Does an individualized learning design improve university student online learning? A randomized field experiment

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Abstract

University courses often employ "one-size-fits-all" approaches, disregarding the heterogeneity in students' cognitive and motivational characteristics. This intervention study reports on an individualized learning design for online teaching in higher education. In a randomized field experiment with N = 438 university students (57% female, mean age *M* = 20.96 years), we investigated the effects of the learning design on students' motivation (self-concept, self-efficacy, intrinsic and utility task values), on their performance, and, because our sample consisted of teacher students, on their professional development with regard to inclusive education. Employing structural equation modeling, we found that the intervention positively affected the self-concepts of effort avoidant students. The intervention also positively impacted students' attitudes and self-efficacy towards inclusive education, but had no effect on course performance, course-related self-efficacy and task values. Moreover, learning analytics data revealed in-depth information on students' learning behavior. Results are discussed regarding possible intervention strategies to be implemented in future versions of the learning design.

Keywords: individualized learning design, online learning, student motivation, performance, attitudes towards inclusive education, teacher students

1. Introduction

In university courses, like in any other group of learners, individual students differ greatly in their cognitive and motivational characteristics. For example, while Emma, a student teacher, enjoys learning about digital tools she can use in her math classes, her friend Edmund finds this less useful for his future PE lessons. University courses, especially lectures, often disregard such heterogeneity and employ „one-size-fits-all“ approaches. This also applies to the remote teaching during the COVID-19 pandemic, when courses had to be switched from classroom and combined online and offline settings to fully digital formats. In this context, addressing the diversity in students’ cognitive and motivational characteristics presents a particular challenge to higher education teachers, as to teachers in schools. However, digital technology yields the potential to individually support learners in their learning process, if the technology is embedded within a suitable learning design.

Learning design is concerned with learning environments to achieve particular educational aims in a given educational context and with use of digital technology (Mangaroska & Giannakos, 2019; Rienties & Toetenel, 2016). Learning design focuses not only on the “content and the way to present it” (Wasson & Kirschner, 2020, p. 824), but also on the activities, tools, materials, and the experiences students make, thus on the learning environment as a whole. In this paper, we introduce a type of learning design that aims to address the challenge of heterogeneous learner characteristics. We explain some general psychological mechanisms which educators might capitalize upon when planning learning activities, and present one concrete design example from a large lecture course in teacher education. We examine effects of this learning design on the motivation, on the performance, and on the professional development of our target group students with a randomized field experiment. We additionally used learning analytics to inform future adaptations of this learning design in the present context (Blumenstein, 2020; Mangaroska & Giannakos, 2019).

2. Theoretical background

A strength of the here presented learning design is its foundation in educational psychological theory and evidence on motivational and cognitive processes, as well as teacher professional development. In the following, this theoretical background is presented and hypotheses are derived, detailing how the efficiency of the learning design is expected to explicitly benefit from using digital technology. This being said, our study addresses the need to base learning design in learning theory (Bodily, Leary, & West, 2019; Rapanta et al., 2020).

2.1 Individualized learning design

Before presenting the theoretical background of our learning design, we give a brief overview about its core features. This type of learning design is called digital differentiation grid (Greiner, Kämpfe, Weber-Liel, Kracke, & Dietrich, 2019). Its overall educational objective, addressing heterogeneity, is broken down into formulating learning objectives on different levels. Each learning objective is associated with one or more learning activities. The learning objectives are classified into levels on two dimensions: a knowledge dimension called thematic complexity, and a cognitive process dimension called cognitive complexity. Learning activities within the learning design are classified along these two dimensions so that a grid structure results as shown in Figure 1, with increasing requirements from left to right and from bottom to top. The elements of a grid are the grid fields. For each grid field the teacher or educator selects a learning activity which fits with the specific learning objective of this field. The position of each field in the grid then reveals the complexity level (i.e., level of requirement) of a selected learning activity to the student. How many complexity levels are needed and which learning activity is planned by the educator to correspond to a given objective is part of the design process in the particular teaching context and depends on the particular subject and course. In addition, depending on the complexity of the topic(s) in the learning design, the educator decides whether to offer one or multiple grids. Key of the individualized learning design is that students neither need to go through all learning activities in the same sequence, nor do they need to accomplish all offered learning objectives at all (Castro, 2019). Rather, students can individually select learning objectives and corresponding activities based on their cognitive (e.g., prior knowledge) and motivational characteristics (e.g., level of interest). For the task-selection to be effective, students need guidance (Kostons, Gog, & Paas, 2012). Hence, instructions for students how to navigate through the grids and learning activities are part of the learning design.

