backfisch, Lachner, Stürmer, & Scheiter, 2020). Therefore, this study aimed to address how students' perceptions of instructional quality depended on teachers' technology innovativeness as well as on students' learning characteristics. The sample included 575 seventh grade math students and 23 math teachers from 14 schools.

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2

New technology, new role of parents: How parents' beliefs and behavior affect students' digital media self-efficacy

Hammer, M., Scheiter, K., Stürmer, K. (under review). New technology, new role of parents: How parents' beliefs and behavior affect students' digital media self-efficacy. *Computers and Human Behavior*.

Abstract

Increasingly more research is exploring how digital media can be used for teaching but is largely focused on how teachers shape digital media use. Besides teachers in the classroom, parents at home may also have a pivotal role in shaping students' beliefs towards digital media which are in turn an important precursor to students' use of technology for learning. Previous research shows parent factors are related to students' ICT self-efficacy; however, the underlying mechanisms explaining these relations are less clear. Following Eccles et al.'s parent socialization model (1983), we investigate whether parents' behaviors including modeling and provision of digital media mediate the relation between parents' beliefs regarding digital media and students' digital media self-efficacy. Data were drawn from parents and student questionnaires collected as part of a study to investigate conditions for successful digital media use in classrooms ($N = 1,206$ students and their parents). Results show while parents' beliefs are related to students' digital media self-efficacy, only parents' provision of smart phones mediates this relation. Findings indicate the importance of parents' beliefs regarding digital media and the need for future research into at home factors that influence students' digital media self-efficacy.

Keywords: digital media; self-efficacy; expectancy-value model; parent beliefs; parent behaviors; secondary education

2.1 Introduction

There is broad consensus worldwide that students need digital media skills for the future (e.g., Fishman & Dede, 2016; OECD, 2015; European Commission, 2013). However, the results of the 2018 International Computer and Information Literacy Study (ICILS) indicate that in most countries, the majority of students need support using digital media such as computers to complete basic information-gathering and management tasks. Additionally, across the participating countries, 18% of students were found to be working below the lowest level of proficiency, indicating a lack of functional working knowledge of computers as tools. In general, results indicate that students are not well prepared for study, work, and life in a digital world (Fraillon, Ainley, Schulz, Friedman, & Duckworth, 2019).

In order to address students' lack of digital media skills, we need to better understand how these skills are shaped. One important prerequisite is digital media self-efficacy. Self-efficacy beliefs are developed through different sources including students' experiences at home and their interactions with their parents (Bandura, 1977). Accordingly, in the present paper we investigate whether parents' beliefs and behaviors at home regarding digital media relate to students' digital media self-efficacy.

2.2 Theoretical Background

2.2.1 Digital media self-efficacy

One prerequisite for digital media skills is digital media self-efficacy. Applying the definition from Bong and Skaavali (2003), digital media self-efficacy can be understood as the extent to which a student believes he or she can successfully operate digital media. It is largely formed by students' prior experiences with using digital devices successfully or not. In turn, students who believe that they are capable and that they can and will perform well in an activity are more likely to put forth effort in this endeavor (Bandura, 1977). Throughout the paper, we refer to digital media self-efficacy to describe students' self-efficacy beliefs regarding the use of digital media. Although ICT self-efficacy is a similar construct encompassing beliefs towards internet and technology use, we use digital media self-efficacy unless referring to specific studies that have used different terms. Regarding students' beliefs towards and use of digital media, previous research has shown students' perception of their ICT abilities are positively related to both internet and computer performance as well as students' motivation towards using technology (Aesaert & van Braak, 2014).

Furthermore, results from the ICILS 2013 showed positive correlations between students' ICT self-efficacy and students' computer and information literacy both nationally and

internationally (Fraillon, Ainley, Schulz, Friedman, & Gebhardt, 2014). Building off these results and using ICILS 2013 data, Hatlevik, Throndsen, Loi, and Gudmundsdottir (2018) found students' ICT self-efficacy was positively related to students' computer and information literacy when controlling for students' cultural capital, migration status, language integration, parental educational attainment and occupational status, and socioeconomic status. In addition, Meelissen and Drent (2008) found that students' self-efficacy in computer use positively influenced their computer attitudes including enjoyment and utility perceptions.

Regarding learning with digital media, Tsai and Tsai (2003) found students with high self-efficacy in using the internet had better information-searching strategies and performance in web-based learning tasks than students with low internet self-efficacy. Compared to students with high internet self-efficacy, students with low internet self-efficacy lacked the confidence in their ability to use the internet to try new approaches for searching for information and solving problems themselves. Additionally, Lee and Wu (2017) found students with better attitudes towards computers and more confidence in completing high-level ICT tasks had higher engagement in online reading activities and in turn higher reading literacy. They propose while reading performance may not be students' goal when working with computers, their attitude and confidence towards computers and ICT tasks lead them to be more engaged in online reading activities, accumulate online reading experiences, and ultimately enhance students' reading performance. Furthermore, a literature review by Moos and Azevedo (2009) showed students' computer self-efficacy is further related to students' learning in computer-based learning environments. In general, students with positive self-efficacy tend to engage thoughtfully and as a result succeed in learning activities (Bandura, Barbaranelli, Caprara, & Pastorelli, 2001). The OECD reports “. . . computer use can make the difference in educational performance if the student has the appropriate set of competences, skills and attitudes. Without these, no matter how intense the student's use of a computer, the expected benefits will not be realized,” (2010, p. 172). Altogether, digital media self-efficacy is seen as a precursor to students' digital media skills as well as meaningful learning processes with digital media.

The ICILS 2018 findings also reveal across all participating countries students more frequently use computers outside school than inside. Increasingly more research exploring factors related to students' beliefs and competences using digital media are pointing towards parents' attitudes and factors at home (Rohtagi, Scherer, & Hatlevik, 2016; Aesaert & van Braak, 2014; Zhong, 2011). Using a multilevel approach to evaluate student, class, and school level factors associated with primary school students' ICT self-efficacy, Aesaert and van Braak (2014) found 95% of the variance in Flemish students' ICT self-efficacy was due to differences

between students, specifically students' ICT experience and ICT attitude. Previously, Zhong (2011) used PISA data from 16 countries to examine the country, school, and individual level factors that explained the divide in adolescent students' self-reported digital skills and found between 70 and 76% of the variance was due to individual factors. Notably, both studies found family factors to be significantly related to both primary and secondary students' ICT self-efficacy and more predictive than school factors. Zhong (2011) explains home ICT access had a stronger effect on self-reported digital skills than school ICT access. Additionally, Aesaert and van Braak (2014) found teachers' ICT attitude and experience in the classroom did not contribute to students' ICT self-efficacy whereas parents' ICT attitude and experience at home did. Though Aesaert and van Braak (2014) further point out that the frequency of ICT use was much lower at school than at home, possibly explaining why there were non-significant effects of the classroom and school level variables. The home environment may be particularly important for students to develop positive beliefs towards using ICT because they have greater flexibility in choosing online activities at home than at school where activities are dominated by teachers' choice. In line with this reasoning, Lee and Wu (2017) found the higher the availability of ICT at home, the higher the engagement of online reading activities as well as reading performance. In contrast, ICT availability at school had no effect on students' engagement in online reading activities or reading performance. Building off these studies that point to the importance of parent attitudes and at home experiences with ICT, the present study aims to more closely examine *how* parents contribute to students' digital media self-efficacy.

2.2.2 The role of parent beliefs and behavior in shaping student beliefs

According to Eccles' expectancy-value model and numerous subsequent longitudinal studies, parents play a pivotal role in influencing their children's beliefs (Jacobs & Eccles, 2000). Typically, this research has shown when parents have positive beliefs about a school subject such as math, they pass these beliefs onto their children through their behavior such as encouraging their children to like math or performing math activities together (Simpkins, Fredricks, & Eccles, 2012). Besides academic subjects, these studies extend to leisure domains such as sports and music (Simpkins et al., 2012). Specifically, Simpkins et al. (2012) found mothers' behavior mediated the link between mothers' and adolescents' beliefs in sports, music, and math, but not in reading. However, there is a lack of research on how parents may shape students' beliefs in their abilities regarding digital media use. Building off these studies, we aim to understand if parents' beliefs and behavior regarding digital media also affect their children's beliefs about their ability to use digital media, namely digital media self-efficacy. In the

following section, the links between parents' beliefs, parents' behaviors, and student's beliefs are explained in more detail.

2.2.2.1 How parents' beliefs shape parents' behaviors

Following the parent socialization model (Eccles et al., 1983), one link of the expectancy-value model framework, parents have general beliefs about the world as well as child-specific beliefs, and these combined beliefs influence their parenting behaviors. Parents' general beliefs include their personal values about a domain in general while child-specific beliefs regard how parents value a domain for their child. In turn, parents' values and beliefs may also predict their children's own competence and value beliefs. Jacobs and Eccles (2000) explain three ways that parents may transfer their beliefs about a specific domain to their children: 1) structuring opportunities, 2) interpreting reality, and 3) imparting their values. First, parents decide the structure and type of activities in which their children participate and exposure to various activities affects their children's preference and skill acquisition and therefore perceived competence. By choosing whether their children participate in a given activity on a regular vs. infrequent basis, for leisure vs. for productivity, in an organized vs. an informal way, parents provide the context to develop values in certain domains, which are informed by parents' own values and preferences. Additionally, parents act as 'interpreters of reality' by conveying messages to their children about their value of various domains as well as how they perceive their children's competence in domain activities. Lastly, in addition to providing particular opportunities and conveying messages about certain activities, parents impart messages about their own beliefs and values. Parents may impart these values through direct instruction or by modeling involvement in various activities.

2.2.2.2 How parents' behaviors shape students' beliefs

Parenting behavior such as modeling involvement in valued activities and providing specific experiences in turn shapes children's beliefs (Jacobs & Eccles, 2000). First, parents influence their children by modeling leisure pursuits and behavioral choices. In turn, children may observe their parents and make choices based on a desire to be like their parents (Bandura, 1997; Eccles et al., 1983). According to Jacobs and Eccles (2000), children observe how their parents spend time, how they choose between available activities, as well as their parents' sense of self-competence. Altogether, these behaviors convey messages to children about activities that are valued and are acceptable ways to spend time. Second, in accordance with sociocultural theory, parents' provision of materials may influence children's beliefs by exposing them to particular experiences and value systems (Vygotsky, 1978). Simpkins et al., (under review) explain parents actively manage the home environment and structure their children's experience

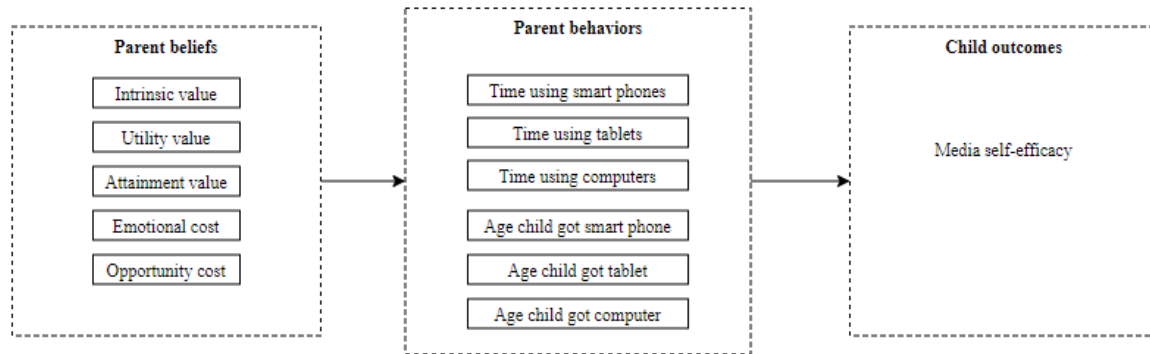
by choosing which toys, equipment, books and other learning activities to provide their children. The authors further explain that higher exposure leads to children's comfort, engagement, and learning in a domain. This idea is supported by research that shows children who had access to children's books and to activities such as shared reading and library visits had more positive attitudes about reading, engaged in more leisure reading, and had increased reading achievement (Whitehurst & Lonigan, 2001). Provision of materials was also found to be an important predictor in leisure domains such as music where provision of instruments, books, and CDs was also linked to children's musical participation (McPherson, 2009). Continuing this idea, when parents provide their children with particular experiences and materials at an earlier age, their children naturally acquire more exposure which in turn could lead to more comfort, engagement, and development of skills. Regarding the provision of digital media, previous research indicates the age when children start using technology particularly impacts their future technological competences. Specifically, Juhaňák, Zounek, Záleská, Bárta, and Vlčková (2019) found using PISA 2015 data that children who start using a computer at a later age have significantly lower ICT competence and ICT autonomy at the age of fifteen even when controlling for gender and socio-economic status.

Following the parent socialization model (Eccles et al., 1983), parents' general beliefs and behaviors influence the way they interpret their children's performance and how that interpretation is conveyed to their children in turn influences their children's beliefs (Jacobs & Eccles, 2000). Parents' general beliefs include how parents personally value certain activities. In relation to digital media, if parents enjoy using digital media (intrinsic value), find digital media useful (utility value) or consider using digital media to be important for one's self (attainment value), their parenting practices regarding digital media could in turn endorse using digital media. In contrast, if parents perceive using digital media to be exhausting or distressing (emotional cost) or come at the expense of other, more enriching activities (opportunity cost), then their parenting practices could be against the use of digital media. Subsequently, parent specific behaviors such as the provision of specific experiences, like lessons or equipment, and modeling involvement in valued activities can affect how children value and engage with different activities (Jacobs & Eccles, 2000). As shown in the adapted model in Figure 2.1, regarding the use of digital media. if parents provide their children with smart phones, tablets, and computers or laptops at an earlier age, their children have more opportunities to spend time with these devices which, in turn, may influence how they perceive their ability to use digital media. Additionally, when parents choose to spend their own time using digital media and convey self-competence using these devices, they may send the message that using digital

media is a valued activity and an acceptable way to spend time, thus prompting their children to value and use digital media. Taken together, children may gain more experience successfully using digital media and develop digital media self-efficacy.

Figure 2.1

Simplified parent socialization model applied to the use of digital media (Adapted from Eccles et al., 1983)



Note. Terminology refers to operationalizations used in the present study.

Previous literature applying the parent socialization model (Eccles et al., 1983) has shown the role of parents in shaping students' self-beliefs in domains such as math, sports, and music (Simpkins et al., 2012). However, no research to date has looked whether this model may apply to students' self-beliefs about using digital media. Further using the expectancy-value theory framework, parents' beliefs are examined through task values regarding digital media, including intrinsic, utility, and attainment values as well as opportunity and emotional cost. In this way, parents' beliefs are measured taking into account the perceived costs and benefits of using digital media.

Therefore, in the present study, we aim to answer the following research question: How do parent behaviors including modeling and provision of digital media mediate the relationship between parents' beliefs regarding digital media and students' digital media self-efficacy? We hypothesize that parents who have positive beliefs regarding digital media, such as perceiving digital media to be enjoyable or useful, will use digital media more at home and provide digital media for their children at a younger age. In turn, students will perceive using digital media as a valuable activity, gain positive experiences using digital media, and develop digital media self-efficacy. In contrast, if parents have negative beliefs regarding digital media, such as perceiving digital media to be exhausting or replacing other, more valuable activities, then parents will spend less time using digital media at home and not buy or buy digital devices for their children at a later age. In turn, students may perceive using digital media unfavorably, lack experience using digital media, and not develop digital media self-efficacy.

2.3 Methods

2.3.1 Participants and study design

Data was collected within a multi-cohort, longitudinal project that investigates whether and under what conditions digital media enable successful teaching and learning processes in the classroom. The data stemmed from a school initiative which was funded by the Ministry for Culture, Youth and Sport Baden-Württemberg, with the aim to support schools in the effective use of digital media for teaching. All academic track schools across Baden-Württemberg were invited to apply and informed that select schools would be provided with a full class set of tablets for two classes. The Ministry then chose schools based on whether there was a concept for integrating digital media into their school and to ensure that schools across the four districts of the state would be represented in the study. Following this selection process, 56 classes in 28 schools were randomly assigned to tablet and control conditions. Within schools assigned to the tablet condition, students from two classes were each equipped with tablets. Participants' prerequisites for learning with digital media were assessed via questionnaires and tests at four measurement points over the course of three years from grade 7 to grade 9. Students' entry characteristics were assessed at a first measurement point before students in the tablet condition received their tablets, the first cohort of seventh grade students in February 2018 ($n = 1,278$) and the second cohort of seventh grade students in February 2019 ($n = 1,141$). The student data used in the current analysis was collected before students in the tablet condition received their tablets. Parents were separately asked to participate in a questionnaire when they were asked to sign consent forms for their children to participate in the study. Only parents who agreed to participate were sent a questionnaire with the identification code of their child which was then used to match parent questionnaire with student questionnaires. Of the 2,082 parents who agreed to participate and were sent questionnaires, 1,448 were received (return rate of 69.5%). Additionally, students were asked about the number of books in their home as an indicator of socioeconomic status (Baumert, Bos, & Watermann, 2000). Families in which parents participated had significantly higher socioeconomic status ($M = 3.69$, $SD = 1.36$) than families in which parents did not participate ($M = 3.45$, $SD = 1.44$) ($t(2,328) = 4.101$, $p = .00$).

In the current analysis, 1,206 parent questionnaires could be matched with student questionnaires from both cohorts. Parent or student questionnaires that could not be matched using the identification code were excluded from the analysis. The mean age of the female (52.6%) and male students was 13.32 years ($SD = 0.51$), and the mean age of the female (66.7%) and male parents was 46.7 years ($SD = 5.17$). All parents were invited to participate and when two parents responded corresponding to one student ($n = 236$), we found an intra-class

correlation of .836 reflecting high agreement between parent pairs. Therefore, their responses were aggregated together to avoid using data from the same student twice.

2.3.2 Instruments

We developed a parent questionnaire using the task values from Eccles et al.'s expectancy-value model (1983) and applying them to digital media use. The questionnaire asks parents about their beliefs concerning digital media, including *intrinsic values* (e.g., 'I like using digital media'), *utility values* (e.g., 'Understanding digital media has many benefits in my daily life'), *attainment value* (e.g., 'Using digital media makes me a more knowledgeable person'), *emotional cost* (e.g., 'When I deal with digital media, I get annoyed'), and *opportunity cost* (e.g., 'My reading and writing skills suffer because of using digital media'). All items were rated on a four-point scale ranging from 1 = strongly disagree to 4 = strongly agree. We conducted reliability analyses using Cronbach's Alpha for each task value, as shown in Table 2.1. Each value is above 0.70, suggesting the items have relatively high internal consistency. Additionally, we investigated the validity of the task value scales. We conducted exploratory factor analyses and verified that each scale was unidimensional.

Table 2.1
Internal Consistency Measure

Scale	No. items	Cronbach's Alpha
Intrinsic value	4	.92
Utility value	8	.88
Attainment value	4	.83
Emotional cost	4	.86
Opportunity cost	9	.90

Additionally, parents were asked to provide information on two behaviors, modeling and provision, based on the parent socialization model that suggests modeling and provision are two ways that parents may influence their children (Jacobs & Eccles, 2000). In line with Simpkins et al. (2012) modeling was measured by asking parents how much time they spent using digital devices at home. Similar to Laurciella, Wartella, and Rideout (2015), parents were asked how much time they spent at home using smart phones, tablets, or computer or laptops on a typical weekday and a typical weekend day. These numbers were then weighted to calculate the average screen time per day for each owned technology. This resulted in three variables: parent smart phone time, parent tablet time, and parent computer or laptop time.

Notably, Laurciella et al. (2015) found that parents who were low users on one device were not necessarily low users on another device. For this reason, we calculated times on each device separately. In line with Simpkins et al. (2012), provision was measured by separately asking parents whether their child had their own smart phone, tablet, and computer or laptop. Additionally, departing from Simpkins et al. (2012), if parents responded yes, they were asked at which age their child received the digital device. This resulted in three variables: age of smart phone provision, age of tablet provision, and age of computer or laptop provision. Although using age has not been taken into account before, recent research shows that age is an important construct when understanding how adolescents' technological skills are formed (e.g., Juhaňák et al., 2019). Using age takes into account that the earlier children receive their own digital device may reflect parents' beliefs as well as indicate that children who receive digital devices at an earlier age acquire more years of experience and therefore more opportunity to gain successful experiences using digital media.

Lastly, students' digital media self-efficacy was measured at the first measurement point, before students received their school tablets, using a scale containing seven items adapted from the 2015 PISA (Reiss, Sälzer, Schiepe-Tiska, Klieme, & Köller, 2016; see Table 2.2). All items were rated on a four-point scale ranging from 1 = strongly disagree to 4 = strongly agree. Cronbach's α was 0.83, indicating relatively high internal consistency.

Table 2.2
Digital Media Self-Efficacy Scale

#	Item
1	I'm good with digital devices.
2	I also feel good about using digital devices that I'm less familiar with.
3	If friends or relatives want to buy new digital devices or applications, I can give you advice.
4	I feel good using my digital devices at home.
5	If there is a problem with a digital device, I think I can solve it.
6	If my friends or relatives have a problem with a digital device, I can help them.
7	When a digital device causes problems, I feel rather helpless.

2.3.3 Data analysis

Before conducting a mediation analysis to detect the relation between parents' beliefs and behaviors regarding digital media and students' digital media self-efficacy, we checked whether there were significant correlations between each of the parents' task value beliefs and students' digital media self-efficacy as well as whether there were significant correlations

between parents' task value beliefs and parents' behaviors. After meeting these preconditions, we tested five parallel multiple mediator models in Mplus. In each of the models, parents' task values beliefs were modeled to exert its effects on students' digital media self-efficacy through any of the proposed modeling and provision indicators (Hayes, 2017). The six modeling and provision indicators may play different roles in the relationship between parents' beliefs regarding digital media and students' digital media self-efficacy. Therefore, estimating indirect effects in a parallel multiple mediator model allows to test each mediator while accounting for the association between them (Hayes, 2017). To check the significance of specific indirect effects, 95% confidence intervals based on 10,000 bootstrap samples were used. In all models, the mediator variables were set to correlate with each other. Missing data was handled by using the maximum likelihood estimator in Mplus.

2.4 Results

2.4.1 Descriptive results

Parents' intrinsic ($M = 3.06$, $SD = .69$), utility ($M = 2.96$, $SD = .59$), and attainment ($M = 2.31$, $SD = .65$) values and emotional costs ($M = 1.73$, $SD = .68$) were significantly correlated with their children's digital media self-efficacy ($M = 2.92$, $SD = .57$) as shown in Table 2.3 (correlations ranged from $-.075$ to $.128$). Parents' perceived opportunity cost ($M = 1.97$, $SD = .68$) did not significantly correlate. Parents who value digital media for being fun, useful, and important, spend more time using digital devices and buy devices for their children when they are younger. Furthermore, parents with high intrinsic, utility, and attainment values have children with higher media self-efficacy. In contrast, perceived emotional cost was negatively correlated to the time parents spent using digital devices and students' digital media self-efficacy. However, even when parents found digital media to be emotionally exhausting, they still bought digital devices for their children when they were younger.