Differenzierungsmatrix für Themenkomplex "Lernen"

	Definition und zentrale Begriffe	Theoretische Modelle/Ansätze	Theorie- und themenübergreifende Vernetzung/ Interventionsmaßnahmen
AFB III: Argumentieren/Reflektieren/Beurteilen	✓	✓	✓
AFB IIb: Vergleichen/Einordnen/Abgrenzen	✓	✓	✓
AFB IIa: Anwenden/Übertragen	✓	✓	✓
AFB I: Erinnern (Wiedererkennen & Reproduzieren)	✓	✓	✓

Figure 1. Schematic representation of the learning design and screenshot from the implementation in Moodle. Cognitive complexity increases on the Y-axis, thematic complexity increases on the X-axis. In the present learning design, cognitive complexity was divided into four instead of three levels.

The actual learning activities can be chosen according to different taxonomies. Referring to the Open University Learning Design Initiative taxonomy of learning design activities

(Rienties & Toetenel, 2016), a grid could for instance contain assimilative activities (attending to information), activities to find and handle information, and productive activities (actively constructing). A learning design activity like assessment could, however, be designed to stimulate different cognitive processes. Therefore, additional taxonomies like Bloom's taxonomy of learning objectives (Anderson & Krathwohl, 2001) or the ICAP taxonomy of interactive, constructive, active and passive modes of cognitive engagement (Chi & Wylie, 2014) may be used in the learning design process.

Contextualizing our learning design and the present empirical study within the C♭-model of technology-enhanced learning activities in higher education (Sailer, Schultz-Pernice, & Fischer, this issue), we were concerned mainly with the link between students' learning activities and their knowledge, skills, and abilities. All activities of our learning design were implemented as self-assessment activities (Rienties & Toetenel, 2016) on different levels of complexity. Our learning design comprised of five grids in total, corresponding to five different topics of the course.

Our target group in the present study was teacher students. For this group of learners, the individualized learning design can be related to theoretical models of teacher professional competence. According to the COACTIV model (Professional Competence of Teachers, Cognitively Activating Instruction, and the Development of Students' Mathematical Literacy, Baumert & Kunter, 2013), teacher competence consists of professional knowledge, of professional values, beliefs, and goals, of motivational orientations and of professional self-regulation skills. The overarching objective of our individualized learning design was that students acquire pedagogical/psychological knowledge through the content topics of the learning design. This general, subject-independent type of knowledge enables teachers to "create and optimize teaching-learning situations" (Voss, Kunter, & Baumert, 2011, p. 953). Moreover, through making the learning design transparent to the students we aimed to develop their knowledge about educational technologies, again a general and subject-independent type of knowledge (technological pedagogical knowledge, Mishra & Koehler, 2006). In addition to these cognitive aspects of teacher competence, the learning design aimed to support motivational orientations and beliefs, as detailed in the following sections.

2.2 Motivational processes within the learning design

In line with modern expectancy-value theories (Eccles & Wigfield, 2020; Pekrun, 2018), motivational benefits of the learning design could be achieved on two different dimensions: Students' competence-related self-evaluations and success expectancies, on the one hand, and their value appraisals, on the other hand. In this study, we assessed motivation with respect to the subject of the course where the learning design was implemented, i.e., educational psychology for teacher students. From the teacher competence perspective, teachers' motivational characteristics, such as valuing psychological knowledge, are vital for developing the willingness to act professionally in their future job (Baumert & Kunter, 2013).

There are various related conceptions of expectancy (see Anderman, 2020). One is a learner's self-efficacy, that is, the person's belief that he or she can successfully deal with a future situation or accomplish a future task (Bandura, 1982; Eccles & Wigfield, 2020). The academic self-concept, another expectancy-related construct, refers to more stable and broad beliefs about competence in a given domain (Marsh & Craven, 2006), reflecting students' self-evaluations based on their past successes. Students' expectancies will be higher in well-structured learning designs, because then students know better what they are expected to do (Pekrun, 2018) and thus are focused on specific goals (Locke & Latham, 1990). Moreover, expectancies will increase following learning successes (Marsh & Craven, 2006; Pekrun, 2018), and especially self-concept benefits from temporal comparisons, where students compare their own performance over time (Marsh & Craven, 2006).

Due to the transparent structure of the learning design, students receive a systematic overview of the criteria for succeeding in the course. These may function as clear and specific goals (Locke & Latham, 1990; Pekrun, 2018). To what extent students meet these requirements is feedbacked immediately after having completed the selected learning activity. As such, the personalized feedback within the structured learning design enables students to evaluate their subject-specific knowledge and skills. Moreover, the personalized feedback can facilitate learning successes (Hattie & Timperley, 2007), and consequently improve students' expectancies. This effect may be amplified when self-concepts successively improve through temporal comparisons, as students' knowledge increases (Marsh & Craven, 2006). Finally, learning successes are more likely in learning activities, where students' skills directly meet or are slightly below the requirements (Pekrun, 2018; Csikszentmihalyi, 1990). A fit of the learning activity and the needs of the learners could be achieved more easily in a structured learning design like the present one compared to a learning design with unstructured activities.

The task value component of motivation reflects the qualities of a learning activity that increase or decrease a learner's willingness to engage (Eccles & Wigfield, 2020). This study examined the intrinsic value, that is, the extent to which students like and enjoy engaging with the learning activity. We further focused on utility value, which here denotes the subjective perception of how well the contents of a particular learning activity are relevant to the students' future job as teachers (Gaspard et al., 2015). Intrinsic value can be promoted by satisfying students' needs for autonomy, competence, and relatedness (Deci & Ryan, 2000). Perceived utility value, in turn, can be fostered by helping students to understand how their coursework relates to their future goals (Harackiewicz & Priniski, 2018).

Within the learning design, the activity choices offered to the students can be intrinsically motivating by satisfying the need for autonomy. And because students can skip the learning activities they find too easy or too difficult, their need for competence is met (Katz & Assor, 2007). Moreover, with increasing complexity levels in our learning design, the practical relevance of the given learning activities increases. Students are made aware of this structure and can move from rather abstract and simple learning activities to more practically relevant and complex learning activities. This strategy aligns with explicitly explaining the relevance of learning materials to enhance utility value (Harackiewicz, Tibbetts, Canning, & Hyde, 2014).

2.3 Cognitive processes

In addition to motivation, our learning design targets students' acquisition of pedagogical/psychological knowledge (Voss et al., 2011). Feedback (Alfieri et al., 2011; Hattie, 2009), retrieval practice (McDermott, 2021), and guided instruction (Kirschner et al., 2006; Paas, Renkl & Sweller, 2004) are implemented to aid cognitive learning processes.

Students receive timely and individualized feedback after each learning activity. This feedback combines knowledge of performance (how many points students earned for a learning activity), knowledge of the correct response, and feedback about the quality of the response for each question (Narciss, 2013). Moreover, our learning design supports students' understanding of the learning activity requirements to support feedback efficiency.

Moreover, students can go through each learning activity repeatedly, and as often as they wish. This might benefit practicing the retrieval of newly learned information (Dunlosky, Rawson, Marsh, Nathan, & Willingham 2013; Rowland, 2014), which itself is correlated with students' performance on exams (Hartwig & Dunlosky, 2012). Although retrieval practice is also possible with offline learning tasks, effects could be stronger when using digital technology. This is because students receive specific feedback regarding their performance (Alfieri et al., 2011; Hattie & Timperley, 2007), enabling a more reliable performance assessment and a higher likelihood of task repetition.

Our learning design provides another advantage concerning students' cognitive resources. In the present type of learning design, a multitude of learning activities is required to meet the needs of students with different pre-knowledge. The resulting volume of learning activities may be overwhelming to students' working memory, and guided instruction is needed for activity selection (Kirschner et al., 2006; Kostons et al., 2012). This guidance is given through the structure of the grids and the transparent activity requirements. Likewise, the computerized feedback demands fewer cognitive resources compared to a learning situation in which students need to correct test results themselves. Guided instruction is an important characteristic of complex learning designs aiming to avoid heavy working memory load, which itself is detrimental to learning effectiveness (e.g., Paas et al., 2004).

2.4 Professional development of future teachers

The learning design aimed to support a third aspect of teacher professional competence, referring to teachers' beliefs (Baumert & Kunter, 2013). A current priority on the political agenda in many countries is the inclusion of students with special educational needs (e.g., concerning cognitive, emotional or affective differences) in mainstream schools (United Nations, 2008). Consequently, there is a growing body of research regarding inclusive education and factors that support teachers in implementing an inclusive classroom, which means addressing individual needs in heterogeneous learning groups (for an overview see de Boer, Pijl, & Minnaert, 2011; van Mieghem, Verschueren, Petry, & Struyf, 2018). Teacher education at university plays a key role in the successful implementation of inclusive education in the future (Ahsan & Sharma, 2018). Especially, self-efficacy beliefs and attitudes towards inclusion need to be taken into account (e.g., Hecht, 2014). Learning designs aiming to address the development of more positive attitudes and higher self-efficacy towards inclusive education are more effective if they contain exemplary elements for a professional approach to heterogeneity (Avramidis, Bayliss & Burden, 2000; Burke & Sutherland, 2004). We conceptualized the learning design with the aim of providing student teachers with an exemplary way and impulse for considering the heterogeneity of learners (Greiner & Kracke, 2018).

2.5 The present study

The aims of this study were twofold: (1) To measure possible effects of our above-described learning design in a randomized field experiment, and (2) to use learning analytics to inform possible future adaptations of the learning design. Regarding (1) we posed the following hypotheses.

First, in the present learning design students could choose their own learning paths through the grids based on their interests and perceived competences (Corbalan, Kester & van Merriënboer, 2009). Students' motivation was therefore expected to increase.