2.4.2 Model test

As seen in Table 2.4, the mediation models had adequate fit to the data. To assess model fit, the comparative fit index, root mean-square error of approximation, and the chi-square test were used (Hu & Bentler, 1999).

Table 2.3*Correlations between Parents' Beliefs and Behaviors and Students' Digital Media Self-Efficacy*

	IV	UV	AV	EC	OC	Phone time	Tablet time	Comp time	Phone age	Tablet age	Comp age
IV											
UV	.649**										
AV	.480**	.581**									
EC	-.560**	-.478**	-.251**								
OC	-.267**	-.262**	-.074**	.498**							
Phone time	.246**	.148**	.134**	-.125**	.067*						
Tablet time	.173**	.088**	.131**	-.063**	.095**	.100**					
Comp time	.076**	.087**	.083**	-.053*	.043	.179**	.001				
Phone age	-.152**	-.157**	-.102**	-.056*	-.014	.075**	-.034	-.015			
Tablet age	-.074	-.130**	-.127*	-.088**	-.023	.094**	.055	.003	.138**		
Comp age	-.128**	-.169**	-.070	-.076**	-.048	.073*	-.022	.014	.106**	.067*	
Self-efficacy	.128**	.097**	.103**	-.075*	-.015	.072*	.046	-.009	.110**	.122**	.157**

Note. IV = intrinsic value. UV= utility value. AV= attainment value. EC = emotional cost. OC = opportunity cost.

* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 2.4
Model Fit Indicators

Model	χ^2	CFI	RMSEA
Intrinsic value	(28) 390.13***	.99	.04
Utility value	(28) 329.65***	.99	.04
Attainment value	(28) 325.35***	.99	.04
Emotional cost	(28) 310.19***	.99	.04
Opportunity cost	(28) 286.14***	.99	.05

Note. CFI = comparative fit index; RMSEA = root mean square error of approximation.

*** $p < .001$.

2.4.3 Tests of mediation

There was a basic relationship between parents' beliefs, as measured by parents' task values regarding digital media, and students' digital media self-efficacy, however, we aimed to investigate this relationship in greater depth. Therefore, we tested whether parents' behaviors including modeling and provision of digital media mediated the relations between parents' task value beliefs regarding digital media and students' digital media self-efficacy. We tested five parallel multiple mediator models. In each model, one of the parents' task values was the independent variable and each proposed mediator was tested for its effect on students' digital media self-efficacy while accounting for the shared variance between them (Hayes, 2017). Using parallel mediation, in Table 2.5 the first row shows the standardized effect of each parent task value on students' digital media self-efficacy when keeping mediators constant. The following rows show the standardized effect of each mediator on students' digital media self-efficacy controlling for parents' beliefs and the other mediators. Doing so, allows to see the separate impact of each of the parents' beliefs and proposed mediators on students' digital media self-efficacy. To further illustrate the links between parents' beliefs to parents' behaviors and parents' behaviors to students' self-beliefs, Figures 2.2 through 2.6 additionally show the standardized effect of parents' task values on parents' behavior indicators. For example, parents' intrinsic value of using digital media, as seen in Figure 2.2, positively predicted parents' modeling of digital media and students' digital media self-efficacy and mostly negatively predicted the age at which parents bought their children digital devices, meaning parents bought devices for their children when they were younger. For every 1-unit increase in parents' intrinsic value, parents' time spent using smart phones significantly increased .238 units, time spent using tablets increased .168 units, time spent using computers increased .076

Table 2.5*Standardized Path Estimates and Confidence Intervals of the Specific Indirect Effects*

	Est.	C.I.		Est.	C.I.		Est.	C.I.		Est.	C.I.		Est.	C.I.
IV	.08**	[0.014, 0.118]	UV	.04	[-0.017, 0.104]	AV	.07*	[0.006, 0.113]	EC	-.03	[-0.090, 0.033]	OC	.02	[-0.032, 0.068]
Time spent on devices (Modeling)														
Phone	.03	[-0.019, 0.054]	Phone	.04	[-0.117, 0.098]	Phone	.04	[-0.042, 0.094]	Phone	.05	[-0.008, 0.110]	Phone	.03	[-0.002, 0.069]
Tablet	.03	[-0.018, 0.082]	Tablet	.04	[-0.011, 0.092]	Tablet	.04	[-0.013, 0.271]	Tablet	.05	[-0.011, 0.103]	Tablet	.05	[-0.011, 0.109]
Comp	-.02	[-0.046, 0.025]	Comp	-.01	[-0.075, 0.039]	Comp	-.02	[-0.049, 0.087]	Comp	-.01	[-0.093, 0.043]	Comp	-.01	[-0.048, 0.026]
Age child got their device (Provision)														
Phone	-.11***	[-0.086, -0.026]	Phone	-.08*	[-0.175, -0.053]	Phone	-.12***	[-0.089, -0.029]	Phone	-.11**	[-0.168, -0.042]	Phone	-.06***	[-0.086, -0.025]
Tablet	-.09	[-0.071, 0.005]	Tablet	-.07	[-0.184, 0.026]	Tablet	-.08	[-0.067, 0.009]	Tablet	-.12*	[-0.224, -0.003]	Tablet	-.04*	[-0.079, -0.001]
Comp	-.10	[-0.094, 0.003]	Comp	-.13*	[-0.205, 0.006]	Comp	-.11*	[-0.096, 0.000]	Comp	-.10	[-0.200, 0.013]	Comp	-.05	[-0.093, 0.005]

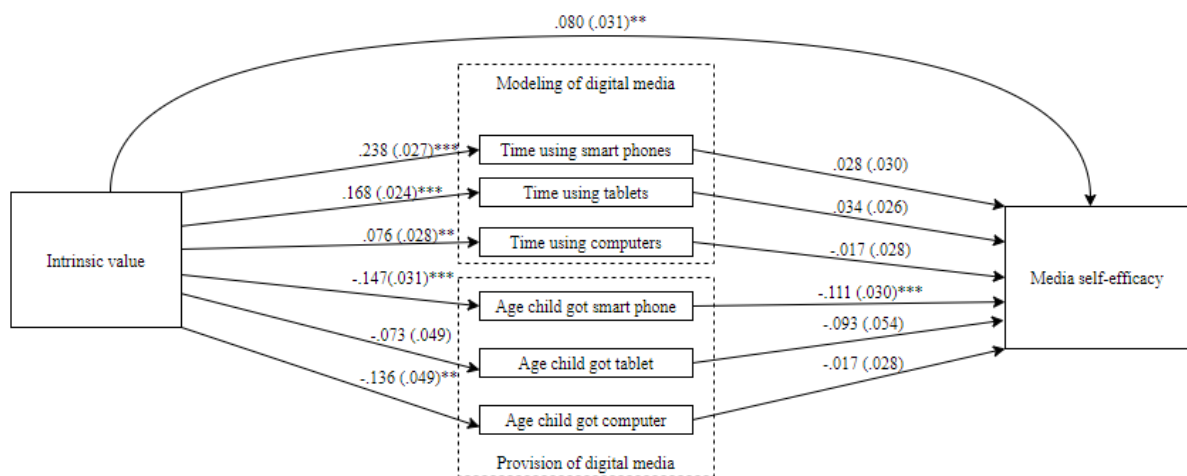
Note. IV = intrinsic value. UV= utility value. AV= attainment value. EC = emotional cost. OC = opportunity cost. All confidence intervals are 95%. C.I. = Confidence intervals. Confidence intervals that do not contain zero are statistically significant.

*p < .05. **p < .01. ***p < .0

units, the age parents got their child their own smart phone decreased by .147 units, age child got their own computer or laptop decreased by .136 units, and students' digital media self-efficacy increased .080 units. Alternatively, as seen in Figure 2.3, parents' emotional cost of using digital media negatively predicted their modeling of digital media and positively predicted the age at which parents bought their children digital devices, meaning parents bought devices for their children when they were older. For every 1-unit increase in parents' utility value, parents' time spent using smart phones significantly decreased .126 units, the age parents got their child their own smart phone increased by .145 units, and age child got their own tablet decreased by .121 units. However, as with parents' intrinsic value, the only mediator that significantly predicted students' digital media self-efficacy was the age parents got their child their own smart phone.

Regarding the specific indirect effects of parents' beliefs on students' self-beliefs through each of the proposed mediators, 95% confidence intervals based on 10,000 bootstrap samples were computed and reported in Table 2.5. Across the five models, the only indirect effects that were different from zero with 95% confidence was the age children got their smart phone. Through age child got a smart phone, every 1-unit increase in parents' intrinsic, utility, and attainment values and opportunity and emotional costs resulted in a change of .016, .017, .011, -.013, and -.008 in students' digital media self-efficacy, holding all other variables constant.

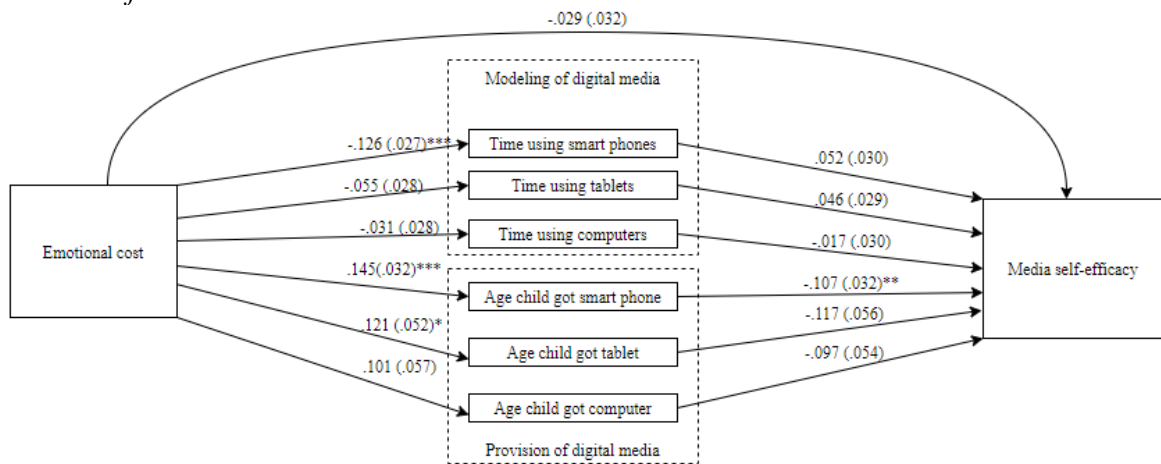
Figure 2.2
Path Model of Parents' Intrinsic Values



Note. Path coefficients were standardized. Numbers in the parentheses were standard errors of the path coefficients.

* $p < .05$. ** $p < .01$. *** $p < .001$.

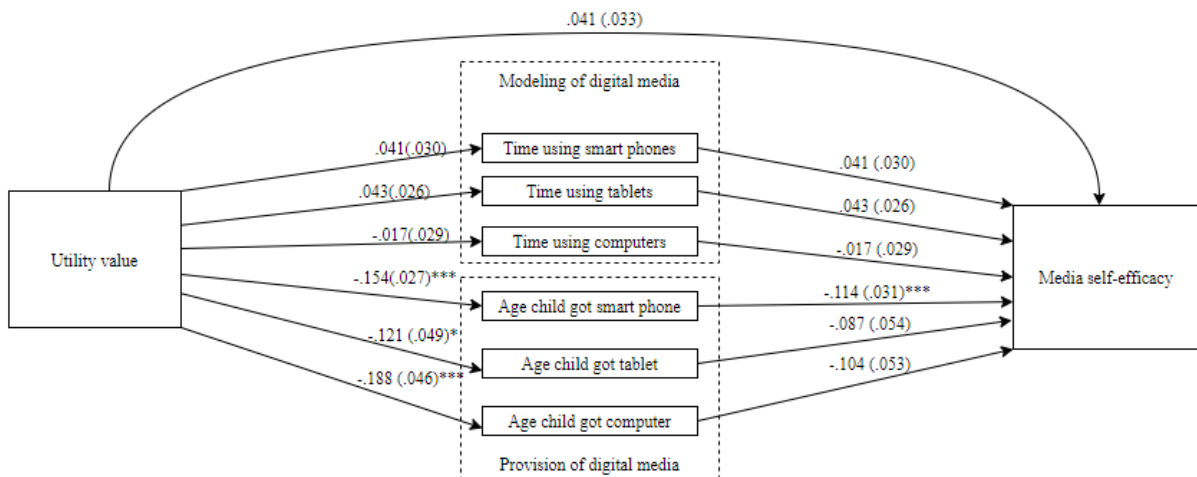
Figure 2.3
Path Model of Parents' Emotional Costs



Note. Path coefficients were standardized. Numbers in the parentheses were standard errors of the path coefficients.

* $p < .05$. ** $p < .01$. *** $p < .001$.

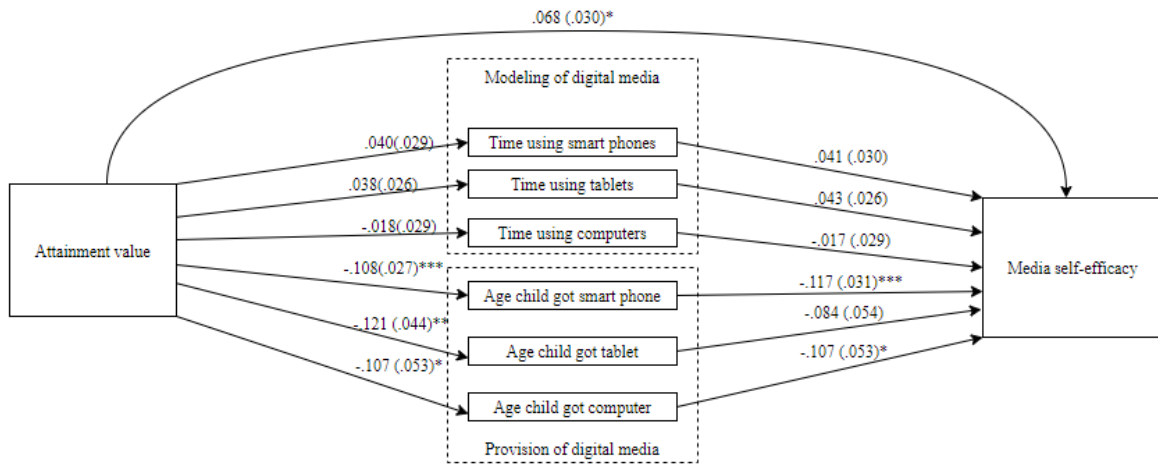
Figure 2.4
Path Model of Parents' Utility Values



Note. Path coefficients were standardized. Numbers in the parentheses were standard errors of the path coefficients.

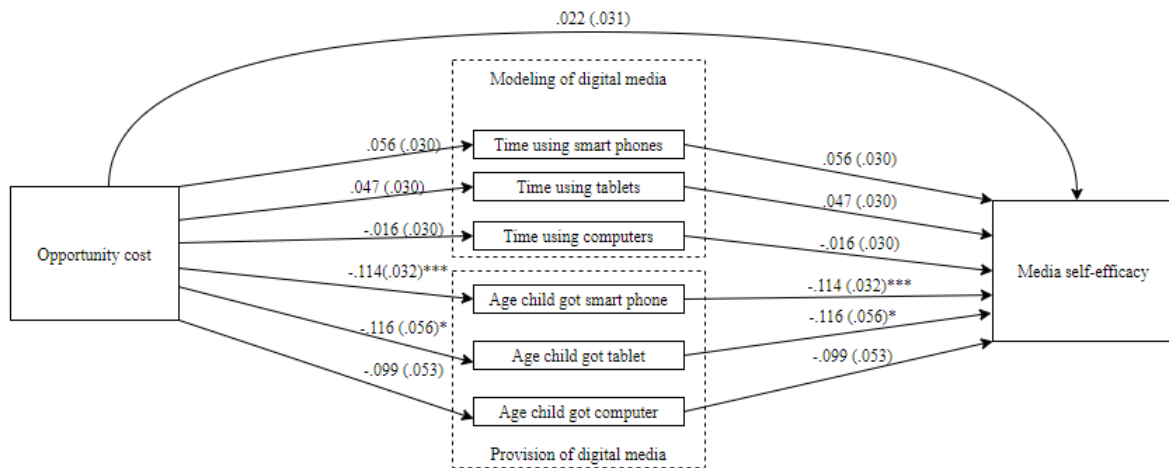
* $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 2.5
Path Model of Parents' Attainment Values



Note. Path coefficients were standardized. Numbers in the parentheses were standard errors of the path coefficients.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 2.6
Path Model of Parents' Opportunity Costs



Note. Path coefficients were standardized. Numbers in the parentheses were standard errors of the path coefficients.
* $p < .05$. ** $p < .01$. *** $p < .001$.

2.5 Discussion

Across the globe, there is widespread recognition that students need digital media skills for the future (e.g., Fishman & Dede, 2016; OECD, 2015; European Commission, 2013). At the same time, results from the recent ICILS study indicate that many students are not developing these skills in school and rather use digital media more often outside of school (Fraillon et al., 2019). These results mirror similar findings using PISA data (Lee & Wu, 2017; Aesaert & van Braak, 2014; Zhong, 2011) that show differences in students' experiences at home and parent attitudes contribute to students' ICT related beliefs and competences. Given this importance, the present study aimed to more closely examine the role of parents and their behaviors at home in shaping students' digital media self-efficacy, an important prerequisite for students' digital media competences and performance (Aesaert & van Braak, 2014; Hatlevik et al., 2018; Lee & Wu, 2017). To do so, we used the parent socialization model, part of the expectancy-value theory framework (Eccles et al., 1983), that proposes parents' beliefs predict parent behaviors which in turn predict students' self-beliefs. Whereas previous studies have shown these links between parents and adolescents' self-beliefs in sports, math, and science (e.g., Simpkins et al., 2012), the current study aimed to apply this model to parent beliefs and behaviors regarding digital media.

In the current paper, we found parents' intrinsic, utility, attainment values and emotional costs were correlated to their children's digital media self-efficacy. However, unlike what was proposed based on the parent socialization model from Eccles et al. (1983), parenting behaviors including modeling and provision of digital media mostly did not mediate the relationship between parents' value beliefs and students' digital media self-efficacy. Although parents' value beliefs were significantly related to how much time they spent using digital devices, in which parents' task values were positively correlated and parents' emotional costs were negatively correlated, parents' task values as well as emotional costs were negatively related to the age at which parents bought their children smart phones, tablets, and computers or laptops. Even parents who perceived high emotional cost of using digital media and do not have smart phones themselves, buy smart phones for their children, indicating a disconnect between parents' beliefs and parenting behavior. Furthermore, while the parent socialization model suggests that children observe and follow how their parents spend time at home, the amount of time that parents spend using digital media at home does not appear to impact students' digital media self-efficacy. The only parenting behavior that did mediate the relation between parents' value beliefs and students' digital media self-efficacy was the age at which parents bought their

children their own smart phone, suggesting that the earlier adolescents obtain their own smart phone, the more time they have to obtain experience and develop digital media self-efficacy.

Following the parent socialization model (Eccles et al., 1983), parents influence their children by the opportunities they provide. These opportunities depend on many factors including what is available in the community, economic resources due to high costs, time constraints with some families having less time to devote to any given activity depending on number of earners in a household and number of children, and parents' values for a particular endeavor (Jacobs & Eccles, 2000). However, in the case of digital media, devices such as smart phones and tablets have become much more affordable and ubiquitous to the extent that access to digital media is no longer necessarily a question of cost (Warschauer & Matuchniak, 2010). Furthermore, many families have more than one device (Fomby, Goode, Truong-Vu, & Mollborn, 2019), meaning using digital media is typically an independent activity not dependent on parents' time. Most notably, whereas computer skills depended on social support from family members (e.g., Barron, Martin, Takeuchi, & Fithian, 2009), the current generation of students that have grown up with digital media may be more suited to teach their parents how to operate digital media than the other way around (Mesch, 2006). Altogether, even when parents may not have time or value digital media, adolescents can develop views regarding digital media independent of their parents as well as increase their competence and interest by exposure. On the other hand, considering the availability of digital media, the frequency indicators may be too distal to explain the effects on children, and more qualitative behavioral indicators such as working strategies with digital media or more specific behavioral activities are required.

Students' digital media self-efficacy is an important prerequisite for digital media literacy, motivation to use media, and meaningfully learning with digital media. Currently use of digital media is limited in schools (ICILS, 2018), therefore students must develop digital media self-efficacy in other contexts. While parents' value beliefs appear to be related to students' digital media self-efficacy, other contextual factors may be more relevant, such as students' own time spent and experiences using digital media at home (Fomby et al., 2019).

2.6 Limitations

Our results cannot be interpreted with regard to causality because we cannot show whether parents' beliefs precede children's beliefs and do not examine whether there is a reciprocal link of child's beliefs affecting parents' beliefs or even child's behaviors affecting parents' behaviors or beliefs. Additionally, further research investigating the role of parents in shaping their children's beliefs regarding digital media should take into account how often

parents discuss their beliefs regarding digital media with their children. While the parent socialization model (Eccles et al., 1983) proposes that parents' beliefs also directly influence students' beliefs such as by encouraging their children to engage in certain activities, in the current study it is unclear whether parents also expressly communicated their beliefs regarding digital media to their children. Furthermore, the study uses self-report measures to capture how much time parents spend on various devices on an average day as well as retrospectively asked the age at which parents provided children with their own device. Therefore, it is possible that some parents underreported their use or misrepresented the age, such as if parents bought a device many years ago. Future studies examining the relations between parents' behavior and their children's beliefs could utilize other approaches such as time diaries or electronic devices that measure parents' actual use (e.g., Fomby et al., 2019). Lastly, we found families in which parents participated had significantly higher socioeconomic status than families in which parents did not participate, as measured by asking students to approximate the number of books their parents own. While this result was surprising considering all parents were equally invited to participate in the questionnaire and limits the generalizability of the results, it also raises questions about how to better target and measure parents' beliefs and behaviors regarding digital media across socioeconomic groups. Conversely, considering privacy and accuracy concerns related to more proximal indicators such as family income or parental occupation, books at home is often used as a proxy for SES (Broer, Bai, & Fonseca, 2019). However, in view of society changing to become more digital, perhaps other indicators to measure SES are needed.

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3

For whom do tablets make a difference? Examining student profiles and perceptions of instruction with tablets

Hammer, M., Göllner, R., Scheiter, K., Fauth, B., Stürmer, K. (under review). For whom do tablets make a difference? Examining student profiles and perceptions of instruction with tablets. *Computers and Education*.