Hypothesis 1a*: Students who are offered the individualized learning design with digital learning activities in a grid structure (in the following labelled the intervention condition) develop a more positive self-concept of educational psychology, and higher self-efficacy towards their performance in the upcoming exam, compared to students in a control condition).*

Hypothesis 1b*: The intrinsic and utility values of students in the intervention condition develop more positively compared to those in the control condition.*

Second, the learning design is a form of guided instruction (Kirschner, Sweller, & Clark, 2006) offering personalized, instant feedback on performance (Alfieri, Brooks, Aldrich, &

Tenenbaum, 2011; Narciss, 2013) and allowing for retrieval practice (McDermott, 2021; Rowland, 2014), which was expected to improve knowledge acquisition.

Hypothesis 2*: Students in the intervention condition show higher course performance compared to the control condition.*

Third, for the target group of student teachers, the learning design provides a model for dealing with the diversity of students at schools and in such assumably positively affects attitudes and self-efficacy towards inclusive education (Burke & Sutherland, 2004).

Hypothesis 3*: We state that students in the intervention condition report more positive attitudes and higher self-efficacy for dealing with diversity as future teachers compared to the control condition*.

In addition to studying the effects of our learning design on student outcomes, we used learning analytics to obtain information that may guide future adaptations of the learning design. The technical possibilities of learning management systems enable researchers to track and analyze students' learning behavior, termed learning analytics (Nistor & Hernández-García, 2018). It has been suggested that learning analytics may inform learning design decisions (Mangaroska & Giannakos, 2019).

We were, first, interested in students' time investment, i.e., the quantity of learning. Time investment in self-study activities has been shown to increase as students get closer to exams, and has been shown related to study satisfaction and performance (Liborius, Bellhäuser, & Schmitz, 2019; Lerche & Kiel, 2018). In our learning design, the number of accessed grids, the number of accessed grid fields, and the total number of accesses are suitable indicators for time investment. We were also interested in the student characteristics that would be associated with time investment. Moreover, because of the high degree of autonomy in online learning environments, students need self-regulation skills to engage successfully (Sailer, Schultz-Pernice, & Fischer, this issue; de Boer, Donker-Bergstra, Kostons, & Korpershoek, 2013). Regarding our learning design, it was of interest to what extent students made use of the possibility to repeatedly go through learning activities as part of a retrieval practice strategy (McDermott, 2021). Finally, we explored two measures, which are specific for our learning design. We examined to what extent students followed the instructions about how to start working with a grid for a new topic. And we graphically analyzed how individual students navigated through the learning activities to learn about frequent and rare learning pathways (Blikstein et al., 2014).

3. Methods

3.1 Sample and Design

The study participants consisted of German university students in a teacher education program. A total of N = 521 students (participation rate 71 %) agreed to participate in the study. The participating students gave written informed consent in accordance with the Declaration of Helsinki, including the consent to use their online data from the Moodle learning management system. An ethics approval was not required at the time the study was conducted as per the then applicable institutional and national guidelines and regulations.

The analysis sample for the primary analyses in this article comprised of 438 students (239 female, 180 male, 1 non-binary, 18 missing or inconsistent information from pre- to post-test). Students' mean age was M = 20.96 years (SD = 2.51; range: 18-45 years).

Participants were recruited in a large lecture (for details about this lecture, see (Dietrich, Viljaranta, Moeller, & Kracke, 2017)). Students who had enrolled for the lecture, were randomly assigned to the intervention (n = 215) or the control condition (n = 223). Intervention condition students had access to the learning design as described in section 3.2 through the learning management system Moodle. Control condition students received the same course, but the learning activities were presented in pdf-documents without the scaffold and interactivity (e.g., personalized feedback). We chose this alternative-treatment control group instead of a no-treatment control group to disentangle the effect of the structured assessment activities using digital technology from retrieval practice/testing effects alone (McDermott, 2021; Rowland, 2014), which might also occur when students use the pdf-based assessment activities.

3.2 Description of the learning design

Course description. The class was designed as a blended learning course with face-to-face lectures every second week. The subject of the lecture was an introduction to educational psychology. The lecture ended with a written exam. Course contents were taught in face-to-face and in video lectures. The contents were divided into 11 topics. Our learning design comprised of five grids in total, corresponding to five topics of the course. Several times during the course, students were prompted by the teacher to use the learning design by showing 1-2 example activities from the grid pertaining to the current topic. In these prompts, the teacher showed in which grid fields the learning activities were located and explained how these represented the cognitive process dimensions underlying the learning design structure. This was done to address the students' professional development as future teachers.

Structure of our learning design. The learning activities were structured along two complexity dimensions as shown in Figure 1. The *cognitive complexity dimension* (Y-axis) was based on Bloom's/Krathwohl's taxonomy of cognitive processes (Krathwohl, 2002). We classified the cognitive processes into four levels, labelled as "Anforderungsbereiche" ("levels of requirement", abbreviated as AFB) in accordance with current practice in teacher education. These levels were (1) remembering (recognizing and recalling), (2) understanding and applying, (3) analyzing (organizing and differentiating), and (4) evaluating and creating. The *thematic complexity dimension* (X-axis) divided the knowledge contents into three levels (adapted from Krathwohl, 2002 and Körndle, Narciss, & Proske, 2004): (1) concepts and definitions, (2) theoretical principles and models, and (3) cross-thematic connections. Given the 3-by-4 structure, each grid contained 12 grid fields, each filled with learning activities. The learning activities increased in practical relevance and became more extensive from low to high complexity. Because of this, the number of activities per grid field was higher in the lower left area of a grid than in the upper right area.

Learning activities and feedback. The less complex learning activities consisted of simple questions with closed answer formats (e.g., single choice, multiple choice, drag and drop), whereas problem-based questions dominated the learning activities with higher complexity (for examples see Appendix A in the online supplement at https://osf.io/9zbuk/). Problem-based activities typically comprised of a vignette with several related questions. Similar to the less complex activities and whenever possible, the questions were given in closed answer formats such as multiple choice. However, the reflection and creation of solutions for complex problems also required questions in open answer formats like free text.

After having completed the learning activities within a given grid field, students received immediate computerized feedback. The feedback in less complex assessment activities comprised of students' total performance (points earned), knowledge of the solution for each question (flagging correct and incorrect responses) and knowledge of the correct answer (highlighted in green color). The feedback in more complex assessment activities additionally contained elaborations about the key concepts addressed in each question, and explanations why the single answer options were correct or incorrect. Automated personalized feedback was not available for open-ended free text questions in the present learning management system and given the large number of students neither was personalized teacher feedback. Therefore, the feedback in free text questions consisted of sample solutions revealing the correct response, and again explanations for the solutions.

Instructions to students. At the beginning of the semester students received instructions in the first face-to-face lecture, and through text and video in the learning management system. Contents of the instructions were: (1) the benefits of using the learning design as preparation for the final exam, (2) the activity requirements, and (3) learning strategies for working with the learning design. Regarding (2), the instructions described the requirements for learning activities on each cognitive complexity level in order to help learners understand the activity requirements. This was done to support feedback efficiency (Narciss, 2013) and to declare clear learning goals supporting expectancy beliefs (Pekrun, 2018). The questions contained operators corresponding to the specific cognitive process dimensions (e.g., “name” or “evaluate”), and the relationships between the operators and the corresponding cognitive processes were explicitly addressed in the instructions. The requirements descriptions also addressed the fact that the more complex learning activities addressed practical problems from teachers’ everyday lives. With this we aimed at increasing the perceived relevance and thus the utility value of the learning contents (Harackiewicz et al., 2014). Regarding (3), students were instructed to start working with a new grid by selecting a learning activity of medium complexity. Depending on the result of this first assessment, they were guided to move to higher or lower complexity levels. This procedure was developed to prevent frequent under- or overchallenges and to allow for learning successes which may strengthen self-concept and self-efficacy (Marsh & Craven, 2006). To address the heterogeneity in intrinsic motivation, students were instructed that course success did not require working through every single learning task; rather they could select tasks in their preferred content areas (Deci & Ryan, 2000). Finally, for each learning activity the option of unlimited number of trials was highlighted in order to encourage a strategy of repeated self-assessment.

Technical implementation. The learning design was implemented as a plugin to the learning management system Moodle. The learning activities were implemented as Moodle quiz activities. To aid students’ monitoring of their learning progress, all worked-on learning activities changed color from white to yellow (activity begun) and green (activity completed).

3.3 Measures

Motivation. Students completed pre- and post-questionnaires with instruments measuring four motivation facets with three items each on 4-point Likert scales (1 = *does not apply*, 4 = *fully applies*). Students were prompted to think about the topics of educational psychology. Self-concept items were selected from Baumert, Gruehn, Heyn, Köller, and Schnabel (1997, e.g., “I am good at these topics”, McDonald’s ω pre/post = .75/.80). Self-efficacy items were adapted from Pintrich, Smith, García, and McKeachie (1991, e.g., “I am certain that I will get a good grad in this class”, ω pre/post = .82/.84). Values were measured with items from Gaspard, Dicke, Flunger, Schreier, Häfner, Trautwein et al. (2015). Intrinsic value (example: “I like these contents”) had a reliability of ω pre/post = .80/.86 and utility value (“These topics will be useful in my future job as teacher”) of ω pre/post = .80/.88.

Course performance was measured as students' performance in the final exam which took place one week after post-test. The exam consisted of forty items (each graded with one point), of which 25 tapped contents that were part of the grid-related learning activities. We computed two scores from the exam data: a total score (range 10 to 38 points, M = 27.62, SD = 4.95), and a grid-related score pertaining only to the learning activities that were part of a differentiation grid (range 4 to 25 points, M = 16.54, SD = 3.57).

Teacher professional development. Attitudes towards inclusive education (4 items, e.g. "Students with special needs learn more in regular school classes", ω pre/post = .71/.77) and self-efficacy beliefs towards inclusive education (5 items, e.g., "I am certain that I can plan instruction in a way that high achieving students can benefit from low achieving students", ω pre/post = .66/.75) were measured on 4-point Likert scales (1 = *fully disagree*, 4 = *fully agree*; Bosse & Spörer, 2014).