Abstract

Tablets are being increasingly used in classrooms, yet we know little about how students perceive instruction with tablets. Using student ratings of supportive climate can begin to show how supportive students perceive instruction with tablets. However, students' perceptions can vary within classrooms depending on their learning characteristics. The present study employs latent profile analysis to investigate differences in students' perceptions depending on cognitive and motivational characteristics in classes with and without tablets. Results indicate unmotivated and struggling students perceive more supportive climate in classes with tablets than the corresponding profiles perceiving instruction in classes without tablets. Furthermore, while students' perceptions seem to fall over time in classes that did not work with tablets, students' perceptions in classes with tablets remain more stable. Investigating both students' characteristics and their perceptions of supportive climate shows how different types of students are affected by the addition of tablets to the classroom.

Keywords: tablets; supportive climate; student characteristics; student profiles; latent profile analysis.

3.1 Introduction

The use of technology as educational tools for teaching and learning in classrooms has been identified and emphasized as a significant priority across OECD countries (OECD, 2015). Particularly in Germany that has fallen behind other OECD countries in implementing technology into the classroom (Gerick, Eickelmann, & Bos, 2017), increasingly more schools are being equipped for the first time with personal, mobile devices such as tablets towards the aim of improving teaching and learning processes in the classroom (KMK, 2016). However, the addition of tablets represents a significant change in German classrooms, prompting the question how students initially perceive the shift in their educational setting. In turn, these perceptions can better inform how the use of tablets could impact students' learning processes and learning outcomes.

Previous research indicates how students perceive their educational setting and especially whether they perceive it as supportive can be powerful predictors of student motivation as well as a prerequisite for learning gains (e.g., Baumert et al., 2010, Klieme, Pauli, & Reusser, 2009; Pianta & Hamre, 2009). Yet, even in countries where digital media is regularly used in the classroom, there is still a lack of empirical evidence regarding how students perceive the changes accompanied by the use of mobile devices. In order to overcome this gap, we investigate students' perceptions of supportive climate when tablets are introduced and to what extent students in classes with tablets perceive instruction as supportive compared to students in classes without tablets.

Additionally, we follow the position by Kozma (1991) suggesting that media per se will not make a difference for learning; rather, the impact depends on the educational context as well as the particular learning characteristics of the students. This is in line with a long tradition of teaching research showing individual learning prerequisites are among the most important determinants of successful learning processes (Snow, Corno, & Jackson, 1996). Furthermore, not only learning processes and learning outcomes are influenced by individual characteristics, also how students perceive the same educational setting is systematically linked to students' cognitive and motivational-affective characteristics (Seidel, 2006). Therefore, we investigate for whom instruction with tablets makes a difference. To do so, we investigate differences in students' perceptions depending on their individual learning characteristics. Further, we analyze whether these perceptions change for students with different characteristics before and after tablets are introduced.

3.2 Theoretical Background

3.2.1 The use of technology in German classrooms

Although Germany has a highly developed education system, technology use for educational purposes has not been as pervasive as in other OECD countries (Gerick et al., 2017). Results from the first International Computer and Information Literacy Study (ICILS) conducted in 2013 indicated in Germany less than a third (31.4%) of eighth-graders stated that they used computers in class at least once a week and that all other eighth-graders used digital media in school less often or not at all (Eickelmann, Schaumburg, Drossel & Lorenz, 2014). Following these results, in 2016 the Ministers of Education and Cultural Affairs decided on a national strategy to improve digital infrastructure in schools (Gerick et al., 2017). However, the most recent ICILS conducted in 2018, before the joint national strategy went into effect, indicate that schools in Germany continue to lag in international comparisons. The ICILS 2018 showed only a quarter of the students in Germany attended a school where teachers and students have access to Wi-Fi compared to 64% internationally. Additionally, in Germany there are ten students per computer provided by the school, although this is still above the international average of 15 students per computer. Furthermore, Germany is the only country where frequency of using technology in school is significantly negatively correlated with computer and information literacy (Drossel, Eickelmann, Schaumburg, & Labusch, 2019). However, the situation in Germany presents a unique opportunity. Since digital media is not presently part of everyday teaching, Germany offers a suitable research context to investigate whether the use of digital media can have a positive impact on learning, starting with whether adding digital media to the classroom changes how students perceive instruction. In turn, students' perceptions are important determinants for learning success with tablets.

3.2.2 Students' perceptions of supportive climate

Students' perceptions are widely used to gain unique insight into the educational setting and have been found to be powerful predictors of student learning outcomes (Göllner, Wagner, Eccles, & Trautwein, 2018; Fauth, Decristan, Riser, Klieme, & Büttner, 2014). For example, Göllner et al., (2018) showed that secondary education students with more positive perceptions of their teacher's instructional practices had higher math achievement, a better math grade, more math enjoyment, and greater experienced competences in math. Shuell (1996) describes the ways in which students perceive the instructional environment is more important in determining what the student will learn than the actions of the teacher. Göllner (2018) explain this in line with the conception of learning activities as an offer that must be perceived and utilized by students in order

for learning to take place (e.g., Creemers, Kyriakides, & Antoniou, 2013). In this way, students' idiosyncratic perceptions mediate the effect that an instructional practice will have on individual students' development (Den Brok, Fisher, Rickards, & Bull, 2006). Altogether, students' subjective perceptions of their educational settings matter for learning. Given this importance, investigating how students perceive their educational settings when learning activities take place with tablets can further elucidate what actually happens in classrooms when tablets are introduced and in which ways tablets may affect students' learning processes.

In particular, we examine how students perceive being supported by their educational setting. A supportive climate is considered an essential aspect of high-quality instruction and has consistently been shown to be a valid indicator for learning success (e.g., Klieme et al., 2009; Pianta & Hamre, 2009). Research shows students' perceptions of support is linked to their motivational development (Klieme et al., 2009) and is negatively related to emotions such as anxiety and boredom (Lazarides & Bucholz, 2019). Perceiving support is characterized by experiencing "supportive teacher-student relationships, positive and constructive teacher feedback, a positive approach to students' errors and misconceptions, individual learner support, and caring teacher behavior" (Klieme et al., 2009, p. 141). In turn, students perceiving support is a necessary precondition for them to engage in insightful learning processes and more challenging tasks (Baumert et al., 2010).

Although supportive climate has been linked to positive development of student motivation in traditional educational settings (Klieme et al., 2009), it may be even more important in educational settings with tablets. Providing mobile devices to every student allows more opportunities for learning activities in which students' roles can change from passive recipients of information to active participants in constructing and sharing knowledge (Montrieux, Raes, & Schellens, 2017; Pelgrum, 2001). However, whether students perceive this shift positively may also depend on how teachers support them to use the technology. In one study by Montrieux et al. (2017), secondary students were divided into varying conditions of inquiry-based learning with tablets. Results showed students strongly preferred the traditional approach of listening to their teacher because they were not accustomed to being actively involved throughout the entire course and being responsible to use tablets in an autonomous way. While the use of technology can facilitate a shift from a teacher to a student-centered classroom, teachers still have the pivotal role of guiding students to use the technology (Montrieux et al., 2017). Perceiving supportive climate may therefore be even more important in the new educational setting with tablets.

3.2.3 The influence of students' learning characteristics on perceptions

How students perceive their educational settings with tablets may not only depend on its particular implementation in the classroom, but also on students' individual characteristics. Previous research using student ratings have shown students can differ widely in their individual perceptions of the same instruction (Göllner et al., 2018; Schenke, 2018; Schenke, Ruzek, Lam, Karabenick, & Eccles, 2018). These idiosyncratic perceptions may indicate meaningful differences between how students with particular learning characteristics perceive instruction. For example, Lazarides and Ittel (2012) found secondary education students who perceived high instructional quality were significantly more likely to have higher math interest and self-concept than students who perceived lower instructional quality. With respect to students' perceptions of the supportive conditions of their educational settings, student ratings have been systematically linked to students' general cognitive ability, prior content knowledge, and subject-related interest and self-concept in physics instruction (Seidel, 2006). The author found students with high prior content knowledge, self-concept, and interest were most likely to perceive the same instruction as more supportive than students with overall more challenging characteristics, such as low cognitive ability or low interest, or students who underestimated their ability. These results indicate micro-learning environments within the same classroom for different students (Seidel, 2006; Schweig, 2016).

Furthermore, Seidel (2006) utilized a person-centered approach that classifies students according to distinct learning characteristics. In this vein, increasingly more research is showing not a single variable can explain students' differing perceptions but rather a combination (Huber & Seidel, 2018). Huber and Seidel describe studies using person-centered approaches that find students who "are able but not confident, knowledgeable but not interested, or self-efficacious but only moderate achievers" (p.1). Rather than students with overall uniform characteristics, such as high cognitive abilities, high self-concept and high motivation, studies find incoherence in the interplay of characteristics, such as students with high cognitive abilities but low motivation or high motivation and low cognitive abilities.

Emerging research is beginning to show students may also perceive learning with technology differently depending on their characteristics. Barkatsas, Kasimatas, and Gialamas (2009) found secondary students with low math confidence, affective and behavioral engagement, and achievement but high confidence with technology perceived learning math with technology more positively. Similarly, Salmela-Aro, Muokta, Alho, Hakkarainen, and Lonka (2016) found that sixth grade students who were cynical towards school, characterized by high levels of burnout, exhaustion, and feelings of inadequacy, reported they would be more academically engaged and

hardworking if there was greater use of ICT in schools. However, less research is known on how students specifically perceive instruction with tablets.

In general, previous research shows secondary students appreciate tablets for being an ‘all-in-one’ device allowing them to instantly search additional information, take pictures and integrate notes, as well as spontaneously communicate with their teachers and peers. Students also value tablets for being easy to use, fast at accessing a variety of learning materials, and for replacing heavy textbooks (Montrieux, Vanderlinde, Schellens, & De Marez, 2015). Moreover, initial findings show positive effects on motivational-affective aspects of student learning when students start working with tablets. Burden, Hopkins, Male, Martin and Trala (2012) evaluated the effects of iPads in schools and identified personal ownership of a tablet as the most important factor in increasing motivation, promoting student autonomy, and encouraging students to take more responsibility for their own learning. Accordingly, mobile devices such as tablets have been shown to reinforce motivation or increase engagement (Sung, Chang, & Liu, 2016). This boost might be particularly important in secondary education when students may begin to lose interest in science compared to other subjects (Gaspard, Häfner, Parrisius, Trautwein, & Nagengast, 2017). Particularly in science classes, tablets along with other mobile devices and applications are being used to increase students’ engagement by enabling more interactive learning experiences (Ahmed & Parsons, 2013).

Besides these findings, tablets could also be used to improve how students perceive being supported in their educational settings. The availability of tablets provides more opportunities for teachers to offer ongoing feedback as well as collect cumulative assessment data (Goodwin, 2012). Tablets can also be used to enable computer-based feedback that can be employed in a targeted manner to provide adaptive feedback or to assign different tasks to students (Lachner, Burkhart, & Nückles, 2017). Additionally, communicating online enhanced students’ willingness to ask for help from their teacher because of a greater sense of anonymity and decreased intimidation by social cues (Bures, Abrami, & Amundsen, 2000). However, despite the capabilities of tablets to support students in their educational settings, previous research in traditional environments show students perceive supportive climate differently depending on their learning characteristics (Seidel, 2006). Whether these differences persist in educational settings with tablets has not yet been investigated.

3.2.4 Overview on study and hypotheses

The present study investigated students’ perceptions of supportive climate in biology classes comparing classrooms with and without tablets. A science domain was chosen because in general students’ motivation towards science has been shown to decrease over the course of schooling (Gaspard et al., 2017). However, the use of tablets has been shown particularly in science classes

to increase learning engagement (Ahmed & Parsons, 2013). Whereas in traditional instruction, previous research shows students with more challenging learning characteristics such as low interest and prior content knowledge perceive less support than students with more positive characteristics (Seidel, 2006), we were interested in how students with different characteristics would perceive instruction with tablets. To this end, we followed the approach by Seidel (2006) and used latent profile analysis (LPA) to determine students with different profiles based on their individual characteristics.

In a first step, we investigated whether different profiles of students could be identified in biology classes with and without tablets and whether these profiles differed in their perceptions of supportive climate, thereby attempting to replicate and extend prior findings by Seidel (2006). We expected there would be significant differences in both learning contexts across student perceptions depending on the profile (Hypothesis 1).

Second, we investigated whether these profile-dependent perceptions would differ between tablet and non-tablet classes. Against the backdrop of preliminary findings regarding students' perceptions of instruction with technology (Barkatsas et al., 2009; Salmela-Aro et al., 2016), we expected especially students in profiles with more challenging learning characteristics would have more positive perceptions in tablet than in non-tablet classes (Hypothesis 2).

Third, we investigated profile perceptions over time in tablet and non-tablet classes. On the one hand, findings by Montrieux et al. (2017) suggests students may feel overwhelmed with tablet-based instruction when first introduced into the classroom. On the other hand, over time positive effects on students' perceptions may become more visible when teachers and students become more familiar with the use of tablets for teaching and learning. In turn, students' perceptions of instruction were generally expected to become more favorable over time in tablet classes as compared with non-tablet classes (Hypothesis 3). In addition, we explored whether these positive developments of perceptions within tablet (compared with non-tablet) classes would be especially true for students in profiles with more challenging learning characteristics.

3.3 Method

3.3.1 Participants and procedure

Data was collected within a longitudinal project that investigates whether and under what conditions digital media enable successful teaching and learning processes in the classroom. The data stemmed from a school initiative which was funded by the Ministry of Education, Culture, Youth and Sports of Baden-Württemberg, with the aim to support schools in the effective use of digital media for teaching. Academic track schools across Baden-Württemberg, applied to

participate and were randomly assigned to tablet and control conditions by which schools in the tablet condition were equipped with tablets for each student. Schools then decided which two classes would participate. Under the conditions of the initiative set out by the Ministry, the teachers in tablet classes were asked to integrate tablets into their daily classroom practices, however, they were not enrolled in professional development programs or instructed how to use tablets in their classes. Participants included students and teachers who take part in questionnaires and tests at four points over the course of three years from grade 7 to grade 9. Parents were informed and asked to sign consent forms for their children to participate in the study, and ethical approval was obtained from the Ministry.

The sample of the current analysis include the first cohort of 1,058 biology students from 56 classes in 28 schools of the school initiative. Half of the classes received personal tablets and acted as the tablet group ($n = 518$ students) while the other half did not receive tablets and represented the control group ($n = 540$ students). The mean age of the female (48.2%) and male students was 13.31 years ($SD = 0.53$). Questionnaire and test data measuring student characteristics was collected before students received their personal tablets in February 2018, measurement point one (t_0), and again after four months of tablet use in July, measurement point one (t_1). At t_0 , all students were asked to rate their perceptions of supportive climate regarding their general instruction. At t_1 , students in the tablet group were asked to separately rate their perception of supportive climate, first considering the instruction in which they had not worked with tablets and second, considering instruction in which they had worked with tablets. The latter ratings refer to on average nine times of use in their biology instruction (*Frequency of using tablets*, $M = 8.86$, $SD = 6.40$, $Min = 0$, $Max = 20$). With regard to the learning activities, students reported they mostly used tablets to present learning content such as with Powerpoint, to read from a digital textbook, for homework, and for editing partner and/or group work. At t_1 , students in the control group were only asked to rate their perception of supportive climate regarding general instruction.

Comparing students with different characteristics across different contexts involving tablets has so far not been investigated. Although there are no existing methods to perform a power analysis, we feel confident the sample size is large enough to detect effects. To the best of our knowledge, we do not know of any study in this field investigating students' perceptions of instruction with and without tablets that has a comparable sample size.

3.3.2 Measures

3.3.2.1 Profile indicators.

Cognitive characteristics were measured in two ways. General cognitive ability was assessed by a cognitive ability subtest on figure analogies (Heller & Perleth, 2000), which consisted of 25

items coded as correct or not ($M = 18.29$, $SD = 5.40$). As the acquisition of subject-specific knowledge is often measured by content-related achievement such as grades (Pielmeier, Huber, & Seidel, 2018), students' self-reported biology grades from the previous semester were used as an indicator of prior content knowledge ($M = 2.47$, $SD = 0.86$). In Germany, grades range from 1 to 6, with 1 being the best. Students' motivational-affective characteristics were measured with two established scales based on Gaspard et al., (2017). Biology interest (e.g., 'Biology is fun for me'; Cronbach's $\alpha = .94$) and biology self-concept (e.g., 'I am good in Biology'; Cronbach's $\alpha = .77$) were each assessed with four items rated on a four-point scale ranging from 1 = strong disagree to 4 = strongly agree.

3.3.2.2 Supportive climate

Students' perceptions of supportive climate were measured with three subscales that have been widely used in large-scale assessments in Germany (e.g., Rakoczy, Buff, & Lipowsky, 2005). Constructive approach to errors contained four items based off Rakoczy et al. (2005; e.g., 'Our teacher is patient when a student makes a mistake'; Cronbach's $\alpha = .85$). Clarity in teaching was investigated with three items based off Baumert et al. (2008; e.g., 'Our teacher can explain things well'; Cronbach's $\alpha = .91$). Lastly, interestingness and relevance was measured with three items based off Rakoczy et al., (2005; e.g., 'Our teacher makes dry material interesting'; $\alpha = .89$). All items were rated on a four-point scale ranging from 1 = strongly disagree to 4 = strongly agree.

At both t_0 and t_1 , students in tablet and control classes rated the supportive climate subscales referring to general instruction. Additionally, at t_1 , students in tablet classes rated the subscales once more referring to instruction with tablets. The subscales used the same item stems and only differed referring to the context. To verify the supportive climate subscales referring to classes with and without tablets would be comparable yet distinct constructs, confirmatory factor analysis (CFA) was used. First, a CFA was conducted in which the supportive climate subscales with and without tablets were modelled as separate factors. First, a CFA was conducted in which the supportive climate subscales with and without tablets were modelled as separate factors. Given the common wording stem of the items with and without tablets, it was expected there would be high correlations (Fauth et al., 2014). The correlation between constructive approach to errors without tablets and with tablets was 0.92, clarity in teaching was 0.91, and interestingness and relevance was 0.85. Although high, Wagner et al., (2013) showed correlations between different scales in the range of up to 0.96 behaved differently in empirical studies. Fit indices also indicated good model fit (RMSEA = .02, CFI = .99, TLI = .99, SRMR = .03). Additionally, a chi-square difference test showed the more restrictive model constraining the factor loadings to be equal versus the less

restrictive model freely estimating the factor loadings did not result in lower model fit ($\chi^2(7) = 8.09$, $p > .05$), indicating the equivalence of the measures.

In order to compare instruction with tablets in tablet classes and general instruction in control classes, a multiple-group CFA was used. The chi-square difference test showed constraining the factor loadings to be equal across groups did not result in lower model fit ($\chi^2(7) = 3.61$, $p > .05$), suggesting that the constructs across groups were comparable.

3.3.3 Data analyses

All analyses were conducted using Mplus (Muthén & Muthén, 2017). In the first step, we used the entire sample to determine the optimal number of latent classes by comparing statistical indices of models with increasing numbers of classes. Each time we added another class, we recorded the Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), and the adjusted BIC (ABIC) for which smaller values indicate better model fit. Additionally, we used the Lo-Mendell-Rubin likelihood ratio (LMR LR) test to look for significant p -values indicating a model with one more class fits the data better (Nylund, Asparouhov, & Muthén, 2007). Once the model with the optimal number of latent classes was chosen, we examined the quality of the latent class solution by looking at the posterior class-membership probability information. Students were assigned to the profile for which they had the greatest probability according to their observed response patterns. Probability values should be 0.80 or larger for a good class solution (Geiser, 2013). In addition, we looked at the class misclassification as measured by the entropy value. Entropy values should be 0.60 or higher to provide sufficiently good class separation (Asparouhov & Muthén, 2014). Finally, we defined the latent profiles according to the estimated class means of the observed variables in each of the classes. In doing so, we checked whether we could interpret the profiles substantively and whether they matched previous research and theory (Seidel, 2006).

Next, we used an automatic three-step approach to investigate the predictive validity of the latent classification on students' perceptions of supportive climate. Asparouhov and Muthén (2014) showed the Bolck-Croon-Hagenaars (BCH) method outperformed all other three-step approaches predicting distal outcomes with a latent class model without distorting the class solution. Unlike other methods, the BCH method uses a weighted multiple group analysis to evaluate the means across profiles when including an auxiliary variable to avoid shifting the latent classes in the final stage (Bakk, Tekkle, & Vermunt, 2013). In the first step, the underlying latent class model was estimated using only the latent class indicator variables. Second, individuals were assigned to latent classes and saved as class specific weights. Third, the BCH method was used to estimate the profile-specific means of the supportive climate subscales considering instruction at t_0 and again at t_1 . Chi-square tests were used to test for significant differences between the profiles.

Additionally, in only the tablet classes, the BCH method was used to estimate the profile-specific means of the supportive climate subscales in classes with tablets at t1. Lastly, to take into account students were nested into classes, cluster-robust standard errors were used (McNeish, Stapleton, & Silverman, 2017).

To test for significant differences in profile perceptions between the tablet and the control classes at t1, we used the manual BCH approach. In the first step, we used school type as an additional independent variable in order to form the latent classes in tablet classes and control classes and to save the BCH weights as before. However, two weights were saved for each of the five profiles resulting in a total of 10 weights corresponding to the profile in tablet and control classes. Subsequently in the next step, the profile means of general instruction in control classes and instruction with tablets in tablet classes were estimated in a single analysis. To test for significant differences between the profiles, we created new parameters using the Model Constraint command for each difference in the profile-specific means and computed z -tests.

To test for significant differences in profile perceptions from t0 to t1 within tablet classes, we also used the manual BCH approach and in the first steps formed the latent classes and saved the BCH weights. Next, the profile-specific means of supportive climate considering general instruction at t0 and instruction with tablets at t1 were estimated. Additionally, the differences between each pair of profiles at t0 and t1 were computed. We followed the same procedure to test for significant differences over time within the control classes.

3.4 Results

3.4.1 Relation between profiles and perceptions

To test how profiles combining student characteristics relate to student perceptions of supportive climate, in a first step we identified the student profiles. As the AIC, BIC, and the ABIC decreased with the addition of each class, we relied on the LMR LR test to narrow the selection of the number of classes. The p -value became insignificant with the addition of the sixth class, indicating no more significant improvement in model fit. Using the model output of the five-class solution, we examined the quality of the latent class membership classification. First, we looked at the posterior-class membership probability given the individuals' response patterns on the observed items. We found values ranging from .79 to .87, indicating a high precision of the classification (see Table 3.1). Additionally, we compared the final class counts and proportions for the latent class patterns based on estimated posterior probabilities to the classification of individuals based on their most likely latent class membership. These values did not differ considerably and indicated an entropy value of 0.74.