Learning behavior within the learning design. Behavioral log data (trace data) from the learning management system (Moodle) were available in the intervention condition allowing to examine students learning behavior, i.e. how often and when they accessed the learning activities. The basis for our analyses were the completed learning activities, for which the system tracked date and time. We discarded unfinished activities where students might just have opened a quiz without working on the actual tasks, and without receiving feedback.

Covariates. Student *gender* was coded as 0 = female, 1 = male, and 2 = non-binary. Given only one non-binary student, we used the female and male categories in our analyses. We assessed prior achievement with two measures: as the *grade point average* (GPA) students had achieved in their final high school examinations (German: Abiturnote, possible ranges are 1 = *very good* to 4 = *passed*); and as a course grade they had achieved in a lecture on school pedagogy measuring *study-specific prior achievement*. The mean high school GPA was M = 2.124 (SD = .574), and the mean study-specific achievement was M = 2.673 (SD = .766). Also, at pre- and post-test, students reported their *effort avoidance* on a three-item scale (ω = .62). Items were selected from the German Effort Avoidance Test (e.g., "If I hadn't had to work that hard, I'd be a good student", Rollett & Bertram, 1998) with Likert-scaled items from 1 = *does not apply* to 5 *fully applies*.

Our pre- and post-questionnaires contained further measures not used in the present analyses. We measured students' self-regulated learning strategies but failed to establish a measurement model with acceptable fit. Moreover, we measured students perceived satisfaction of the needs for autonomy and competence based on Basic Need Satisfaction Scale (Deci & Ryan, 2000). We decided against using these scales, because unavoidable differences in wording ('educational studies' as reference at pre-test vs. 'this course' as reference at post-test) led to greatly different means between pre- and post-test for the same items.

3.4 Analysis strategy

We used structural equation modelling to test our hypotheses. We first established strong measurement invariance for all questionnaire measures at pre- and post-test. We used the effects coding method to define the latent variables, which resulted in latent means reflecting the means of all items measuring a given construct (Little, Slegers, & Card, 2006). In latent change models (McArdle, 2009), we then regressed latent pre-test and pre-post change variables on a dummy variable coding intervention and control conditions (0 = control condition, 1 = intervention condition), and on covariates. To test possible covariate x treatment (intervention) interactions, we added product terms (centered covariate x treatment variables) to the latent change models. Significant interaction effects were further explored by computing separate (simple slope) models by condition. The model for course performance contained the manifest course performance as dependent variable. Figure 2 shows a schematic representation of the latent-change models. All models were run in Mplus 8 (Muthén & Muthén, 1998-2017) with robust maximum likelihood estimation (MLR). Missing data were handled with full information maximum likelihood (FIML). To compile results, we used the Mplus Automation package for R 4.0.2 (Hallquist & Wiley, 2018). Outputs are available in the online supplement (Appendix B at https://osf.io/9zbuk/).

We examined students' learning behavior with descriptive statistics of their log data, which we also linked to the covariates measured at pre- and post-test. Using state space grids, (Lewis, Lamey, & Douglas, 1999) we generated two-dimensional visualizations of students' learning behavior from grid field to grid field (see Appendix C in the online supplement).