Table 3.1

Profile Descriptions, Group Size, Number of Students, and Probability of Expected Class Membership for the Five Latent Profiles (N = 1,058)

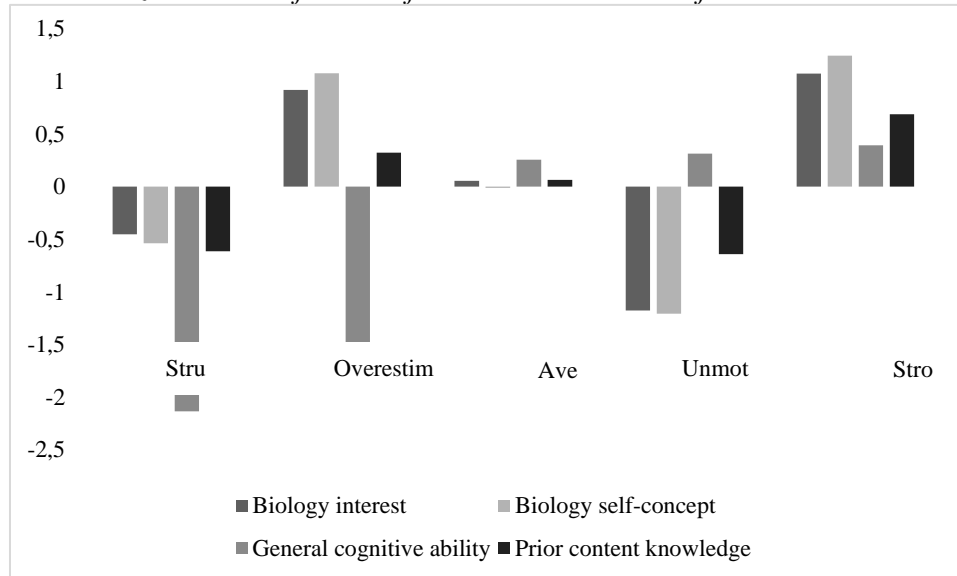
Label	Description	Number	Proportion	Probability of Expected Profile Membership
struggling	uniformly low values	93	8.79%	0.85
average	values similar to overall means	519	49.05%	0.79
unmotivated	low interest, self-concept, and content knowledge but high cognitive ability	154	14.56%	0.84
overestimating	high interest and self-concept but fairly low cognitive ability	74	7.00%	0.83
strong	uniformly high values	218	20.60%	0.87

Based on the LPA, five distinct profiles of student learning characteristics were identified. The ‘unmotivated’ profile was characterized for having the lowest biology interest, low self-concept, and low prior content knowledge in biology yet high general cognitive ability ($n = 154$, 14.56%). Although these students underestimated their ability in biology, they actually had general cognitive abilities on par with the strongest profile. This combination of characteristics suggests these students have the cognitive ability to be high performing but may lack the motivation to perform better in class, as reflected by their low interest and grades. Students in the ‘average’ profile accounted for almost half of the participants ($n = 519$, 49.05%). This profile contained means closely resembling the overall average of the entire sample, except for slightly below average self-concept as well as slightly above average general cognitive ability. We found similar characteristics as in Seidel (2006) for the remaining profiles and therefore refer to them using the same labels. Students in an ‘overestimating’ profile were characterized as having high interest and high self-concept, similar to the strongest profile, but below average general cognitive ability and average prior content knowledge ($n = 74$, 7.00%). Students in a ‘strong’ profile demonstrated overall high values on all characteristics including the highest values for interest and self-concept as well as prior content knowledge ($n = 218$, 20.60%). Lastly, students in a ‘struggling’ profile had below average means on all indicators ($n = 93$, 8.79%). Although these students had higher values in interest and self-concept than the ‘unmotivated’ profile, their general cognitive ability was far below the average (see Figure 3.1). In addition to the entire sample, we followed the same procedure to identify the optimal number of profiles and to check the validity of the profile solution

statistically and substantively using only the tablet classes and separately using only the control classes. We found the same set of profiles in both the control and the tablet classes.

Figure 3.1

Standardized Means of the Profile Indicators Per Profile



Note. To better illustrate the differences between the latent classes, the variables were centered and standardized to have a grand mean equal to zero and a standard deviation equal to one. Previous biology grade was used as a proxy for prior content knowledge and reverse coded so higher grades indicated more prior content knowledge.

After identifying the five-profile solution, we next looked at the relationship between the profiles and students' perceptions to see whether the profiles would differentially predict students' perceptions of supportive climate. We found in both control and tablet classes at t0 and t1 there were almost always significant differences between students' perceptions of supportive climate depending on the profile (see Table 3.2). Struggling and unmotivated students perceived instruction significantly more negatively than overestimating and strong students. However, there were less significant differences between the perceptions of the strong and overestimating profiles, suggesting that students in the overestimating and strong profiles perceived supportive climate in similar ways. Additionally, in the control classes, there were no significant differences between the perceptions of the struggling and unmotivated profiles, whereas in the tablet classes, there were no significant differences between the perceptions of the struggling and average profiles. Furthermore, using only the tablet classes, we found significant differences between the profiles considering

Table 3.2

Profile-Specific Means (and Standard Errors) of Supportive Climate Subscales Considering General Instruction in Tablet and Control Classes at T0 and at T1 (N = 1,058)

Profiles	T0				T1			
	Tablet classes	D	Control classes	D	Tablet classes	D	Control classes	D
	Constructive approach to errors							
(1) struggling	3.06 (0.09)	1 vs. 4/5	2.55 (0.21)	1 vs. 4/5	2.97 (0.12)	1 vs. 4/5	2.26 (0.19)	1 vs. 2*/4/5
(2) average	3.14 (0.10)	2 vs. 4/5	2.82 (0.09)	2 vs. 3*/4/5	3.09 (0.07)	2 vs. 3*/4*	2.73 (0.08)	2 vs. 4/5
(3) unmotivated	2.93 (0.10)	3 vs. 4/5	2.40 (0.20)	3 vs. 4/5	2.85 (0.14)	3 vs. 4/5	2.38 (0.18)	3 vs. 4
(4) overestimating	3.80 (0.13)	4 vs. 5*	3.34 (0.15)	4 vs. 5	3.45 (0.18)		3.18 (0.13)	4 vs. 5
(5) strong	3.55 (0.05)		3.26 (0.09)		3.37 (0.11)		3.14 (0.12)	
	Clarity in teaching							
(1) struggling	3.17 (0.11)	1 vs. 3/4/5	2.41 (0.19)	1 vs. 2/4/5	3.04 (0.10)	1 vs. 3/5	1.99 (0.21)	1 vs. 2/4/5
(2) average	3.20 (0.06)	2 vs. 3/4/5	2.79 (0.10)	2 vs. 3*/4/5	3.17 (0.08)	2 vs. 3*/5	2.68 (0.10)	2 vs. 3/4/5
(3) unmotivated	2.76 (0.10)	3 vs. 4/5	2.26 (0.21)	3 vs. 4	2.64 (0.13)	3 vs. 4/5	2.09 (0.17)	3 vs. 4
(4) overestimating	3.85 (0.15)		3.40 (0.14)	4 vs. 5	3.35 (0.25)		3.34 (0.13)	4 vs. 5
(5) strong	3.77 (0.05)		3.36 (0.11)		3.49 (0.10)		3.30 (0.12)	
	Interestingness and relevance							
(1) struggling	2.82 (0.12)	1 vs. 3/4/5	2.25 (0.23)	1 vs. 2*/4/5	2.84 (0.14)	1 vs. 2/3*/4*/5	2.16 (0.21)	1 vs. 4/5
(2) average	3.07 (0.08)	2 vs. 3/4/5	2.66 (0.10)	2 vs. 3/4/5	3.15 (0.08)	2 vs. 3	2.48 (0.11)	2 vs. 3/4/5
(3) unmotivated	2.39 (0.09)	3 vs. 4/5	1.84 (0.16)	3 vs. 4	2.58 (0.09)	3 vs. 4/5	1.96 (0.14)	3 vs. 4
(4) overestimating	3.68 (0.17)		3.34 (0.14)	4 vs. 5	3.34 (0.19)		3.21 (0.15)	4 vs. 5
(5) strong	3.59 (0.07)		3.25 (0.10)		3.23 (0.10)		3.07 (0.13)	

Note. Supportive climate subscales were rated on 4-point Likert scales. D = Significant differences between a given pair of student profiles.

$p < .01$. * $p < .05$.

instruction with tablets. Although there were the same significant differences regarding interestingness and relevance, there were fewer significant differences regarding constructive approach to errors and clarity in teaching.

3.4.2 Differences across tablet and non-tablet classes

Using the manual BCH approach, in addition to estimating the latent class model and the profile-specific means of the supportive climate subscales in the control and tablet classes, we tested for significant differences between the respective profiles at t1 (after tablet classes already worked with tablets for four months). Tablet students in the average, unmotivated, and struggling profiles perceived instruction with tablets as significantly more supportive than control students in the same profiles perceiving instruction without tablets (see Table 3.3). Because there were significant differences at t0 between tablet and control classes in the struggling and the strong profiles regarding students' perceptions across the three subscales, we also controlled for t0 when estimating the profile-specific means and testing for significant differences. After controlling for t0, we found significant differences between the tablet and control classes in the struggling and unmotivated profiles considering constructive approach to errors and clarity in teaching and significant differences in the average and unmotivated profile considering interestingness and relevance. Of these significant differences, the students in the tablet classes perceived the supportive climate subscales significantly more positively.

Table 3.3

Profile-Specific Means (and Standard Errors) of Students' Perceptions of Supportive Climate in Control Classes and in Tablets Classes at T1

Profiles	Control classes General instruction	Tablet classes Instruction with tablets	<i>p</i>
Constructive approach to errors			
struggling	2.34 (0.19)	3.06 (0.19)	0.007
average	2.79 (0.08)	3.09 (0.12)	0.041
unmotivated	2.31 (0.15)	2.89 (0.16)	0.008
overestimating	3.16 (0.13)	3.43 (0.24)	0.346
strong	3.12 (0.12)	3.42 (0.14)	0.121
	<i>n</i> = 483	<i>n</i> = 270	
Clarity in teaching			
struggling	2.08 (0.23)	3.17 (0.13)	0.000
average	2.77 (0.11)	3.11 (0.11)	0.031
unmotivated	2.01 (0.16)	2.72 (0.17)	0.002
overestimating	3.31 (0.13)	3.51 (0.26)	0.487
strong	3.27 (0.12)	3.48 (0.08)	0.164
	<i>n</i> = 465	<i>n</i> = 271	
Interestingness and relevance			
struggling	2.24 (0.23)	2.87 (0.21)	0.043
average	2.56 (0.11)	3.14 (0.13)	0.001
unmotivated	1.87 (0.12)	2.59 (0.14)	0.000
overestimating	3.18 (0.15)	3.71 (0.22)	0.047
strong	3.06 (0.14)	3.19 (0.16)	0.552
	<i>n</i> = 484	<i>n</i> = 262	

Note. Bold indicates significant values. The profile analysis is based on simultaneously considering control and tablet schools, and for this reason the estimated means vary slightly across Tables 3.4 and 3.5.

3.4.3 Differences over time within tablet classes and non-tablet classes

We estimated the profile-specific means of the supportive climate subscales considering instruction without tablets at t0 and instruction with tablets at t1 within the tablet classes and considering instruction without tablets at both t0 and t1 in the control classes. Within the control classes, profile perceptions of supportive climate generally decreased over time, and the average profile perceived interestingness and relevance significantly more negatively (see Table 3.4). However, within the tablet classes, perceptions remained more stable or increased over time, with the exception of the strong profile that perceived clarity in teaching and interestingness and relevance significantly more negatively (see Table 3.5). Notably, the unmotivated profile perceived interestingness and relevance significantly more positively over time.

Table 3.4

Profile-Specific Means (and Standard Errors) of Students' Perceptions of Supportive Climate in Control Classes at T1 and at T0

Profiles	General instruction at t0	General instruction at t1	<i>p</i>
Constructive approach to errors			
struggling	2.55 (0.21)	2.26 (0.19)	0.214
average	2.82 (0.09)	2.73 (0.08)	0.308
unmotivated	2.40 (0.20)	2.38 (0.18)	0.234
overestimating	3.34 (0.15)	3.18 (0.14)	0.355
strong	3.26 (0.09)	3.14 (0.12)	0.274
	<i>n</i> = 483	<i>n</i> = 487	
Clarity in teaching			
struggling	2.41 (0.19)	1.99 (0.21)	0.068
average	2.79 (0.10)	2.68 (0.10)	0.184
unmotivated	2.26 (0.21)	2.09 (0.17)	0.420
overestimating	3.40 (0.14)	3.34 (0.13)	0.623
strong	3.36 (0.11)	3.29 (0.12)	0.491
	<i>n</i> = 485	<i>n</i> = 486	
Interestingness and relevance			
struggling	2.25 (0.23)	2.16 (0.21)	0.730
average	2.66 (0.10)	2.48 (0.11)	0.042
unmotivated	1.84 (0.16)	1.96 (0.14)	0.371
overestimating	3.34 (0.14)	3.21 (0.15)	0.386
strong	3.25 (0.10)	3.07 (0.13)	0.112
	<i>n</i> = 484	<i>n</i> = 481	

Note. Bold indicates significant values. The profile analysis is solely based on the control classes.

Table 3.5

Profile-Specific Means (and Standard Errors) of Supportive Climate in Tablet Classes Considering General Instruction at T0 and Instruction with Tablets at T1

Profiles	General instruction at t0	Instruction with tablets at t1	<i>p</i>
Constructive approach to errors			
struggling	3.06 (0.09)	3.03 (0.18)	0.821
average	3.14 (0.10)	3.17 (0.12)	0.724
unmotivated	2.93 (0.10)	2.88 (0.15)	0.698
overestimating	3.79 (0.13)	3.64 (0.27)	0.634
strong	3.55 (0.05)	3.32 (0.15)	0.091
	<i>n</i> = 466	<i>n</i> = 270	
Clarity in teaching			
struggling	3.17 (0.11)	3.08 (0.14)	0.445
average	3.20 (0.06)	3.17 (0.11)	0.789
unmotivated	2.76 (0.10)	2.77 (0.17)	0.937
overestimating	3.85 (0.15)	3.69 (0.28)	0.645
strong	3.77 (0.05)	3.44 (0.12)	0.005
	<i>n</i> = 466	<i>n</i> = 271	
Interestingness and relevance			
struggling	2.82 (0.12)	2.81 (0.21)	0.960
average	3.07 (0.08)	3.20 (0.12)	0.277
unmotivated	2.39 (0.09)	2.68 (0.12)	0.017
overestimating	3.68 (0.17)	3.86 (0.33)	0.664
strong	3.59 (0.07)	3.15 (0.16)	0.007
	<i>n</i> = 466	<i>n</i> = 262	

Note. Bold indicates significant values. The profile analysis is solely based on the tablet classes.

3.5 Discussion

As more schools in Germany are being equipped with tablets, the present study begins to look at how students perceive this new educational setting using student ratings of supportive climate. Nevertheless, student ratings of the same instruction can differ depending on students' learning characteristics. By looking at both students' characteristics and their perceptions of supportive climate, we can begin to understand how different types of students are affected by the addition of tablets to the classroom.

The first aim of the study was to check whether students could be grouped by their cognitive and motivational-affective characteristics into distinct profiles and whether these profiles would function to predict students' perceptions of supportive climate in both classes with and without tablets. We found the same set of profiles existed in the entire sample as well as for the two subsamples, control and tablet classes, speaking for the robustness of the five-profile solution, and replicates the profiles found in Seidel (2006). Additionally, we found significant differences between student perceptions depending on the profile (e.g., struggling students perceived

instruction significantly differently from overestimating students), and profiles predicted perceptions in the same way at both measurement points and within the two groups (e.g., strong students perceived instruction more positively in all conditions). Taken together, students differ depending on their background characteristics, and these differences matter for how they perceive supportive climate when they learn with and without tablets.

After showing the differential predictions of the five-profile solution, we compared the differences between profile perceptions in tablet and control classes. At t1, there were significant differences with the struggling, unmotivated, and average profiles perceiving instruction with tablets significantly more positively than students with the same profiles in control classes perceiving general instruction. Additionally, there were almost no significant differences between the overestimating and strong profiles in the tablet and control classes. However, there was one notable exception. Tablet students in the overestimating profile had significantly more positive perceptions of interestingness and relevance in instruction with tablets than students from the control classes in the same profile. A possible explanation could be that in line with previous research (e.g., Sung et al., 2016), tablets did have an engaging effect and even overestimating students perceived instruction to be more interesting and relevant with the addition of tablets. On the other hand, students in the strong profile who already perceived instruction positively and have higher cognitive ability compared to the overestimating profile, may have been disappointed by the actual use of tablets in classes, as reported by other students in 1:1 tablet schools (Blikstad-Balas & Davies, 2017). According to surveys and interviews, secondary education students in Norway, Denmark, and the UK were either disappointed that the use of tablets in class did not amount to much or because the effort to use them felt forced. This could also be in line with Ninaus, Moeller, McMullen, and Killi (2017) which found students with already high math interest and intrinsic motivation as well as high prior content knowledge did not benefit from the engaging nature of a digital math game.

In addition to investigating the differences between tablet and control classes at t1, we further analyzed the differences in the perception of supportive climate within tablet classes over time. Unlike in the control classes where students' perceptions mainly fell from t0 to t1, perceptions in the tablet classes remained mostly stable or increased, with the exception of the strong profile where perceptions actually decreased. Besides the possibility that strong students may have been disappointed by the use of tablets in class, a possible explanation for why the strong profile, unlike the other profiles in the tablet classes, perceived instruction with tablets more negatively could be that these students were already content with their instruction as evidenced by their high perceptions and did not want to change their educational setting. Compared to the control classes,

our results suggest that the addition of tablets to the classroom may cushion students' decline in perceptions of supportive climate over time. However, it must be noted that only the addition of tablets was examined in the study. Whether the quality of instruction with tablets could have differential and/or positive effects also on the perception of the strong students, must be shown with further analyses.

While the results seem promising for the use of tablets in classrooms, there are several limitations. First, while schools were randomly assigned into tablet and control conditions, based on the design of the project by the ministry, schools decided which two classes would participate in the project. This could explain why there were differences across the profiles in students' perceptions of supportive climate at t_0 between tablet and control classes. To account for these initial differences, we controlled for students' perceptions at t_0 when calculating the differences across corresponding profiles at t_1 . However, comparing and interpreting the change over time between tablet and control classes must be done carefully considering the initial differences. Additionally, this study can only show whether students' perceptions of supportive climate change with the addition of tablets to the classroom, not whether instructional practices change. Based on these analyses, we cannot explain why struggling and unmotivated students perceive instruction to be more supportive in classes with tablets. Therefore, in future research, greater attention must be paid to investigate what actually happens in classrooms and how tablets are used (for example by analyzing teaching artefacts or video recordings). Furthermore, while we found significant differences between tablet and control classes after four months of tablet use considering all three supportive climate subscales, longitudinal studies have to analyze whether students' perceptions of supportive climate when learning with tablets stay stable or increase over time, or whether this initial finding is still a novelty effect. These analyses should also take into account the different ways teachers use tablets in their instruction and link these practices to students' learning processes. Future research should also be directed at how to best measure the impact of tablets, whether it be with student ratings, changes in grades or test scores, or new instruments that could capture other skills students may learn as a result of using tablets, such as the abilities to work independently and locate and use Internet resources (Zheng et al., 2016).

3.6 Conclusion

Using student ratings of supportive climate and linking them to student characteristics can already begin to show that using tablets may differentially benefit certain types of students and change the way they feel supported by their educational setting. In particular, students who were characterized as having low interest and self-concept along with low grades in biology class perceived supportive climate more positively with the addition of tablets, which has positive

implications for their motivation and learning outcomes. This result seems promising moving forward that for students who may struggle in traditional educational settings, tablets may make a difference.

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4

The effects of teachers' technology beliefs on students' perceptions: Understanding differences in students' perceptions of instruction with digital media

Hammer, M., Scheiter, K., Stürmer, K. (in preparation). The effects of teacher technology beliefs on students' perceptions: Understanding differences in students' perceptions of instruction with digital media.

Abstract

Despite the potential of digital media for learning, there is currently a lack of research indicating how digital media can be used in classrooms to enable students' learning processes. The current paper investigates how students perceive cognitive activation and supportive climate in classes with digital media depending on their cognitive and motivational-affective characteristics as well as teachers' technology innovativeness. Cognitive activation and supportive climate have been found to foster students' learning processes, and teachers' technology innovativeness has been linked to instructional quality in classes with digital media. Results using latent profile analysis and multiple regression indicate that most students perceived instructional practices more positively in classes where teachers have higher technology innovativeness with the exception of an 'unmotivated' profile that perceived instructional practices more negatively. Investigating the extent to which students perceive instruction to be cognitively activating and instructionally supportive depending on their cognitive and motivational-affective characteristics can indicate how the use of digital media may differentially affect students' learning processes.

Keywords: digital media; tablets; cognitive activation; supportive climate; student perceptions; latent profile analysis.

4.1 Introduction

Digital media such as tablets have entered classrooms faster than researchers can investigate the actual effects of tablet use on teaching and learning processes (Escueta, Quan, Nickow, & Oreopoulos, 2017). Although research in this field continues to grow, much of this research has emphasized gains in achievement without enough attention to the processes that precede or underlie student learning (e.g., Lai & Bower, 2020; Sung, Chang, & Liu, 2016). Similarly, research on teaching processes has tended to focus on teacher characteristics and subsequently has shown teachers' beliefs towards using technology is at the core of how effectively teachers integrate technology into teaching and learning activities (e.g., Petko, Presse, & Cantieni, 2018; Scherer, Siddiq, & Tondeur, 2019). Effective digital media integration often assumes a direct effect of teaching with digital media on student learning, and effects are mostly examined in relations to academic outcomes (e.g., Lai & Bower, 2020) or gains in content knowledge (e.g., Sung, et al., 2016). However, effective digital media integration can be viewed in a different way. Extensive research on instructional quality has shown how students perceive cognitive activation and supportive climate is crucial in initiating and maintaining insightful learning processes and linked to motivation development and achievement gains, particularly in math classes (Kunter, Klusmann, Baumert, Richter, Voss, & Hachfeld, 2013; Lipowsky, Rakoczy, Pauli, Drollinger-Vetter, Klieme, & Reusser, 2009). Therefore, investigating how cognitively activating and instructionally supportive students perceive instruction with digital media can offer another way to understand effective learning with digital media from the perspective of the learner.

At the same time, increasingly more research indicates students can differ widely in their individual perceptions of the same instructional practices, and these idiosyncratic perceptions may indicate meaningful differences in how students with particular learning characteristics perceive instruction (Göllner, Wagner, Eccles, & Trautwein, 2018). Taking student characteristics into account can therefore provide meaningful information in how different types of students may differentially perceive and learn with digital media. Combining both the teacher and the student perspective, the present study aims to investigate students' perceptions of cognitive activation and supportive climate in math classes with digital media depending on teachers' technology beliefs towards using technology and students' cognitive and motivational-affective characteristics.

4.2 Theoretical Background

4.2.1 Investigating student learning with digital media

Teaching and learning processes in classrooms are described as complex, reciprocal structures of supply and use, which are co-determined by the preconditions of teachers and learners (Seidel & Shavelson, 2007). In their review of the use of tablets in schools, Major, Haßler, and Hennessy (2017) concluded that tablets have significant potential for enhancing learning, but the most important element remains the teacher and their instructional practices. Although undoubtedly necessary and important, instructional practices alone do not predict student learning. Moving from a process-product model to a social constructivist model of learning indicates learning must also be self-directed. Lipowsky et al. (2009) explain “learning processes cannot be controlled from the outside; rather, the teacher provides learning opportunities that must be perceived and utilized by the student to be effective” (p. 528). Rather than a direct link between instructional practices and students’ learning outcomes, students’ perceptions of their teachers’ instructional practices mediate the effect that an instructional practice will have on student learning (Shuell, 1996). If students’ perceptions do not match with the intention behind the instructional practice, then the instructional practice is not likely to reach its goal (Doyle, 1977).

Generally, instructional quality is studied to determine which instructional practices are effective for student learning (Seidel & Shavelson, 2007). With respect to mathematics instruction, instructional practices identified as being cognitively activating and instructionally supportive have been found to be essential in initiating and maintaining insightful learning processes (Kunter et al., 2013). Klieme, Pauli, and Reusser (2009) describe cognitive activation as an observable pedagogical practice or pattern that “encourages students to engage in (co)-constructive and reflective higher-level thinking and thus to develop an elaborated, content-related knowledge base” (p. 141). Teachers must challenge students with tasks and lines of questioning that engage them in higher cognitive levels of thinking while prompting them to build on what they already know. Key features include challenging tasks, activating prior knowledge, content-related discourse, and participation practices. Furthermore, a supportive classroom climate is characterized by “supportive teacher-student relationships, positive and constructive teacher feedback, a positive approach to students’ errors and misconceptions, individual learner support, and caring teacher behavior” (Klieme et al., 2009, p. 141). Teachers provide individual learning support by continuously monitoring individual students’ learning processes to provide feedback and adaptive instruction while respecting their autonomy (Baumert et al., 2010). To assess cognitive activation and supportive climate, student ratings

are regularly used and have been found to be valid and reliable indicators (Göllner et al., 2018). Extensive research shows students' perceptions of cognitive activation is linked to student achievement, and students' perceptions of supportive climate is linked to motivation development (Baumert et al., 2010; Kunter et al., 2013).

At the same time, students' perceptions of these instructional practices may differ depending on particular learning characteristics (Seidel, 2006). Alongside a social constructivist model of learning, individual learning processes depend on students' individual learning preconditions, including students' cognitive and motivational-affective characteristics (Brophy & Good, 1986; Shuell, 1996). This is evident in a growing body of research examining heterogeneity in students' perceptions (e.g., Schenke, Ruzek, Lam, Karabenick, & Eccles, 2018). Students' perceptions of instructional quality within a classroom can differ tremendously, and these differential perceptions have been linked to students' learning characteristics (Göllner et al., 2018; Seidel, 2006). In particular, Seidel (2006) found secondary physics students could be grouped into five distinct profiles based on cognitive and motivational-affective characteristics. In turn, students' profiles were systematically linked to how they perceived their learning environment. Specifically, Seidel (2006) found students with high prior content knowledge, self-concept, and interest were more likely to perceive instruction as more supportive than students with overall more challenging characteristics, such as low general cognitive ability or low interest, or students who underestimated their ability. In another study, Hammer, Göllner, Scheiter, Fauth, and Stürmer (2020) found secondary education biology students could also be grouped into five distinct profiles using the same cognitive and motivational-characteristics as Seidel (2006), and students' profile membership differentially predicted students' perceptions of supportive climate in classes with and without tablets. Students with overall more positive learning characteristics, a 'strong' profile, and students with high interest and self-concept but low general cognitive ability, an 'overestimating' profile, perceived instruction as more supportive than the students belonging to an 'average' profile, an 'unmotivated' profile, and a 'struggling' profile. The students in an 'average' profile contained characteristics resembling the overall means. An 'unmotivated' profile was characterized for having the lowest biology interest, low self-concept, and low prior content knowledge yet high general cognitive ability. Finally, a 'struggling' profile was characterized for having overall low characteristics. In particular, students belonging to the 'unmotivated' and 'struggling' profile perceived instruction with tablets significantly more positively than the corresponding profiles in classes without tablets perceived instruction. However, there is a lack of research

investigating how the use of digital media in classrooms may affect how students perceive the extent of cognitively activating practices in addition to instructionally supportive practices.

Taking students' learning characteristics into account when considering how digital media affects students' learning is particularly important considering the wide variability previously found in technology effects on student learning. In their second-order meta-analysis spanning 40 years of research, Tamim, Bernard, Borokhovski, Abrami, and Schmid (2011) found the average student in a classroom where technology was used performed 12 percentile points higher than the average student in a traditional setting where technology was not used. However, Tamim et al. (2011) offered this with a caveat, average effects should be interpreted cautiously because of the wide range of factors that affect how technology was leveraged to enhance learning. By the same token that "educational technology is not a homogenous 'intervention'" (Ross, Morrison, & Lowther, 2010, p. 19), digital media should not be assumed to have a homogenous effect on students.

4.2.2 Conceptualizing how digital media affects students' perceptions

Given the potential of digital media in teaching and learning, the use of digital media in classrooms may offer the most promise or the most damage to students' perception of cognitively activating processes. On the one hand, teachers are limited by the availability of what applications are currently on the market (Ward, Finley, Keil, & Clay, 2013). Depending on the subject and domain, there may already be applications with cognitively stimulating designs and content. However, even content-specific applications are not necessarily designed for educational purposes (Ward et al., 2013), potentially placing additional burden on teachers to create novel lessons without previously developed curriculum. Additionally, especially realistic and dynamic visual displays can distract students from relevant information (Renkl & Scheiter, 2015), further placing more stress on the teacher to redirect students to engage them in higher-level thinking. Furthermore, cognitive activation requires a "certain quality" of interaction and participation between teacher and students (Klieme et al., 2009, p. 140). These pedagogical practices can be hard to replicate, even with personalized learning or intelligent software. Cognitive activation involves teachers triggering students' cognitive processes by integrating students' previous knowledge with the current task and challenging students' beliefs so the students can evaluate the validity of their own solutions (Lipowsky et al., 2009). To do so, teachers must provide individual questions and feedback which may not be imitated by just any software, and teachers may not be trained in triggering cognitive processes alongside digital learning. Lastly, while digital media offers immediate access to information, the sheer ease and

availability of so much information may promote “mile wide, inch deep” thinking and a resistance to information that requires more effort (Giedd, 2013).

Digital media may also support teacher-student relationships and facilitate opportunities for teachers to offer more individual learner support while allowing students to retain their autonomy. In turn, students may perceive instruction with digital media to provide a more supportive climate. Digital media provide opportunities for teachers to offer ongoing feedback as well as collect cumulative assessment data (Goodwin, 2012). Communicating online can also enhance students’ willingness to ask for help from their teacher because of a greater sense of anonymity and decreased intimidation by social cues (Bures, Abrami, & Amundsen, 2000). In a study of a one-to-one laptop school, Lei (2010) found social-communication technologies provided students more opportunities to ask questions, especially for students who were too shy to ask questions in the classroom, and students reported it more convenient to email their teachers questions or set up an appointment. Conversely, in a study investigating primary students’ use of iPads, Falloon (2014) raises the issue that although students may appear to be engaged in learning with an app, recordings of their activity revealed many were actually skimming information or had converted the learning task into a game. This case indicates the added challenge teachers may have in monitoring depth of learning and identifying learning difficulties preventing them from offering individual learning support and constructive or adaptive feedback.

Investigating cognitive activation and supportive climate in traditional classrooms has underscored the importance of certain teacher characteristics in predicting how well teachers provide high-quality instruction (e.g., Kunter et al., 2013). Regarding instruction with digital media, emerging research is beginning to show teachers’ technology innovativeness is a key determinant in how teachers integrate digital media into the classroom and use digital media in cognitively activating and instructionally supportive ways.

4.2.3 Examining the role of teachers’ technology innovativeness

There are many ways for teachers to make their lessons cognitively activating and supporting. In this vein, teachers can also integrate digital media in very different ways that are effective for learning. However, extensive research indicates whether teachers meaningfully integrate technology into the classroom depends on teachers’ beliefs towards using technology (Petko et al., 2018). That is to say, if teachers do not believe that a technology is beneficial for teaching and learning, they are unlikely to use it in an effective way. Specifically, considering a range of factors including quality of educational technology and school support, Petko et al. (2018) found the use of educational technology in classrooms was dependent on teacher

readiness, defined as both the belief that educational technology improves teaching and learning and having sufficient confidence in teaching with technology. Similarly, in a meta-analytic review of 114 empirical studies investigating teachers' adoption and integration of educational technology, Scherer et al. (2019) found teachers' self-efficacy beliefs to use educational technology and perceived educational technology usefulness largely predicted teachers' intention to use technology in class subsequently resulting in a higher degree of technology integration.

Generally, van Braak, Tondeur, and Valcke (2004) explain innovativeness is studied to understand why individuals adopt a certain innovation or not and refers to the willingness to change or adapt to an innovation as compared to others in the same social system (Rogers & Shoemaker, 1971). Importantly, technological innovativeness encompasses not only a positive attitude or favorable disposition towards a new technology but also an intentional dimension. Two recent studies indicate that teachers' perceived technology innovativeness (also referred to as teacher's utility value for technology), more so than self-efficacy beliefs, largely explained instructional quality with technology whereby higher technology innovativeness was associated with greater instructional quality when using technology. Specifically, Backfisch, Lachner, Hirsche, Loose, and Scheiter (2020a) asked teachers varying in years of experience to answer a test measuring their professional knowledge, report their motivational beliefs regarding technology use, and provide a lesson plan on the introduction of the Pythagorean theorem. The described teaching methods in the lesson plans were assessed by trained raters in terms of potential cognitive activation and supportive climate. The authors found that expert teachers provided lesson plans involving methods of higher instructional quality and technology exploitation than novice teachers. However, teachers' professional knowledge did not mediate the effect of teacher expertise on the quality of technology integration; rather teachers' perceived technology innovativeness largely accounted for higher instructional quality. Furthermore, the effect of teacher expertise on the quality of the lesson plans could be explained by teachers' perceived technology innovativeness, but not by their self-efficacy beliefs regarding using technology.

In another study investigating the relations between teachers' technology motivation and quality of technology integration in the classroom, Backfisch, Lachner, Stürmer, and Scheiter (2020b) used an experience sampling approach over a course of six weeks. At the end of each week, teachers were asked to document in a web-based diary how often they used technology and to describe one technology-based lesson. The lesson documentations were then rated for technology exploitation and task-specific instructional quality. The authors found teachers'

perceived technology innovativeness was significantly related to instructional quality across lessons and subjects. Specifically, the teachers who perceived high technology innovativeness integrated technology with higher instructional quality. As a possible explanation, the authors suggested teachers with higher perceived technology innovativeness think more about the distinct potential of various technologies which could lead to the higher exploitation of the technology. Overall, across extensive research investigating relevant teacher characteristics, teachers' technology innovativeness has been identified as an important determinant of instructional practices integrating digital media.

In sum, despite the potential of digital media for learning in classrooms, there is currently a lack of research indicating how digital media such as tablets actually affects students' learning processes. To address this gap, rather than focus on what determines how teachers integrate tablets into the classroom, the current paper investigates how students perceive instructional practices with digital media depending on their cognitive and motivational-affective characteristics as well as teachers' technology innovativeness. Previous research has shown how students perceive cognitively activating and instructionally supportive practices in math classes facilitates insightful learning processes resulting in motivation development and achievement gains (Kunter et al., 2013), indicating the importance of student perceptions. At the same time, increasingly more research has shown students can and do perceive the same instructional practice in different ways (e.g., Schweig, 2016; Seidel, 2006), indicating the potential benefit of cognitively activating and instructionally supportive practices may not be realized by all students. Regarding learning with digital media, additional research has demonstrated teachers' technology innovativeness largely predicted how teachers used technology to heighten cognitively activating and instructionally supportive practices, as rated by external reviewers (Backfisch et al., 2020a; Backfisch et al., 2020b). However, it is unknown how students themselves perceived the differences in cognitively activating and instructionally supportive practices based on teachers' technology innovativeness. Therefore, in the present paper, we aim to investigate students' perceptions of cognitive activation and supportive climate in math classes with tablets and investigate how these perceptions may depend on students' cognitive and motivational-affective characteristics as well as teachers' technology innovativeness. In these ways, the present study aims to understand how the use of the digital media may affect student learning from the perspective of students.

4.3 Research questions

1. How do students' cognitive and motivational-affective characteristics relate to how they perceive supportive climate and cognitive activation with tablets in math classes?

2. Do teachers' technology innovativeness moderate the relation between student profiles and student perceptions?

Previous research shows the interplay of motivational and cognitive-affective characteristics systematically affect how students perceive learning conditions (Seidel, 2006; Hammer et al., under review). Therefore, in the first step we aim to replicate the profiles used by Seidel (2006), and Hammer et al. (2020) by using the same learning characteristics as profile indicators and extend the findings by looking at the effect of profiles on students' perceptions of instructional quality with tablets, including cognitive activation in addition to supportive climate.

Secondly, we aim to investigate whether the effect of profile membership on students' perceptions of cognitive activation and supportive climate with tablets differs across levels of teachers' technology innovativeness. On the one hand, teachers' technology innovativeness may have an overall positive effect across all profiles, whereby in classrooms with teachers that have higher technology innovativeness, students' perceptions of instructional quality with tablets are also higher. This would be in line with Backfisch et al. (2020a) and Backfisch et al. (2020b) that showed teachers' technology innovativeness largely predicted teachers' technology integration and instructional quality as rated in lessons plans as well as in teacher diaries, suggesting how students perceive instructional quality with tablets would also be affected by the extent of teachers' technology innovativeness. If this is the case, we would expect to find significant and positive interaction effects across all profiles and subscales of instructional quality.

On the other hand, teachers' technology innovativeness may have differential effects on the relation between profile membership and students' perceptions whereby some profiles are affected by teachers' technology innovativeness and other profiles are not. For example, the way teachers' use technology in the classroom may have an antagonistic effect in the 'struggling' and 'unmotivated' profiles, assuaging the negative effect more challenging characteristics, such as low interest or low general cognitive ability, have on students' perceptions of instruction with tablets. This would be in line with previous research (Hammer et al., 2020) that compared students' profile-specific perceptions in classes with and without tablets and found only students in the 'struggling' and 'unmotivated' profiles perceived instruction with tablets significantly more positively than the corresponding profiles in classes without tablets. In contrast, students with more positive learning characteristics such as high self-concept and prior content knowledge, students belonging to a 'strong' profile, may have positive perceptions of instruction with tablets regardless of the way teachers use tablets in the

math classroom. This would be in line with Göllner et al. (2018) that found students with higher math achievement, a better math grade, more math enjoyment, and greater experienced competencies in math had more positive perceptions of instructional quality in general. If this is the case, we would expect to find significant interaction effects for ‘struggling’ and ‘unmotivated’ profiles but not the ‘strong’ profile.

4.4 Method

4.4.1 Participants and Study Design

Data was collected within a multi-cohort, longitudinal project that investigates whether and under what conditions digital media enable successful teaching and learning processes in the classroom. The data stemmed from a school initiative which was funded by the Ministry of Education, Culture, Youth and Sports of Baden-Württemberg. Academic track schools across the state applied to participate and were informed that selected schools would be provided with two class sets of tablets. The Ministry then chose schools based on whether there was a concept for integrating digital media into their school and to ensure that schools across the four districts of the state would be represented in the study. The Ministry randomly assigned schools to tablet and control conditions, and then schools decided which two classes would participate. Under the conditions of the initiative set out by the Ministry, the teachers in tablet classes were asked to integrate tablets into their daily classroom practices, however, they were not enrolled in professional development programs or instructed how to use tablets in their classes. Parents were informed and asked to sign consent forms for their children to participate in the study, and ethical approval was obtained from the Ministry.

The sample of the current analysis included 575 seventh grade math students and 23 math teachers from 14 schools. In most schools, two teachers volunteered to participate in the teacher questionnaire but under the conditions of the school initiative set out by the Ministry, participation was neither incentivized nor compulsory. The mean age of the female (50.2%) and male students was 13.48 years ($SD = 0.58$), and the mean age of the female (58.3%) and male teachers was 38.33 years ($SD = 7.99$). Questionnaire and test data measuring student characteristics was collected before students received their personal tablets in February 2018, measurement point zero (t_0), and again after four months of tablet use in July, measurement point one (t_1). At t_0 , students were asked to rate their perceptions of supportive climate and cognitive activation regarding instruction without tablets, and at t_1 , students were asked to rate their perceptions of supportive climate and cognitive activation regarding instruction with tablets. Teacher characteristics were also measured with a questionnaire at t_0 .

4.4.2 Instruments

4.4.2.1 Student profile indicators.

Students' cognitive characteristics were measured in two ways. General cognitive ability was assessed by a cognitive ability subtest on figure analogies (Heller & Perleth, 2000), which consisted of 25 items coded as correct or not ($M = 18.61$, $SD = 5.10$). As the acquisition of subject-specific knowledge is often measured by content-related achievement such as grades (Pielmeier, Huber, & Seidel, 2018), students' self-reported math grades from the previous semester were used as an indicator of prior content knowledge ($M = 2.60$, $SD = 0.86$). In Germany, grades range from 1 to 6, with 1 being the best. Students' motivational-affective characteristics were measured with two established scales based on Gaspard, Häfner, Parissius, Trautwein, and Nagengast (2017). Math interest (e.g., 'Math is fun for me'; Cronbach's $\alpha = .95$) and math self-concept (e.g., 'I am good in Math;'; Cronbach's $\alpha = .91$) were each assessed with four items rated on a four-point scale ranging from 1 = strong disagree to 4 = strongly agree.

4.4.2.2 Supportive climate and cognitive activation.

Students' perceptions of supportive climate and cognitive activation were measured with three subscales that have been widely used in large-scale assessments in Germany (e.g., Rakoczy, Buff, & Lipowsky, 2005). Regarding supportive climate, clarity in teaching was investigated with three items based off Baumert et al. (2008; e.g., 'Our teacher can explain things well'; Cronbach's $\alpha = .91$). Second, interestingness and relevance was measured with three items based off Rakoczy et al., (2005; e.g., 'Our teacher makes dry material interesting'; $\alpha = .87$). Cognitive activation was assessed with one subscale containing four items measuring challenging practice (2008; e.g., 'Among the questions and tasks, there are again and again those that one has to really think about'; Cronbach's $\alpha = .91$). All items were rated on a four-point scale ranging from 1 = strongly disagree to 4 = strongly agree.

4.4.2.3 Teachers' technology innovativeness.

Teachers' technology innovativeness was measured with a scale adapted from van Braak et al., (2004). Teachers' technology innovativeness can be defined as an "attitude towards the need to introduce technology (ICT) in education, coupled with a personal willingness to introduce computer technology in the classroom" (p. 411). Although the original scale included five items, factor analysis showed one item to load poorly and was subsequently removed.

4.4.3 Data analysis

In the first step, we created the student profiles using latent profile analysis (LPA) in Mplus (Muthén & Muthén, 2017). Based on Seidel (2006), we used students' general cognitive ability, and math prior content knowledge, interest, and self-concept as profile indicators. We determined the optimal number of latent classes by comparing statistical indices of models with increasing numbers of classes and evaluated the latent class solution by looking at the posterior class-membership probability information. Each time we added another class, we recorded the Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), and the adjusted BIC (ABIC) for which smaller values indicate better model fit. Additionally, we used the Lo-Mendell-Rubin likelihood ratio (LMR LR) and the adjusted LMR LR (ALMR) test to look for significant *p*-values indicating a model with one more class fits the data better (Nylund, Asparouhov, & Muthén, 2007). To take into account that students were nested into classes, cluster-robust standard errors were used (Mplus TYPE=COMPLEX; see McNeish, Stapleton, & Silverman, 2017). Notably, although the Bootstrap Ratio Likelihood Test (BLRT) is frequently used to evaluate whether an additional class fits the data better (Nylund et al., 2007), the BLRT test is not available for mixture complex models in Mplus. In line with LPA, students were assigned to the profile for which they had the greatest probability according to their observed response patterns on the profile indicators. Probability values should be 0.80 or larger for a good class solution (Geiser, 2013). In addition, we looked at the class misclassification as measured by the entropy value. Entropy values should be 0.60 or higher to provide sufficiently good class separation (Asparouhov & Muthén, 2014). Lastly, profiles were defined according to the estimated classes of the observed variable. In doing so, profiles were also evaluated whether they could be interpreted substantively and whether they matched previous theory (e.g., Seidel, 2006).

Next, we sought to see the relation between profile membership and students' perceptions of instructional quality with tablets. To do so, we used the three-step Bolck-Croon-Hagenaars (BCH) approach in Mplus which uses a weighted multiple group analysis to evaluate the means of a distal outcome, the instructional quality subscales, across profiles without distorting the model solution (Bakk, Tekkle, & Vermunt, 2013).

After showing the relation between student profiles and students' perceptions of instructional quality with tablets, we exported the class membership results to SPSS to test the moderating effects of teachers' technology innovativeness using regression models. First, using the single latent categorical variable assigning each student into one of the four profiles, three dummy coded variables were created where each student was coded '1' if the student had a

particular profile and coded '0' otherwise. Since there were four profiles, three dummy variables were set up using the 'average' profile as the reference category since the 'average' profile was the majority group. Then, three new interaction terms were computed by multiplying each of the dummy group profile variables by teachers' technology innovativeness. Finally, three regression models were fit for each of the instructional quality with tablets subscales acting as the outcome variables.

4.5 Results

4.5.1 Identification of the student profiles

In the first step, student profiles were identified based on students' general cognitive ability, math prior content knowledge, math interest, and math self-concept. As shown in Table 4.1, the AIC, BIC, and ABIC decreased with the addition of each class, however the p -value of the LMR LR test and the adjusted ALMR LR test become insignificant with the addition of the fifth class, indicating no more significant improvement in model fit. Additionally, the highest entropy value was found in the four-profile solution. Investigating the quality of the latent class membership classification in the four-profile solution, the posterior-class membership probability given the individuals' response patterns on the observed items ranged from .866 to .918.