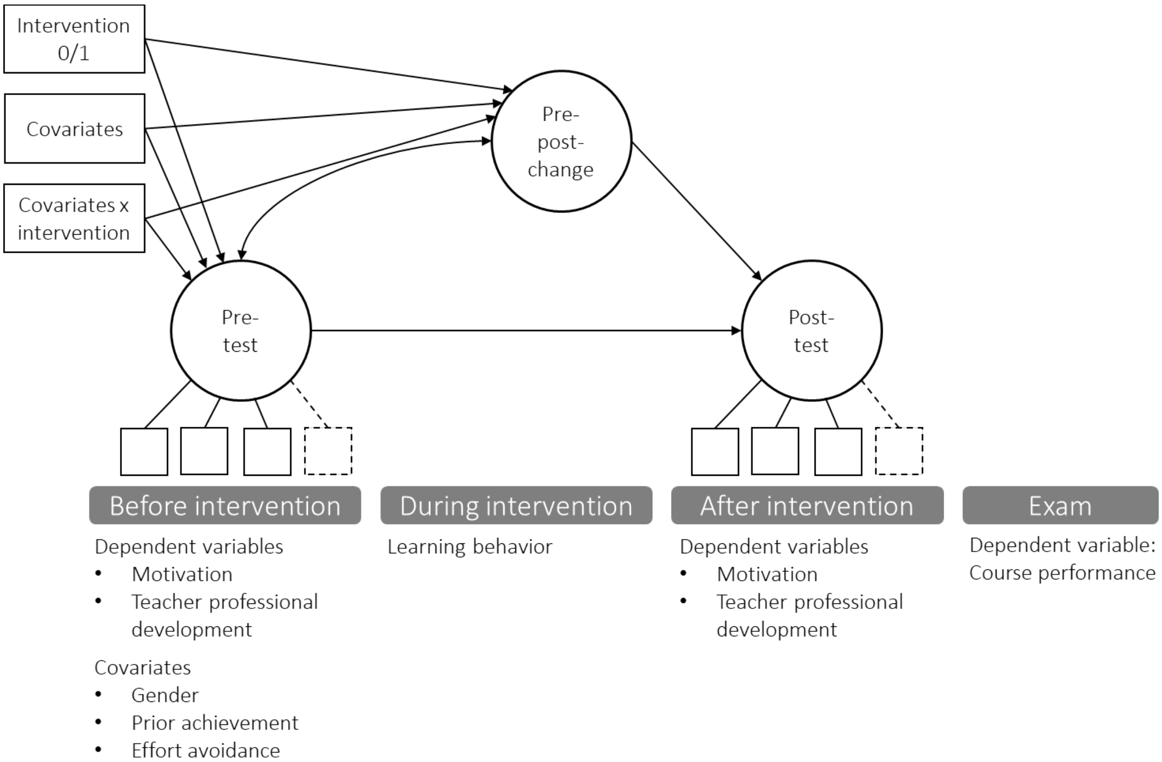

Figure 2. Schematic representation of the latent-change model and the sequence of measurements

4. Results

4.1 Intervention effects

Given the number of parameters in relation to the number of participants, we computed separate models for course-specific motivation, for course performance, and for teacher professional development, respectively. Mplus outputs are available in the online supplement (https://osf.io/9zbuk/). Table 1 shows unconditional means and mean changes in the intervention and control conditions, and Table 2 shows the results of the latent change models with covariates (cf. Figure 2).

In both conditions, course-specific intrinsic value and course-specific self-efficacy decreased from the beginning to the end of the semester, while course-specific utility value and self-concept remained unchanged (Table 1). Contradicting Hypothesis 1, we found no intervention main effects on course-specific motivation (see Table 2). Cohen's *d* effect sizes for the intervention main effects ranged .023 to -.066. However, there were covariate x treatment interactions. The intervention effect on self-concept depended on students' effort avoidance (standardized $\beta = .335$, $SE =.105$, $p = .001$; bivariate $r = .311$, medium effect according to Cohen, 1988). Course-specific self-concept increased for students with high effort avoidance in the intervention condition ($\beta = .263$, $SE =.116$, $p = .023$; $r = .226$, small effect), but decreased for effort avoidant students in the control condition ($\beta = -.297$, $SE =.143$, $p = .038$; $r = -.269$, small effect). There were further covariate x treatment interactions involving students' prior grades and gender, but these effects were likely related to differences between intervention and control condition that were already present at pre-test (see Appendix D in the online supplement, https://osf.io/9zbuk/).

As Table 2 shows, and contradicting Hypothesis 2, we found no difference in course performance between intervention and control condition students. Effect sizes were $d = -.044$ (total performance) and -.097 (grid-related performance).

Finally, we found support for our Hypothesis 3 with intervention main effects for teacher professional development. As expected (Table 2), taking the intervention positively impacted teacher students' attitudes ($d = .373$) and self-efficacy towards inclusive education ($d = .356$). While intervention condition students showed increased positive attitudes and self-efficacy towards inclusive education from pre- to post-test, these beliefs did not change in the control condition (see Table 1 for effect sizes of these changes). There were no interactions with covariates in predicting teacher professional development variables.

As an additional analysis we explored to what extent the outcomes in the intervention condition were related to the number of grids (range 0 to 5) the students had utilized during the semester. We therefore regressed the pre-post changes in the intervention condition on the number of grids. There were no associations with motivation (pre-post change in intrinsic value: standardized $\beta = -.124$, $SE = .093$, $p = .182$; utility value: $\beta = -.034$, $SE = .104$, $p = .746$; self-concept: $\beta = .068$, $SE = .109$, $p = .528$; self-efficacy: $\beta = .046$, $SE = .106$, $p = .662$) or teacher professional development (attitudes towards inclusive education: $\beta = -.101$, $SE = .134$, $p = .451$; self-efficacy towards inclusive education: $\beta = -.179$, $SE = .123$, $p = .145$). The number of grids was, however, related to course performance (total performance: $\beta = .260$, $SE = .071$, $p < .001$; grid-related performance: $\beta = .290$, $SE = .071$, $p < .001$).