Table 4.1
Model Fit Statistics

Number of profiles	AIC	BIC	ABIC	Entropy	LMR LR test P -value	ALMR LR test P -value
2	6867.299	6923.906	6882.636	0.775	0	0
3	6727.876	6806.254	6749.112	0.734	0.0165	0.0184
4	6613.188	6713.339	6640.324	0.826	0.0183	0.0204
5	6555.623	6677.545	6588.657	0.817	0.299	0.3092

After identifying four profiles as the optimal solution, the four profiles were defined according to the observed means of the profile indicators. The 'struggling' profile was characterized for having the lowest math interest, self-concept, prior content knowledge, and general cognitive ability ($n = 56$, 9.74%). In contrast, the 'strong' profile was characterized for having the highest values on each profile indicator ($n = 133$, 23.13%). Next, the 'average' profile had the largest number of students ($n = 236$, 41.04%) and contained means closely resembling the overall averages of the entire sample. Lastly, the second largest profile was referred to as the 'unmotivated' profile for demonstrating relatively low interest, self-concept,

and prior content knowledge, similar to the ‘struggling’ profile, but with general cognitive ability on par with the ‘average’ profile ($n = 150$, 26.10%). This combination of characteristics suggested these students have the cognitive ability to be high performing but may lack the motivation to perform better in class, as reflected by their low interest and grades (see Table 4.2). Individual profiles resembled profiles found in both Hammer et al. (2020) and Seidel (2006) and hence used the same labels.

Table 4.2
Observed Means of Profile Indicators

	1	2	3	4	Overall average
KFT	18.588	14.618	18.065	21.017	18.609
Previous grade	2.417	3.548	3.229	1.825	2.599
Interest	2.827	1.395	2.109	3.585	2.667
Self-Concept	2.971	1.266	2.089	3.778	2.753
Label	average	struggling	unmotivated	strong	

4.5.2 Relations between student profiles and perceptions of instructional quality

Next, to address research question 1, we looked at the relations between the student profiles and students’ perceptions of supportive climate and cognitive activation in math classes with tablets. Using the BCH approach, we found there were almost always significant differences between students’ perceptions of challenging practice, clarity in teaching, and interestingness and relevance depending on the profile. Students in the strong profile always perceived instructional quality the most positively, while students in the struggling profile perceived instructional quality the most negatively with one exception. Regarding challenging practice, although the strong profile had significantly different means from the other profiles, there were no significant differences between the average, struggling, and unmotivated profiles (see Table 4.3).

Table 4.3

Profile-Specific Means (and Standard Errors) of Instructional Quality with Tablets and Significant Differences in Pairwise Profile Comparisons.

Profile	Challenging practice	D	Clarity in teaching	D	Interestingness and relevance	D
(1) Average	3.01 (.08)	1 vs. 4	3.06 (.09)	1 vs. 2/3*/4	2.94 (.08)	1 vs. 2/4
(2) Struggling	2.97 (.12)	2 vs. 4	2.10 (.16)	2 vs. 3/4	2.30 (.14)	2 vs. 3*/4
(3) Unmotivated	2.98 (.07)	3 vs. 4	2.75 (.11)	3 vs. 4	2.70 (.13)	3 vs. 4
(4) Strong	3.42 (.07)	1 vs. 4	3.49 (.09)	1 vs. 2/3*/4	3.36 (.12)	1 vs. 2/4

Note. Instructional quality subscales were rated on 4-point Likert scales. D = Significant differences between a given pair of student profiles.

$p < .001$ * $p < .05$.

4.5.3 Effects of teachers' technology innovativeness on students' profile perceptions

With regard to research question 2, regression analyses were conducted to test whether teachers' technology innovativeness moderated the relationship between students' profiles and students' perceptions of instructional quality with tablets. Separate regression models were conducted for each of the three instructional quality subscales acting as the outcome or dependent variable. The dummy coded variables indicating membership in a profile compared to the average profile were used as the focal predictors or independent variables. Across the three subscales, profile membership and teachers' technology innovativeness accounted for a significant amount of variance in students' perceptions, regarding challenging practice, $R^2 = .086$, $F(7, 427) = 5.705$, $p < .001$, clarity in teaching, $R^2 = .194$, $F(7, 430) = 14.775$, $p < .001$, and interestingness and relevance, $R^2 = .103$, $F(7, 423) = 6.957$, $p < .001$. Looking at the first model in Table 4.5, independent of the student profiles, teachers' technology innovativeness did not have a significant effect on students' perceptions of any of the instructional quality subscales. In the second model in Table 4.5, interaction terms between the dummy coded variables indicating profile membership and teachers' technology innovativeness were included. Across the three subscales, there was only a significant interaction effect between the unmotivated profile and teachers' technology innovativeness, but not for the other profiles. Additionally, entering the interactions terms in the second model showed there was a small main effect of teachers' technology innovativeness regarding clarity in teaching ($\beta = .162$, $p < .05$).

In order to visualize the overall effects of teachers' technology innovativeness, Figures 4.1 through 4.3 illustrate the conditional effects of profile membership on students' perceptions

of supportive climate and cognitive activation when teachers' technology innovativeness was 0 and +/- 1 SD from the mean (Hayes & Montoya, 2017). Generally, across the three subscales, moving from low teacher technology innovativeness to high teacher technology innovativeness, the unmotivated profile had a downward slope, whereas all the other profiles had an upward slope. However, there were a few notable exceptions. The strong students consistently perceived instructional quality the most positively at both low and high levels of technology innovativeness, except considering interestingness and relevance. The strong profile perceived

Table 4.4*Regression Models Investigating Student Profiles on Students' Perceptions of Instructional Quality*

	Challenging practice					Clarity in teaching					Interestingness and relevance				
	B	SE	Beta	t	Sig.	B	SE	Beta	t	Sig.	B	SE	Beta	t	Sig.
1 Constant	2.729	0.181	0.000	15.046	0.000	2.626	0.234	0.000	11.210	0.000	2.818	0.252	0.000	11.201	0.000
Struggling	-0.057	0.111	-0.025	-0.510	0.611	-0.909	0.142	-0.298	-6.379	0.000	-0.594	0.154	-0.190	-3.855	0.000
Unmotivated	-0.014	0.077	-0.010	-0.187	0.852	-0.283	0.101	-0.137	-2.792	0.005	-0.212	0.108	-0.101	-1.955	0.051
Strong	0.388	0.082	0.245	4.742	0.000	0.412	0.106	0.190	3.890	0.000	0.377	0.114	0.171	3.316	0.001
TIS	0.088	0.058	0.071	1.516	0.130	0.121	0.075	0.071	1.619	0.106	0.027	0.081	0.015	0.330	0.742
2 Constant	2.477	0.284	0.000	8.723	0.000	2.160	0.369	0.000	5.858	0.000	2.318	0.393	0.000	5.896	0.000
Struggling	-0.491	0.564	-0.219	-0.871	0.384	-1.451	0.708	-0.475	-2.049	0.041	-0.549	0.778	-0.175	-0.705	0.481
Unmotivated	0.891	0.455	0.598	1.959	0.051	1.304	0.591	0.631	2.209	0.028	1.151	0.636	0.549	1.809	0.071
Strong	0.730	0.476	0.461	1.534	0.126	1.048	0.609	0.483	1.723	0.086	1.063	0.664	0.481	1.600	0.110
TIS	0.172	0.093	0.138	1.844	0.066	0.276	0.121	0.162	2.286	0.023	0.193	0.129	0.111	1.497	0.135
StrugTIS	0.150	0.187	0.200	0.801	0.424	0.187	0.234	0.185	0.799	0.425	-0.013	0.258	-0.012	-0.049	0.961
UnmotTIS	-0.295	0.146	-0.625	-2.012	0.045	-0.517	0.190	-0.790	-2.719	0.007	-0.445	0.205	-0.671	-2.172	0.030
StrongTIS	-0.113	0.153	-0.225	-0.738	0.461	-0.210	0.196	-0.306	-1.074	0.284	-0.226	0.213	-0.325	-1.063	0.288

Note. TIS=teachers' technology innovativeness. StrugTIS= interaction variable between struggling profile and TIS. UnmotTIS=interaction variable between unmotivated profile and TIS. StrongTIS=interaction variable between strong profile and TIS.

interestingness and relevance almost as negatively as the struggling profile at the low level of technology innovativeness. Additionally, although the struggling profile perceived challenging practice the most negatively of the profiles at the low level of teachers' technology innovativeness, the struggling profile surpassed the perceptions of both the unmotivated and struggling profiles at the highest level of technology innovativeness. Considering the other two subscales of instructional quality, clarity in teaching and interestingness and relevance, the struggling profile perceived instructional quality more negatively at both low and high levels of technology innovativeness.

Figure 4.1

Students' Profile-Specific Perceptions of Challenging Practice at -1/+1 SD of Mean Centered Teachers' Technology Innovativeness

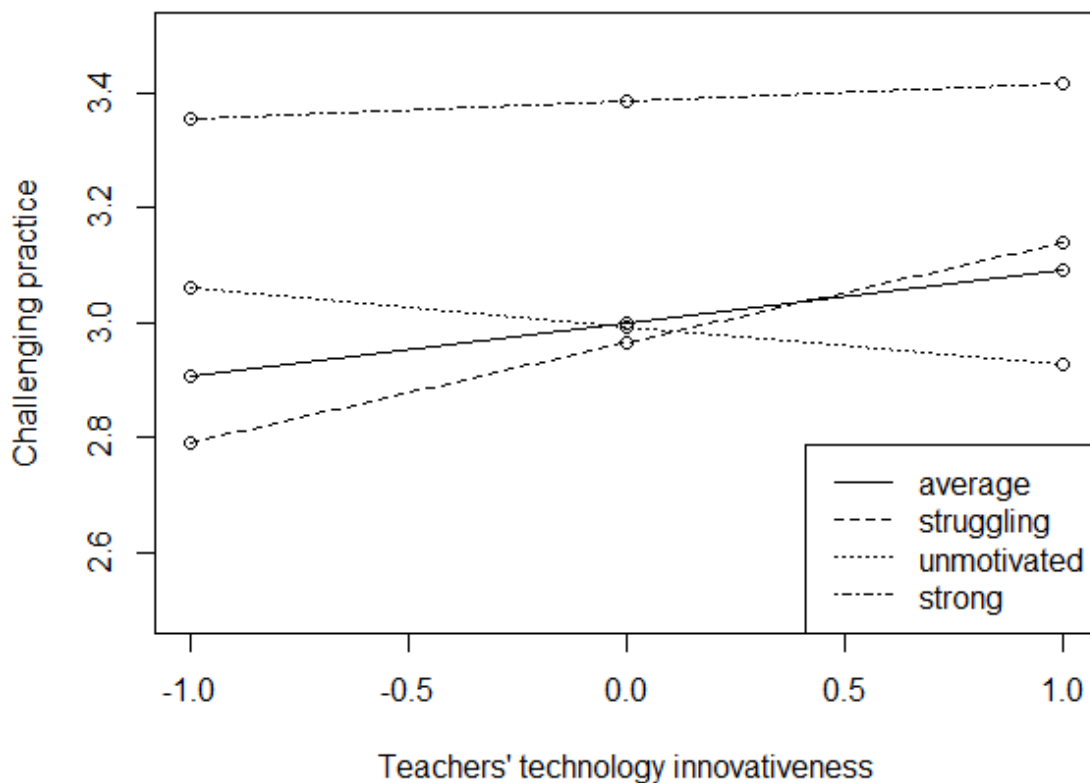


Figure 4.2

Students' Profile-Specific Perceptions of Clarity in Teaching at -1/+1 SD of Mean Centered Teachers' Technology Innovativeness

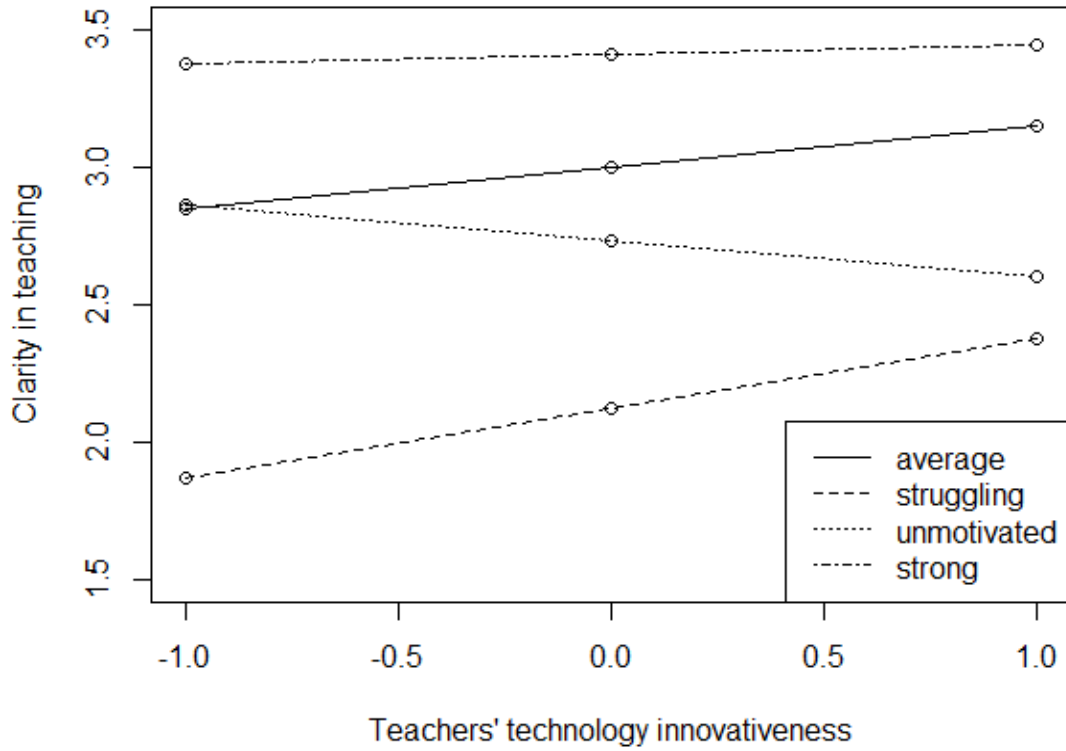
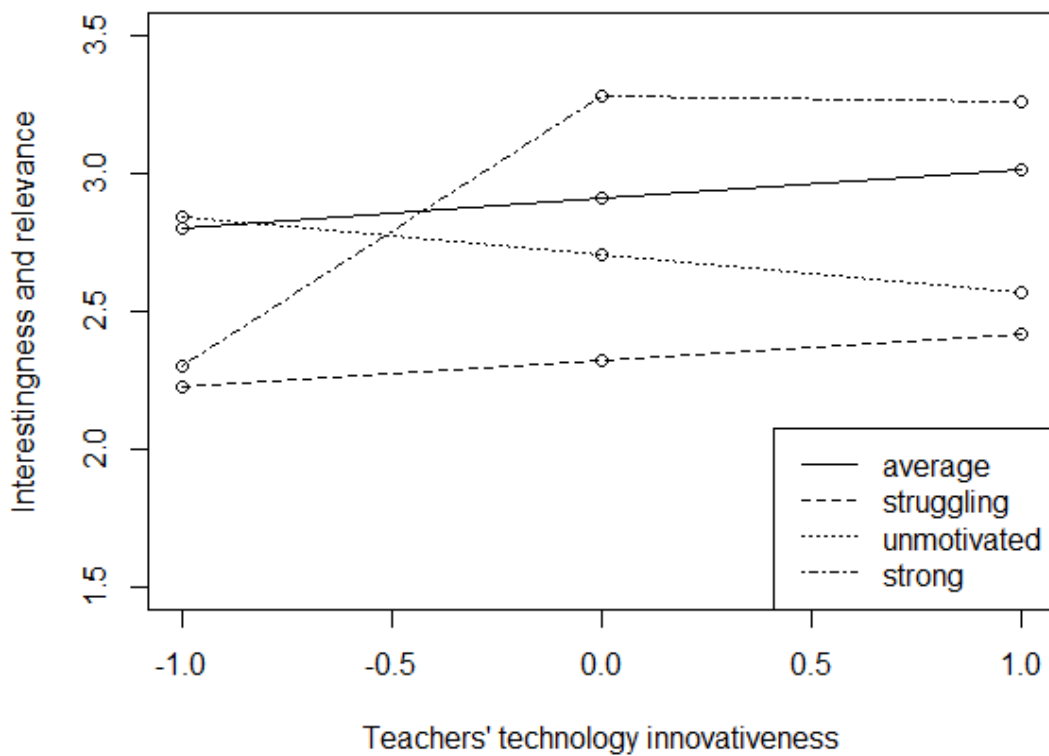


Figure 4.3

Students' Profile-Specific Perceptions of Interestingness and Relevance at -1/+1 SD of Mean Centered Teachers' Technology Innovativeness



With respect to the significant interaction found in the unmotivated profile, there were significant differences between the unmotivated profile and the average profile at both low and high levels of teacher technology innovativeness. At the low level of teacher technology innovativeness, unmotivated students perceived higher challenging practice than students in the average profile ($\beta = .447, p < .001$), whereas at the high level of teacher technology innovativeness, the pattern reversed and the unmotivated profile perceived lower challenging practice than the average profile ($\beta = .325, p < .05$). This pattern continued regarding clarity in teaching at the low level of teacher technology innovativeness ($\beta = .522, p < .001$) and at the high level of teacher technology innovativeness ($\beta = .293, p < .05$). Furthermore, the unmotivated students perceived higher interestingness and relevance than the average profile at the low level of teacher technology innovativeness ($\beta = .495, p < .05$) however the difference was not statistically significant at the high level.

Additionally, testing the equality of the estimated profile means at lower (-1 SD) and higher (+1 SD) technology innovativeness consistently showed a significant effect on students' perceptions. Regarding challenging practice, students' perceptions were significantly different among the profiles when teachers' technology innovativeness was relatively low, $F(3, 427) = 9.520, p < .001$ and relatively high $F(3, 427) = 5.835, p = .001$. Second, regarding clarity in teaching, students' perceptions were significantly different among the profiles when teachers' technology innovativeness was relatively low, $F(3, 430) = 19.640, p < .001$ and relatively high, $F(3, 430) = 14.956, p < .001$. Finally, regarding interestingness and relevance, students' perceptions were significantly different among the profiles when teachers' technology innovativeness was relatively low, $F(3, 423) = 8.298, p < .001$ and relatively high, $F(3, 423) = 8.294, p < .001$. Across the instructional quality subscales, there were significant differences in how students perceived instructional quality at both low and high levels of teacher technology innovativeness.

4.6 Discussion

Digital media such as tablets have entered classrooms faster than researchers can investigate the actual effects of tablet use on teaching and learning processes. Although research in this field continues to grow, much of this research has emphasized student achievement gains, without enough attention to the processes underlying student learning, or has focused on relevant teaching characteristics, without taking into account the diverse ways digital media use such as tablets may affect different types of students. Cognitive activation and supportive climate have been found to be crucial components for fostering students' learning processes in math classes (Kunter et al., 2013). Therefore, investigating the extent to which students perceive

math classes with tablets to be cognitively activating and instructionally supportive can indicate how the use of tablets may actually affect students' learning processes. Furthermore, investigating how students' perceptions may differ depending on both students' learning characteristics and teachers' technology innovativeness can further illustrate how student learning with digital media is affected by the complex interplay of student and teacher characteristics.

The current paper had two goals. First, we aimed to investigate whether students could be grouped into profiles based on cognitive and motivational-affective learning characteristics and whether these profiles would be systematically linked to their perceptions of supportive climate and cognitive activation with tablets, thereby replicating and extending previous results by Seidel (2006) and Hammer et al. (2020). After showing these profiles and their relation to an additional measure of students' perceptions of instructional quality with tablets, we aimed to investigate whether teachers' technology innovativeness moderated the effect of students' profiles on students' perceptions. Previous research indicated that across a range of relevant teacher characteristics, teachers' technology innovativeness predominantly explained teachers' instructional quality and technology exploitation as rated in lesson plans (Backfisch et al., 2020a) and quality of technology integration across lessons and instructional contexts (Backfisch et al., 2020b). However, it was unknown whether students would also perceive differences in instructional quality with tablets depending on teachers' technology innovativeness and whether these differences would vary across student profiles.

Results from the latent profile analysis indicated four distinct profiles. In line with previous research (e.g., Hammer et al., 2020; Seidel, 2006), we found significant differences in how students perceived both supportive climate and cognitive activation in classes with tablets based on students' profile membership. Additionally, as suggested by previous research (e.g., Backfisch et al., 2020b), higher teachers' technology innovativeness seemed to be related to more cognitive activation and supportive climate as perceived by the majority of the students, including three out of the four profiles. Furthermore, testing the equality of the estimated profiles means at lower (-1 SD) and higher (+1 SD) levels of technology innovativeness, consistently showed a significant effect. This indicates that at both low and high levels of technology innovativeness, the student profiles matter and students perceived instructional quality differently depending on the profile. Moving forward this is an important finding that teachers who have higher technology innovativeness seem to improve the quality of instruction when teaching with tablets for the majority of students. Nevertheless, there was one notable exception.

The ‘unmotivated’ profile was characterized by low interest and low self-concept but possessing general cognitive ability on par with the ‘average’ profile, suggesting these students have the cognitive ability to have a stronger math grade, the measure used for students’ prior content knowledge. However, the effect of teachers’ technology innovativeness for this profile indicate that as teachers’ technology innovativeness increases, students’ perceptions of supportive climate and cognitive activation with tablets appear to decrease. This result is surprising considering previous research that has linked teachers’ technology innovativeness with higher instructional quality as rated in teachers’ lesson plans (Backfisch et al., 2020b). Additionally, the ‘struggling’ profile which is characterized for having uniform low values of the profile indicators appeared to perceive supportive climate and cognitive activation with tablets more positively the higher the level of teachers’ technology innovativeness. A possible explanation could be that for the ‘unmotivated’ profile, which is on the verge between the ‘struggling’ and ‘average’ profiles regarding math interest and self-concept, they have less to gain from higher levels of technology integration than the ‘struggling’ profile. This would be in line with research that suggests lower ability students have more room to make gains in test scores than high ability students following a computer-assisted learning intervention (Bettinger, Kardanova, Fairlie, Loyalka, Kapuza, & Zakharov, 2020). Additionally, for this group of ‘unmotivated’ students who were already less interested in math than the ‘average’ profile, they may be more susceptible to being distracted by other apps or tablet activities as teachers’ efforts to integrate technology into the classroom may increase the use of tablets. In this way, the more that teachers tried to integrate technology into the classroom, the students who were already less interested in their math classes, may have found the tablets themselves to be more interesting and instruction to be even less challenging (challenging practice) and engaging (interestingness and relevance). In contrast, teachers’ efforts to integrate technology may have resulted in greater fatigue for this group of students who could have been less interested because of the more interactive nature of tablet-based activities (Bettinger et al., 2020). In another study investigating inquiry-based learning with tablets, Montrieux, Raes, and Schellens (2017) found students preferred the traditional approach of listening to their teacher because they were not accustomed to being actively involved throughout the entire course and being responsible to use tablets in an autonomous way.

Considering the graphs depicting the profile perceptions at low and high levels of teacher technology innovativeness, there were a few additional surprising findings. The strong profile perceived interestingness and relevance almost as negatively as the struggling profile at the lowest level of technology innovativeness. The strong profile, characterized by overall positive

values of motivational-affective and cognitive characteristics, almost always perceived instructional quality the most positively of all the profiles, especially compared to the struggling profile. However, perhaps compared to the other profiles, students in the strong profile may have been especially disappointed by the use of tablets in classes where teachers had low technology innovativeness. This would be in line with previous research with students from 1:1 tablet schools in Norway, Denmark, and the UK who were either disappointed that the use of tablets in class did not amount to much or because the effort to use them felt forced (Blikstad-Balas & Davies, 2017). Furthermore, for the struggling profile that typically perceived instructional quality the most negatively, high technology innovativeness seemed to make a big difference regarding challenging practice, and students' perceptions appeared higher than the average profile. This suggests that teachers with high technology innovativeness were able to use the tablets in ways by which the struggling students perceived they had the opportunity to explain their ideas and could understand the material better through questions and tasks. In the future, it would be of great interest to know which instructional practices of the teachers with high technology innovativeness could explain why the 'struggling' students perceived more cognitive activation. Furthermore, it would be interesting to investigate whether teachers identified that the students belonging to the struggling profile needed more cognitively activating instruction because of their lack of prior content knowledge and that may be why the students fitting the struggling profile perceived more cognitive activation than the students in the average profile.

Recognizing how students perceive learning with digital media in addition to how teachers perceive teaching with digital media is particularly important considering the negative potential of substantial discrepancies. In particular, Könings, Seidel, Brand-Gruwel, and van Merriënboer (2014) identified profiles of students and teachers that differ based on their perceptions of their shared learning environment. A 'distal' profile of students was characterized for having the least shared perceptions with their teachers and thus the highest risk to exhibit behaviors incongruent with their teacher's goals. Evidently, although the learning related characteristics of the students with the 'distal' profile did not substantially differ from the more matched 'intermediate' profile, students in the 'distal' profile reported more motivational and affective problems, had less constructive conceptions of learning, and performed worse than the 'closest match' profile. Regarding the present study, Könings et al., (2014) further found 'distal' students were more likely to experience friction and display contrasting learning behaviors when taught by 'idealistic' teachers, characterized for perceiving the learning environment more positively than their students. Considering the discrepancy

between how students' belonging to the 'unmotivated' profile perceived cognitive activation and supportive climate with tablets in classes with teachers who have higher technology innovativeness, there could be negative learning effects for these students.

4.7 Limitations and Implications for Educational Practice

In addition to identifying students most at risk for experiencing large discrepancies, investigating student perceptions can also function as an indicator for the effectiveness of the implementation of an educational innovation such as the integration of tablets into the classroom (Könings et al., 2014). While for the majority of students, their perceptions of supportive climate and cognitive activation seemed to increase with higher technology innovativeness, students displaying learning related characteristics similar to the 'unmotivated' profile may need additional support in order to effectively learn with tablets. In the present study, one quarter of students could be characterized by belonging to the 'unmotivated' profile. However, this pattern of results requires replication and studies that investigate the underlying mechanisms. For educational practice, it would be important to know what teachers with higher technology innovativeness do in classrooms that may explain why the majority of students perceive cognitive activation and supportive climate more positively. For this purpose, future research could use video recording to observe the instructional practices of teachers with high technology innovativeness. Furthermore, it would be important to determine whether these results could be seen in additional samples, and whether they are specific to math classes or could be replicated in other subjects. At the same time, future research would need to further investigate whether teachers' technology innovativeness is simply a proxy for teachers who know how to teach or whether it is specifically related to how teachers integrate technology into their classroom practices. Understanding the role of teachers' technology innovativeness would be important for developing future interventions in teacher education and professional development that could help teachers integrate technology into their classrooms.

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5

General Discussion

5 General Discussion

The purpose of this dissertation was to identify and investigate the antecedent factors from the student side that precede effective learning processes with digital media. Recent conceptions of learning have highlighted that students arrive in the classroom with a range of learning skills, beliefs, prior knowledge, and experiences that significantly influence how they interpret their learning environments and acquire new knowledge (Bransford, Brown, & Cocking, 2000). Instead of a direct effect of teaching practices on student learning outcomes, teaching and learning processes are described as complex, reciprocal structures of supply and use, which are co-determined by the prerequisites of teachers and learners (Seidel & Shavelson, 2007). The opportunity to learn model, also known as the supply-use model, offers a framework to understand the complex interplay of teaching and learning processes that occur within classrooms and lead to diverse student learning outcomes (Brühweiler & Blatchford, 2011; Seidel, 2014). Under this model, students' previous learning environments, including their families, influence students' individual learning prerequisites, such as students' cognitive and motivational-affective characteristics, which in turn affect students' individual learning processes (Seidel, 2014). Research investigating how students learn with digital media in the classroom should therefore also take into account students' family environments and students' individual learning characteristics. However, until now much of the research investigating how students learn with digital media has emphasized gains in student achievement (e.g., Lai & Bower, 2020) and content knowledge (Sung, Chang, & Liu, 2016). Rather than look at student learning outcomes, this dissertation has aimed to build on previous theories and models about how students learn in classrooms to understand the antecedent factors that precede effective learning processes in classrooms with digital media.

The dissertation contributed to the importance of looking at students' motivational-affective and cognitive characteristics in relation to students' perceptions of cognitive activation and supportive climate when considering how students learn with digital media. By looking at diverse profiles of students, distinguished by their learning characteristics, the dissertation discovered that not all students perceive instructional practices with tablets in the same ways. This has important implications moving forward for research investigating how digital media can be used to facilitate learning as well as for teachers implementing digital media in the classroom. Furthermore, although the investigated parenting practices involving digital media mostly did not explain how parents contribute to students' development of digital media self-efficacy, exploring how students develop digital media self-efficacy before students enter the classroom has identified promising directions for future research.

First, I describe the major research questions and give an overview of the state of the art of the research leading up to the research questions (5.1). I then discuss the major findings of each empirical study chapter and how they relate to previous literature (5.2). Next, I address the educational practice and policy implications as well as the theoretical and methodological implications raised by the results found in this dissertation (5.3). Furthermore, I address the limitations of the empirical work as well as provide suggestions for future research (5.4). Lastly, I conclude with the significant contribution of my dissertation (5.5).

5.1 Overview of the Theoretical Background

The major research questions in this dissertation were how parents contribute to students' digital media self-efficacy and what factors determine how students perceive instruction with digital media. Following the opportunity to learn model (Seidel, 2014), students' family environments help shape students' learning prerequisites which in turn affect students' individual learning processes in the classroom, and subsequently learning outcomes. Students' learning prerequisites, also referred to as students' learning preconditions in the literature, can be understood as features of learners that are relevant for learning such as cognitive and motivational-affective characteristics.

To understand how students' family environments shape how students learn with digital media, the role of parents' beliefs and behaviors regarding digital media was examined in relation to students' digital media self-efficacy. Digital media self-efficacy can be considered an important precursor to effectively learning and working with digital media (e.g., Aesaert & van Braak, 2014; Rohtagi, Scherer, & Hatlevik, 2016). Recent international assessments have indicated that students more likely use digital media outside rather than in the classroom (e.g., ICLIS 2018; Fraillon, Ainley, Schulz, Friedman, & Duckworth, 2019), and research investigating factors relating to students' ICT self-efficacy identified parental support as a major factor and more predictive than school factors (e.g., Aesaert & van Braak, 2014; Zhong, 2011). Therefore, this first research question aimed to address *how* parents and their behaviors at home may shape students' digital media self-efficacy. To do so, the parent socialization model, one link of the widely used expectancy-value theory model (Eccles et al., 1983), provides a framework for investigating how parents shape children's motivational beliefs and choices through their own beliefs and behaviors. In particular, the model illustrates that parents convey their beliefs about certain activities through their behaviors at home and how children interpret their parents' behaviors affects their own self-beliefs (Jacobs & Eccles, 2000). Applying this model to the development of students' digital media self-efficacy beliefs and examining parents' beliefs and behaviors at home involving digital media can therefore help to

show how students' family environments precede effective learning processes with digital media in the classroom.

To address the factors that determine how students perceive instruction with digital media, I must first highlight the importance of looking at students' perceptions for understanding how individual students learn with digital media. Using students' perceptions of supportive climate and cognitive activation in classes with digital media offers a systematic way to assess established instructional practices that have been shown to facilitate student learning processes and predict student learning outcomes (e.g., Aldrup, Klusmann, Lüdtke, Göllner, & Trautwein; Klieme, Pauli, & Reusser, 2009; Kunter, Klusmann, Baumert, Richter, Voss, & Hachfeld, 2013; Schenke, 2018). Taking the view that students must perceive instructional practices as cognitively activating and instructionally supportive for the intended benefits to take place (e.g., Lipowsky, Rakoczy, Pauli, Drollinger-Vetter, Klieme, and Reusser, 2009), student perceptions of instructional practices with digital media can offer valuable insight regarding how students learn with digital media. At the same time, students can perceive instructional practices in different ways (Göllner, Wagner, Eccles, & Trautwein, 2018). To understand the differences, previous research has shown students' perceptions are systematically linked to their cognitive (e.g., general cognitive ability and prior content knowledge) and motivational-affective characteristics (e.g., subject-specific interest and self-concept; e.g., Seidel, 2006). Moving beyond the effects of single characteristics using a person-centered approach, such as latent profile analysis, offers a way to investigate the interplay of both cognitive and motivational learning characteristics within students and to link them to students' diverse perceptions and outcomes (Huber & Seidel, 2018). Despite the advantages, person-centered approaches have been rarely used for investigating learning with digital media (Scherer, Rohtagi, & Hatlevik, 2017). Investigating students' cognitive and motivational-affective characteristics in relations to students' individual perceptions offers a more nuanced understanding of how the addition of digital media to the classroom differentially affects subgroups of students. Additionally, identifying the relevant cognitive and motivational-affective characteristics underlying students' differing perceptions in instruction with digital media can help to illustrate the learning prerequisites that affect students' individual learning processes in classrooms with digital media.

5.2 Summary of Major Findings

Before discussing the major findings, I briefly describe the data that was used in all three empirical studies. The data was drawn from the *tabletBW* project, which stemmed from a school initiative funded by the Ministry for Culture, Youth and Sport of Baden-Württemberg.

TabletBW is a school trial in which half of the participating classes were given 1:1 tablets (tablet classes) and the other half was assigned to be a control group (non-tablet classes). All Gymnasiums of Baden-Württemberg were invited to apply to participate, and accepted schools were randomly assigned to tablet ($n = 14$ schools) and non-tablet conditions ($n = 14$ schools). Within the tablet and non-tablet schools, the schools decided which two classes would participate. Accompanying the school trial has been a longitudinal, multi-cohort research project, starting in 2018 and lasting until 2021. From Grade 7 to (planned) Grade 9, starting before students in the tablet schools received their personal tablets, students and teachers from both conditions have been asked to participate in questionnaires and tests. The goal has been to better understand whether and under what conditions digital media enable successful teaching and learning processes in the classroom. The parent questionnaire used in Study 1 was additionally developed, and parents of students in both cohorts were invited to apply in January 2020.

5.2.1 The role of parents' beliefs and behaviors in shaping students' digital media self-efficacy

The first research question was addressed in Study 1 and aimed to investigate how parents' beliefs and behaviors regarding digital media shape students' digital media self-efficacy. In line with previous research investigating how parents contribute to students' self-beliefs in subjects like math and sports (e.g., Simpkins, Fredricks, & Eccles, 2012), we adapted the parent socialization model, one link of the widely used expectancy-value model framework (Eccles et al., 1983), to investigate the development of students' digital media self-efficacy outside of the classroom. Adapting the model suggests parents' beliefs regarding digital media would predict parenting behaviors using digital media which would in turn affect students' digital media self-efficacy. Parents may impart their value beliefs to their children either through direct instruction or behaviors, such as modeling involvement in valued activities or providing materials that expose their children to particular experiences and value systems, which in turn affect how their children value and engage with different activities (Jacobs & Eccles, 2000). In one notable example, Simpkins et al. (2012) found mothers' behaviors, including modeling and provision of materials, mediated the link between mothers' and adolescents' beliefs in sports, music, and math, but not in reading. However, in contrast to these findings, Study 1 showed that parents' behaviors mostly did not explain the effect of parents' beliefs regarding digital media on students' digital media self-efficacy. In line with Simpkins et al. (2012), the investigated parents' behaviors in Study 1 also included modeling, as in time spent using digital devices at home, and provision of digital devices, additionally incorporating the age at which parents

bought their children digital devices. The only parenting behavior that did mediate the relation between parents' beliefs and students' digital media self-efficacy was the age at which parents bought their children their own smart phone. This seems reasonable that the earlier children obtain their own smart phone, the more time they have to gain experience and develop digital media self-efficacy. In line with Bandura (1977) and Usher and Pajares (2008), self-efficacy beliefs are largely formed through students' successful experiences.

Although parents' behaviors mostly did not mediate the effect of parents' beliefs on students' self-beliefs, there were some findings in line with previous research. First, there was a link between parents' beliefs and students' beliefs. Parents' positive beliefs towards using digital media, such as perceiving using digital media to be fun, useful, or important, were significantly correlated with children's digital media self-efficacy. In contrast, parents' negative beliefs towards using digital media, such as perceiving digital media to be distressing or exhausting, were significantly negatively correlated with children's digital media self-efficacy. Additionally, there were some links between parents' beliefs and some parent behaviors. Parents' value beliefs were significantly related to how much time they spent using digital devices, and parents who found using digital media to be fun, useful, or important spent significantly more time using digital devices. Similarly, parents who found using digital media to be distressing or exhausting, spent significantly less time using digital devices. However, even parents who perceived high emotional cost of using digital media and did not have smart phones themselves, bought smart phones for their children, indicating a disconnect between some parents' beliefs and parenting behaviors. Concerning the link between modeling and children's self-beliefs, the parent socialization model suggests that children observe how their parents spend time at home, how they choose between available activities, and their parents' sense of self-competence. In turn, these behaviors convey messages to children about activities that are valued and are acceptable ways to spend time (Jacobs & Eccles, 2000). If parents spent a lot of time at home using digital media, then children may observe and follow their parents, allowing them to gain more experiences successfully using digital media and develop digital media self-efficacy. However, the amount of time that parents spent using digital media at home did not appear to impact students' digital media self-efficacy.

Considering previous research using the parent socialization model, the present results adapting the model to investigate students' digital media self-efficacy are surprising. However, the results do not seem to contradict what we know about digital media. Przybylski and Weinstein (2017) described the proliferation of digital devices, high-speed Internet, flat panel displays, and mobile computing power as having fundamentally changed how humans socialize

and shaping modern childhood. Digital media is so prevalent today that there seem to be other reasons why parents may buy children their own digital devices other than their own personal value beliefs regarding digital media. Some parents even remarked in the parent questionnaire that although they considered digital media to have harmful effects, when every other child has a smart phone, there was a lot of pressure for their child to have one as well. Furthermore, given that households are likely to have more than one device (Fomby, Goode, Truong-Vu, & Mollborn, 2019), it seems reasonable that children at home can develop experience and comfort using digital devices on their own without the support of their parents. Furthermore, although the parent socialization model suggests that children observe and follow how their parents spend time, it also seems that there are different reasons why students choose to spend time on digital devices, not related to wanting to be like their parents. Besides modeling of valued activities, the provision of digital devices seems to be more crucial for ensuring that students have opportunities to develop successful experiences operating digital devices.

5.2.2 The link between student learning characteristics and students' perceptions of instruction with digital media

When considering what factors affect students' perceptions of instruction with digital media, the empirical work done in this dissertation has shown the interplay of students' general cognitive ability and subject-specific prior content knowledge, interest, and self-concept differentially predicted students' perceptions of supportive climate and cognitive activation in classes with tablets. In Study 2, we found five distinct profiles based on students' biology learning characteristics, and in Study 3, we found four distinct profiles based on students' math learning characteristics. In both studies, we identified a 'struggling' profile, characterized for having overall low values and a 'strong' profile, characterized for having overall high values. Additionally, in both studies, the 'average' profile had the largest number of students and contained values closely resembling the overall averages of the entire sample. Lastly, in both studies the 'unmotivated' profile was labeled for demonstrating relatively low interest, self-concept, and prior content knowledge, similar to the 'struggling' profile, but with general cognitive ability on par with the stronger profiles. This combination of characteristics suggests these students would have the cognitive ability to be high performing but may lack the motivation to perform better in class, as reflected by their low interest and grades. In Study 2, we also identified an 'overestimating' profile, characterized for having high interest and high self-concept, similar to the strongest profile, but below average general cognitive ability and average prior content knowledge. This profile contained the smallest number of students,

however statistical tests indicated that the five-profile solution fit the data best in Study 2. Students' profile membership was then shown to differentially predict how students perceived supportive climate and cognitive activation in classes with and without tablets. Previous research investigating student perceptions in traditional instruction without digital media first showed that physics students could be grouped into distinct profiles based on their cognitive and motivational-affective characteristics, and these profiles were systemically linked to how supportive students perceived their learning environments (Seidel, 2006). Therefore, findings from this dissertation complement previous research and extend the findings to instruction with digital media.

Additionally, in Study 2, we first examined whether there were differences between students' perceptions of supportive climate in biology classes that were given tablets and biology classes that were not given tablets. After four months of students in the tablet classes having received their personal tablets, we found significant differences between certain groups of students. In particular, the 'struggling' and 'unmotivated' profiles perceived supportive climate significantly more positively than the same profiles in classes that were not given tablets, controlling for differences at the first measurement point. Although it could be of interest to know how teachers may have used tablets to enhance these students' perceptions of supportive climate, what is important for student learning is whether students perceived instruction as supportive. In this way, we not only got a first look at how the addition of tablets to the classroom affected students' perceptions of their learning environments but the underlying learning characteristics that explained students' differing perceptions.

Building on the findings of Study 2, in Study 3 we investigated whether there were differences between students' perceptions of supportive climate and cognitive activation in math classes that were given tablets. In line with Study 2, we found significant differences in how students perceived both supportive climate and cognitive activation based on students' profile membership. However, whereas in Study 2, we looked for differences in students' profile perceptions between the tablet and non-tablet classes, in Study 3 we aimed to more closely examine the differences in students' profile perceptions within the tablet classes depending on teachers' beliefs towards using technology. In making our hypotheses, we were unsure whether teachers' technology innovativeness would have an overall positive effect across the profiles, or whether teachers' technology innovativeness would have antagonistic effects in some profile perceptions but not in others. We found that the majority of the students perceived more cognitive activation and supportive climate in classes with teachers that had higher technology innovativeness. However, in contrast to the other profiles, we found that the

‘unmotivated’ profile perceived cognitive activation and supportive climate more negatively as teachers’ technology innovativeness increased. These findings indicate in the first place that student profiles matter, and students perceived instructional quality with tablets differently depending on their learning profile. Secondly, in line with previous research (e.g., Backfisch, Lachner, Hirsche, Loose, & Scheiter, 2020a; Backfisch, Lachner, Stürmer, & Scheiter, 2020b), students did indeed perceive differences in instructional quality based on teachers’ technology innovativeness, and higher teachers’ technology innovativeness was related to more cognitive activation and supportive climate as perceived by the majority of the students. Lastly, these findings show that something about the way teachers’ with higher technology innovativeness used tablets in math classrooms seemed to have a negative effect on how ‘unmotivated’ students (i.e., students with low interest, low self-concept, and poor grades, but the cognitive ability to be more high performing) perceived supportive climate and cognitive activation.

5.3 Implications of Major Findings

5.3.1 Policy and practical implications

Digital media such as tablets have entered classrooms faster than researchers can investigate their use. Particularly in Germany that has fallen behind other OECD countries in implementing digital media into the classroom (Gerick, Eickelmann, & Bos, 2017), increasingly more schools are being equipped for the first time with personal, mobile devices such as tablets towards the aim of improving teaching and learning processes in the classroom (KMK, 2016). However, the questions remain: how should digital media be used in the classroom to facilitate student learning processes? Although the use of digital media has great potential to stimulate, facilitate, or enable student learning processes, the conditions in classrooms that lead to effective learning processes are still unclear (Gerjets & Scheiter, 2019). Conducting the studies in this dissertation using data from classrooms helps to identify the ways digital media is currently being used and perceived by students. In turn, this can provide valuable insight in the ways teachers and students still need to be supported in order to effectively use digital media in classrooms. This information can also be used by governments and policymakers when deciding how curriculum should be designed and where money should be invested when designing initiatives such as *tabletBW* or national programs such as the *DigitalPakt*.

Regarding the educational practice implications, the findings of this dissertation have important implications for teachers. In Study 2, we found that the students characterized as ‘struggling’ and ‘unmotivated’ for having low biology interest and self-concept along with poor

grades perceived instruction as more supportive in classes with tablets than the corresponding profiles in the non-tablet classes perceived instruction without tablets. Before the students in the tablet classes received their own tablets, the students in the ‘struggling’ and ‘unmotivated’ profiles perceived supportive climate the most negatively of the profiles. These results seem promising that for students who may struggle in traditional biology classes, the addition of tablets may make a positive difference. For teachers who are skeptical and may be reluctant to implement digital media into the classroom, perhaps this finding can illustrate that the addition of tablets in classroom can be used as a helpful tool to re-engage students who may otherwise perceive biology instruction negatively. This would be in line with the review of Sung et al. (2016) that found mobile devices were often effectively used as a reinforcement tool to stimulate motivation and strengthen engagement. However, the results from Study 2 also indicated that the biology students in tablet classes who were characterized as ‘strong’ for demonstrating overall positive learning characteristics perceived clarity in teaching and interestingness and relevance, two of the supportive climate subscales, significantly more negatively over time. For teachers, this is an indication that the students who may typically perceive instruction to be supportive may not positively perceive the changes that accompany the addition of tablets to the classroom. Based on this, it would be important for teachers not to assume that the addition of digital media to the classroom has an overall positive effect.

Considering further implications on the teacher side, extensive research in the form of meta-analyses and the development and testing of comprehensive models has investigated what predicts teachers’ technology adoption and integration into teaching and learning activities (e.g. Scherer, Siddiq, & Tondeur, 2019). Most studies conclude it largely depends on teachers’ beliefs towards using technology (Petko, Prasse, & Cantieni, 2018). That is to say, if teachers do not believe that a technology is beneficial for teaching and learning, they are unlikely to use it in an effective way. Specifically, a number of studies have identified teachers’ technology innovativeness as a key determinant in how teachers integrate technology, and teachers with higher technology innovativeness were found to integrate technology with higher instructional quality (Backfisch, Lachner, Hirsche, Loose, & Scheiter, 2020a; Backfisch, Lachner, Stürmer, & Scheiter, 2020b). The findings from Study 3 therefore complement existing research and show students also perceive differences in instructional quality measures depending on teachers’ technology innovativeness. This is an important finding moving forward that teachers with higher technology innovativeness seem to improve the quality of teaching for the majority of students.

However, a very notable exception in Study 3 were students belonging to the ‘unmotivated’ profile, who accounted for a quarter of the sample, and perceived supportive climate and cognitive activation more negatively in classes with teachers that had higher technology innovativeness. This indicates that for students who have low interest, self-concept, and poor grades, but the cognitive ability to be more high performing, efforts to integrate more technology into the classroom may result in more negative perceptions. Nonetheless, recognizing that a significant part of the sample perceived instruction more negatively points to areas of interventions for teacher education and professional development (Südkamp, Praetorius, & Spinath, 2017). Specifically, Südkamp et al. (2017) explain that making teachers aware that distinct profiles of students exist and improving teachers’ knowledge about educationally relevant characteristics can help teachers to identify these students and revise their teaching techniques and classroom activities accordingly.

Before moving on to further implications, the differences between the ‘unmotivated’ profiles in Study 2 and in Study 3 and the possible limitations of these studies need to be acknowledged. In Study 2, the ‘unmotivated’ students in biology classes with tablets perceived instruction with tablets as more supportive than the ‘unmotivated’ students in the biology classes without tablets, suggesting a positive effect of the addition of tablets compared to no tablets. In Study 3, the ‘unmotivated’ students in math classes seemed to perceive instruction more negatively as teacher’s technology innovativeness increased, suggesting a negative effect of teachers’ technology innovativeness. However, we did not assess the ‘unmotivated’ students’ perceptions of instruction before the tablets were introduced, so it is possible that the ‘unmotivated’ students’ perceptions in Study 3 were even more negative before the addition of tablets, as found in Study 2. In addition, we did not compare the ‘unmotivated’ students’ perceptions in the classes that were given tablets and in the control classes that were not given tablets. Therefore, it is also possible that the ‘unmotivated’ students’ perceptions in control classes were lower than the ‘unmotivated’ students in the tablet classes, as found in Study 2. Although we assumed in Study 3 that teachers with higher technology innovativeness integrated more technology into the classroom, we do not know exactly how teachers used tablets and therefore cannot explain why the ‘unmotivated’ students perceived less cognitive activation and supportive climate in classes where teachers had higher technology innovativeness. The same can be said about Study 2 that we do not know why the ‘unmotivated’ as well as ‘struggling’ students, who had less biology interest and perceived supportive climate the most negatively of the profiles before the tablets were introduced, may have perceived supportive climate more positively, after four months of tablet use compared to the corresponding profiles in the control

classes. However, previous research suggests that lower ability students have more room to make gains in test scores than high ability students following a computer-assisted learning intervention (Bettinger, Kardanova, Fairlie, Loyalka, Kapuza, & Zakharov, 2020), and perhaps the same can be applied to students' perceptions of instruction with digital media.. Similarly, Ninaus, Moeller, McMullen, and Killi (2017) found that a digital math game was beneficial for students with low prior content knowledge and math interest but not students with better math grades and high math interest. The authors suggested that the engaging nature of the game may explain the success of these typically struggling students compared to the students with already high math interest and intrinsic motivation as well as high prior content knowledge. This would explain why the 'unmotivated' and the 'struggling' students in Study 2 perceived instruction in the classes with tablets more positively, especially compared to the stronger profile. Alternatively, perhaps the 'unmotivated' students in Study 3 were disappointed by the actual use of tablets in classrooms, in line with students from 1:1 tablet schools in Norway, Denmark, and the UK who reported they were either disappointed that the use of tablets in class did not amount to much or because the effort to use them felt forced (Blikstad-Balas & Davies, 2017). Following up with the 'unmotivated' students in Study 3 could provide some answers, such as through qualitative interviews or focus groups. In one example from Finland, students who were identified as being highly cynical towards school, characterized by high levels of burnout, exhaustion, and feelings of inadequacy, reported they would be more academically engaged and hardworking if there was greater use of ICT in schools (Salmela-Aro, Muokta, Alho, Hakkarainen, & Lonka, 2016). The authors explained this could be because of the gap between this group's personal use of socio-digital technologies and the lack of socio-digital technologies in school practices. Perhaps the 'unmotivated' students in Study 3 also perceived a gap between how they use digital media outside of school and how they expected to use digital media in school.

Since the coining of the term digital natives (Prensky, 2001), there has been immense pressure on teachers to change their educational practices and adapt to claims that students need to be constantly entertained or would automatically learn from digital media if given the opportunity (Thompson, 2013). However, the findings of Study 2 and Study 3 show that (a) not all students perceive instruction more positively with the addition of digital media into the classrooms (e.g., the 'strong' students identified in Study 2), and (b) students' learning prerequisites (i.e., their prior experiences, skills, and prior knowledge) largely affect how students perceive instruction with digital media. Petko, Cantieni, and Prasse (2016) commented that the use of digital media needs to be regarded as "just a piece in the puzzle of interrelated

factors influencing quality of instruction, effectiveness of learning, and test performance” (p. 6). Therefore, the responsibility to engage students with digital media should not be completely on teachers.

The findings of Study 1 also have important implications for teachers. Investigating the role of parents and their behaviors at home regarding digital media highlights another source of variability that teachers must address when integrating digital media into the classroom. Some students will have more experience using digital media, whereas other students will need more support in the classroom. On the one hand, this increases the need for teachers to recognize the students that need additional support learning with digital media. Additionally, teachers may need to plan multiple learning activities or design learning activities in a way where students with lower digital media skills can also participate. On the other hand, the important role that parents may play in influencing their children’s self-beliefs suggests another target group for interventions, thus displacing some of the responsibility placed on teachers. Interventions could be designed to instill in parents the importance of digital media skills, which they could transmit to their children, and in turn affect their children’s outcomes with digital media. Specifically, interventions could inform parents about skills such as locating and using Internet resources or content creation that could translate to learning with digital media (e.g., Thompson, 2013). When students can learn how to effectively use digital media outside the classroom, that can help them to learn inside the classroom.

5.3.2 Theoretical and methodological implications

Considering empirical research in classrooms investigating digital media is still relatively sparse, I have chosen to address the theoretical and methodological implications together. I suggest that the methodological findings found in this dissertation have important implications for how to continue building theory regarding how students learn in classrooms with digital media. Alongside this discussion of the theoretical and methodological implications of this work, I address the issue surrounding self-report data and questionnaires in the context of technology-enhanced learning environments. Furthermore, I reiterate the importance of examining not just whether the use of tablets facilitates student learning, but for whom the use of tablets facilitates student learning. To conclude, I demonstrate based on the findings of this dissertation why person-centered approaches should be used moving forward for investigating digital media use in classrooms.

In this dissertation, Study 2 and Study 3 employed person-centered approaches to understand differences in students’ perceptions of instructional quality with tablets based on their cognitive and motivational-affective characteristics. Although student perceptions are

regularly used to assess instructional quality, they appear to be seldomly used in the context of digital media. However, extensive research shows that especially individual student perceptions are an important and valid way for students to convey their individual experiences in the classroom and how they personally interpret the instructional practices of teachers (e.g., Aldrup et al., 2018; Göllner et al., 2018; Lüdtke, Robitzsch, Trautwein, & Kunter, 2009; Scherer, Nilsen, & Jansen 2016; Wallace, Kelcey, & Ruzek, 2016). Lüdtke et al., (2009) wrote “a given student’s behavior can be assumed to be more affected by his or her interpretation of the classroom context than by any objective indicator of that context” (p. 120). Kunter and Baumert (2006) described that student ratings provide the best information regarding whether tasks and interactions are suitable for and agreeable to students. Aldrup et al. (2018) found the teacher ratings of social support were mostly independent of what their students perceived and were unrelated to student development, but students’ individual perceptions of social support were linked to achievement and self-esteem. Furthermore, Göllner et al. (2018) explained “Whereas a teacher’s ability to prevent disruption is more relevant for the class as a whole, students’ idiosyncratic perceptions of their teacher’s sensitivity might be more relevant for understanding individual students’ learning within the classroom” (p. 711). From a practical perspective, student questionnaires also offer a relatively low-cost and unobtrusive way to assess large numbers of students.

Nevertheless, with the onset of technology-enhanced learning environments, there has been growing criticism against the use of self-report measures for studying complex constructs such as motivation or self-regulation (Tempelaar, Rienties, & Ngyugen, 2020). In one example from the field of learning analytics, Tempelaar et al. (2020) examined the strengths and weaknesses of survey data and computer-generated trace data when designing predictive models of academic performance. Although trace data is often perceived as true, unbiased data, the authors found that trace data from learning management systems (e.g., BlackBoard) was not always a reliable predictor of academic performance. Students who need less attempts to solve an exercise or do not need hints can have the same course performance as students who do need more attempts to solve an exercise or need more hints. Although the second group of students is working less efficiently, their personal characteristics, such as conscientiousness, are not incorporated into trace data. Additionally, although survey data is criticized for being invalid because of rating tendencies or the potential for students to under or overestimate their abilities, skills, and knowledge, Tempelaar et al. (2020) found the survey data added predictive power in the explanation of performance data. This is in line with Göllner et al., (2018) that found even with rating tendencies, students’ idiosyncratic perceptions were still associated with individual

student learning outcomes. Therefore, Tempelaar et al. (2020) suggested when investigating technology-enhanced learning environments to use a combination of survey data and trace or online data, i.e., not dismiss survey or questionnaire data completely. It is also worth pointing out that the use of log or trace files raises data privacy concerns, especially for children and particularly in countries like the US and the UK where data privacy laws have not kept up with the pace of learning management systems and digital platforms being implemented into schools (e.g., Stoilova, Nandagiri, & Livingstone, 2019).

The findings of this dissertation suggest that researchers in the field of digital media may benefit from using student perceptions to understand how students learn with digital media and especially how different kinds of students learn with digital media. Although there are limitations to using questionnaire data, especially for high-stakes evaluations like in the US, they are especially valuable for understanding how individual students perceive aspects of instructional quality and in turn learn. Therefore, one methodological implication of this dissertation is that student perceptions offer a valid and meaningful approach for understanding how individual students learn with digital media.

Furthermore, person centered approaches are rarely used in the context of learning with digital media (e.g., Scherer, Rohtagi, & Hatlevik, 2017). Instead, research on students' use of digital media for learning has typically employed variable-centered approach and has examined how educational technology and academic achievement are related (e.g., Lai & Bower, 2020). A variable-centered approach represents "a synthesis (or averaged estimate) of the relationships observed in every individual from the sample under study, without systematically considering the possibility that these relationships may meaningfully differ in subgroups of participants" (Morin, Morizot, Boudrias, & Madore, 2011, p. 59). By contrast, a person-centered approach is based on the proposition that distinct subgroups may exist, and if so, aggregate-level parameters may contradict parameters for groups or individuals (von Eye & Bogat, 2006). The results from the ICILS 2018 indicated that the differences in students' computer and information literacy scores were larger within countries than the differences between countries (Fraillon et al., 2019). Furthermore, Huber and Seidel (2018) found even within tracked classrooms, students' learning prerequisites can vary considerably. This suggests that samples under investigation in research investigating digital media use may have distinct subgroups, whether it is at the country level or at the school or class level, and the parameters of these subgroups may be relevant for how students learn with digital media. Subgroups may exist a priori or can be identified using methods such as latent profile analysis. Latent profile analysis is particularly valuable because it allows to examine individual factors in conjunction with other

factors, rather than comparing the relative importance of each individual variable (Bergman, Magnusson, & El-Khoury, 2003). In the last years, it has also become easier to easily conduct latent profile analysis such as in programs like R (e.g., Rosenberg, Beymer, Anderson, & Schmidt, 2019) or to investigate the effects of profile membership on a distal outcome variable without distorting the profile solution (e.g., Bakk, Tekkle, & Vermunt, 2013). Furthermore, it is worth noting that conducting latent profile analysis in Mplus still allows to take into account that students are nested into classes using cluster-robust standard errors (McNeish, Stapleton, & Silverman, 2017).

This dissertation has shown students' cognitive as well as motivational-affective characteristics are relevant for how students perceive instruction with digital media in the classrooms. As research continues to grow on how students learn with digital media, being able to take multiple factors into account, such as student learning characteristics or variables relating to students' use of digital media such as digital media self-efficacy, can provide further insight into how the use of digital media affects different subgroups of students. Therefore, one methodological implication of this dissertation is to advance the use of person-centered approaches for investigating how students learn with digital media in classrooms. A similar theoretical implication is that students perceive learning with digital media differently depending on the interplay of cognitive and motivational-affective characteristics.

Investigating how the use of digital media in classrooms may affect different types of students is of particular importance amid the corona crisis and the growing 'heterogeneity revolution.' The 'heterogeneity revolution' refers to an increasing recognition of the heterogeneity in treatment effects (Tipton, Bryan, & Yeager, 2020; Kenny & Judd, 2019). Tipton et al. explain (2020) virtually all phenomena occur under certain conditions and not others, yet behavioral intervention researchers and policymakers often fail to recognize the far-reaching implications of sample heterogeneity and the intervention's real-world impact outside of labs and samples drawn from university participant pools. Tipton et al. (2020) further explain the heterogeneity revolution was sparked by the same tipping point as the replication crisis: the failure of promising initial findings to be shown in subsequent evaluations. However, Tipton et al. (2020) point out that instead of considering variation in treatment effects as a negative, understanding how treatment effects vary across contexts can help identify the causal mechanisms underlying the treatment effects.

Regarding learning with digital media, previous research investigating the effects of educational technology in general has shown wide variability (e.g., Tamim, Bernard, Borokhovski, Abrami, and Schmid, 2011). Similarly, although there were strong claims that

educational technology would revolutionize how students learned in classrooms, the subsequent findings have been more mixed (e.g., Petko et al., 2016; Warschauer, Zheng, Niiya, Cotten, & Farkas, 2010). The ‘heterogeneity revolution’ implies these limited results may also be due to a failure to recognize sample heterogeneity and the real-world impact of using technology in dynamic classrooms. Although research on learning with digital media has already moved from labs to real classrooms, we need to know not just how digital media can facilitate student learning, but we must include how digital media can facilitate student learning for samples outside of university participant pools and Gymnasiums. Of extreme relevance, “learning in the time of corona” has exposed the broad inequities that exist among students and that not all students are equally able to learn online. Moving forward, it is important that the research investigating digital media use in classrooms recognizes that students come from different backgrounds, have parents who may or may not be knowledgeable about using digital media, may not have reliable Internet access at home or their own digital device, or may not have a suitable place in their home to work on a digital device. Acknowledging the heterogeneity in student samples and investigating which differences are relevant for learning in classrooms not only helps to better understand how digital media facilitates (or does not) learning but also can help to ensure students of diverse backgrounds are included.

5.4 Limitations and Future Research

A great deal of research has shown the importance of subject-specific self-efficacy beliefs in student outcomes (e.g., Usher & Pajares, 2008) and the importance of ICT self-efficacy for computer and information competencies (e.g., Aesart & van Braak, 2014; Rohtagi et al., 2016). Although this dissertation aimed to investigate the antecedent factors that contribute to student learning with digital media as identified by previous research and theory, future research should test the role of digital media self-efficacy in explaining student learning outcomes with digital media. A useful example comes from Tsai and Tsai (2003) that found students with high self-efficacy in using the Internet had better information-searching strategies and performance in web-based learning tasks than students with low internet self-efficacy. More recently, Lee and Wu (2017) found students with better attitudes towards computers and more confidence in completing high-level ICT tasks, had higher engagement in online reading activities, and in turn higher text-based reading literacy. The authors explained that students who had better attitudes and confidence, read more online texts, which ultimately transferred to and enhanced students’ reading of printed texts. In line with Tsai and Tsai (2003) and Lee and Wu (2017), future research should test digital media self-efficacy as a predictor of learning tasks. Additionally, future research should examine how students’ digital media self-efficacy affects

students' abilities to accomplish personal and professional goals, such as finding and evaluating information online or work-related tasks. It should be noted though that the scale used in Study 1 to measure digital media self-efficacy came from PISA 2015 and assessed self-efficacy regarding digital media use in general and not necessarily regarding digital media use for learning. Therefore, it would be beneficial to develop further measures of self-efficacy that integrate subject or task-specific self-efficacy items with digital media, such as how confident students feel about using digital media in a math or reading class.

Further research investigating how students develop digital media self-efficacy at home should also examine the specific ways that parents and students use digital media. Although we made efforts to ask parents about their use and provision of different digital devices and asked parents how much time they spent using digital devices on an average weekday and average weekend day, we did not ask them about their digital activities. Following the parent socialization model, children observe how their parents spend time at home and how they choose between available activities, which conveys messages about activities that are valued and acceptable ways to spend time (Jacobs & Eccles, 2000). In their review of digital technology use on adolescent well-being, Dienlin and Johannes (2020) found that not all digital activities are created equal, and different activities will lead to different effects, such as passively spending time on social media or actively using digital devices to interact with others. Therefore, when children observe how their parents spend time on digital devices, they may convey to their children which digital activities are valuable and acceptable, and in turn different activities might have distinct effects on students' development of digital media self-efficacy. It would also be interesting to see if other parenting behaviors such as encouragement or co-activity would explain more how parents transmit their beliefs to their children.

Future research should also address the weaknesses in Study 1. First, one weakness in Study 1 was the lack of a longitudinal design. In order to evaluate whether parents' beliefs influence parents' behaviors and in turn children' self-beliefs, it would be important to show parents beliefs preceded parents' behaviors and children's self-beliefs. Second, asking parents to report how much time they spent on various devices on an average day as well as retrospectively asking the age at which they provided children with their own device could have resulted in parents underreporting their use or misrepresenting the age, such as if parents bought a device many years prior. In line with this, Parry, Davidson, Sewall, Fisher, Mieczkowski, and Quintana (2020) recently published a preprint showing self-reported media use was only moderately correlated with device-logged measurements. This suggests that self-reported responses are not a valid measure of the amount of time people actually spend using media.

This could explain why we did not find a link in Study 1 between parents' use of digital media at home and students' digital media self-efficacy. Future research could also use log data from devices to get a clearer picture of how much time parents spend using digital media at home in addition to other information about their digital activities. However, that would most likely result in less parent participation and probably substantial differences in parents who would consent to give access to their log data and parents who would not.

Moving to future areas of research based on the results of Study 2 and Study 3, future research should follow Schenke (2018) and test whether students' perceptions mediate the effect of observed instructional practices with digital media on student learning outcomes. To identify the observed instructional practices, Schenke (2018) used video recordings of classrooms which were then rated by trained reviewers. Future research investigating digital media could also use video recordings in addition to student perceptions of instructional practices. As pointed out by Schenke (2018) though, it would be important to ensure the observed instructional practices aligned with the student perceptions measures as well as the measurement points. Addressing these issues may show that student perceptions of cognitive activation in classes with digital media mediate the effect of observed cognitively activating practices on student achievement outcomes. However, regardless of the observed instructional practices, Schenke (2018) found students' individual ratings of emotional and instructional support significantly predicted students' effort and math achievement.

Regarding the self-report measures used in Study 2 and Study 3, there were also some limitations that could be addressed in future research. Although it is reasonable to measure students' subject-specific interest and subject-specific self-concept through self-report measures, prior content knowledge could be assessed with a subject-specific knowledge test. Although the acquisition of subject-specific knowledge is often measured by content-related achievement such as grades (e.g., Pielmeier, Huber, & Seidel, 2018), asking students to report their most recent grade may not provide the most accurate representation. However, as previously stated, using student ratings of supportive climate and cognitive activation as opposed to teacher reports or external reviews offers unique and valuable insight into the perspective of individual learners. The importance of investigating the student perspective cannot be understated in understanding how digital media may facilitate student learning.

An additional limitation of this dissertation is the lack of diversity in the sample. The *tabletBW* project collected data from academic track schools (e.g., Gymnasiums), which typically have students from higher socioeconomic status backgrounds. Although we found a significant difference in the socioeconomic status between the families who participated and

did not participate in the parent questionnaire (Study 1), it should be noted that the difference was rather small, indicating a limited range of socioeconomic backgrounds in the investigated sample. It would be important in future research to see how socioeconomic status could be incorporated in the parent socialization model (e.g., as a predictor or covariate) in a more socioeconomically diverse sample. Though, the intention behind this dissertation was not to investigate socioeconomic status but rather other family background factors, such as parents' beliefs about using digital media. In a recent study, Eickelmann and Gerick (2020) interviewed a representative sample of teachers in April of 2020 and found less than two-fifths (36.2%) of the teachers at the non-Gymnasium secondary schools stated that their school was already advanced in the use of digital opportunities for teaching and learning before school closures due to COVID-19. This indicates the need for additional research in non-Gymnasium contexts to ensure these students also have the opportunities to develop digital media skills and learn effectively with digital media. Future research should use all the methodological approaches in this dissertation with more diverse samples including students from all school tracks.

With respect to the generalizability of the results found in this dissertation, Study 2 examined students in biology classes and Study 3 examined students in math classes. Future research could test the robustness of the profiles in additional subject domains. Similarly, it should be noted that cognitive activation is considered to be closely related to the subject matter and has been predominantly studied in the context of math instruction as in Study 3 (Fauth, Decristan, Rieser, Klieme, & Büttner, 2014). The results indicating that students perceived more cognitive activation in classes where teachers had higher technology innovativeness may therefore be limited to math instruction. However, Backfisch et al. (2020b) examined teachers' use of technology in diverse subjects and consistently found that teachers' technology innovativeness was associated with greater instructional quality.

In sum, there were a number of limitations of the empirical studies conducted in this dissertation, however they could be addressed in future research. As empirical research continues to grow on how students learn effectively with digital media in the classroom, additional measures will be needed to assess the different ways digital media may affect student learning besides gains in achievement or content knowledge. In general, there should be more measures that assess how students are able to complete tasks with digital media.

5.5 Significance Statement

The original and substantive contribution of this dissertation is that students perceive instruction with digital media differently depending on their cognitive and motivational-affective characteristics. Understanding that not all students will perceive and learn with digital media in the same way has important implications for teachers' use of digital media in the classroom as well as researchers investigating how digital media facilitates student learning. At the same time, students arrive in the classroom with different characteristics and experiences that affect how they learn once inside the classroom. Regarding learning with digital media, students' previous experiences with digital media and characteristics such as digital media self-efficacy can affect how they feel towards and learn with digital media. There is not a direct effect of instructional practices with digital media on student learning outcomes, rather a number of factors including students' learning characteristic and previous experiences may affect how they learn with digital media. Moving forward, research exploring how learning with digital media in classrooms takes place should also examine the factors outside the classroom such as students' experiences with digital media at home.

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