Table 1. Latent means and mean changes

	Intervention condition				Control condition			
	Estimate	*SE*	*p*	ES	Estimate	*SE*	*p*	ES
Level at pre-test								
Intrinsic value	3.118	0.037	0.000		3.190	0.041	0.000	
Utility value	3.486	0.037	0.000		3.604	0.031	0.000	
Self-concept	2.905	0.031	0.000		2.906	0.037	0.000	
Self-efficacy towards exam	2.724	0.036	0.000		2.733	0.036	0.000	
Pre-Post-Change								
Intrinsic value	-0.155	0.062	0.012	0.315	-0.166	0.053	0.002	0.372
Utility value	-0.076	0.060	0.203	0.147	-0.087	0.051	0.089	0.206
Self-concept	-0.040	0.043	0.358	0.118	-0.058	0.048	0.232	0.174
Self-efficacy towards exam	-0.216	0.048	0.000	0.503	-0.184	0.049	0.000	0.408
Level after post-test								
Course performance (total)	27.728	0.379	0.000		27.512	0.368	0.000	
Course performance (grid-related)	16.706	0.268	0.000		16.359	0.271	0.000	
Level at pre-test								
Attitude towards inclusive education	2.866	0.038	0.000		2.878	0.036	0.000	
Self-efficacy towards inclusive education	3.068	0.033	0.000		3.109	0.031	0.000	
Pre-post-change								
Attitude towards inclusive education	0.122	0.050	0.015	0.299	-0.039	0.048	0.419	0.115
Self-efficacy towards inclusive education	0.091	0.039	0.019	0.279	-0.046	0.046	0.326	0.114

Note. Manifest variables for course performance. ES = Cohen's d effect size for the mean changes corrected for the pre-post-correlation.

Table 2. Treatment effects (intervention vs. control condition) on motivation, achievement, and teacher professional development (standardized regression coefficients)

	Model 1: Course-specific motivation											
	Intrinsic value			Utility value			Self-concept			Self-efficacy towards exam		
	β	*SE*	*p*	β	*SE*	*p*	β	*SE*	*p*	β	*SE*	*p*
Level at pre-test												
Intervention	-0.104	0.054	0.054	-0.148	0.055	0.008	-0.014	0.057	0.803	-0.040	0.054	0.464
Male	-0.251	0.053	0.000	-0.079	0.057	0.170	-0.220	0.060	0.000	-0.081	0.056	0.151
High school GPA	-0.112	0.061	0.068	-0.052	0.064	0.420	-0.028	0.067	0.674	-0.020	0.066	0.762
Study-specific prior grade	-0.064	0.067	0.334	-0.055	0.067	0.414	-0.061	0.072	0.400	-0.155	0.066	0.018
Effort avoidance	-0.153	0.054	0.005	-0.212	0.054	0.000	-0.132	0.059	0.026	-0.184	0.060	0.002
Pre-post-change												
Intervention	0.026	0.075	0.733	0.017	0.072	0.811	-0.003	0.084	0.974	-0.046	0.077	0.548
Male	0.134	0.082	0.103	0.037	0.081	0.648	0.171	0.090	0.056	0.187	0.083	0.025
High school GPA	0.028	0.089	0.750	-0.019	0.086	0.829	-0.071	0.111	0.525	0.126	0.101	0.212
Study-specific prior grade	0.067	0.102	0.513	-0.025	0.084	0.768	0.009	0.129	0.946	0.043	0.119	0.717
Effort avoidance	-0.002	0.083	0.979	0.010	0.066	0.879	-0.014	0.094	0.880	-0.157	0.101	0.120

	Model 2: Course performance (total)			Course performance (grid-related)		
	β	*SE*	*p*	β	*SE*	*p*
Level after post-test						
Intervention	0.003	0.048	0.953	0.031	0.049	0.528
Male	-0.049	0.053	0.354	-0.042	0.054	0.444
High school GPA	-0.282	0.061	0.000	-0.250	0.060	0.000
Study-specific prior grade	-0.240	0.062	0.000	-0.216	0.061	0.000
Effort avoidance	0.087	0.050	0.085	0.066	0.050	0.186

	Model 3: Teacher professional development					
	Attitude towards inclusive education			Self-efficacy towards inclusive education		
	β (unstand)	*SE*	*p*	β (unstand)	*SE*	*p*
Level at pre-test						
Intervention	-0.027	0.063	0.672	-0.052	0.063	0.404
Male	-0.195	0.063	0.002	0.024	0.065	0.711
High school GPA	0.113	0.075	0.134	0.009	0.080	0.910
Study-specific prior grade	0.023	0.093	0.805	-0.037	0.082	0.648
Effort avoidance	-0.058	0.070	0.408	-0.133	0.070	0.057
Pre-post-change						
Intervention	0.237	0.094	0.011	0.197	0.089	0.027
Male	-0.034	0.099	0.729	0.007	0.105	0.948
High school GPA	-0.078	0.102	0.447	0.139	0.113	0.218
Study-specific prior grade	0.069	0.127	0.590	0.107	0.098	0.272
Effort avoidance	0.027	0.116	0.818	-0.088	0.104	0.400

Note. Lower values on high school GPA and study-specific prior grade indicate better grades (1 = highest grade, 4 = lowest grade).

4.2 Learning behavior within the learning design

In the following, we give a brief summary of the learning analytics results. Detailed statistics are reported in Appendix C in the online supplement (https://osf.io/9zbuk/). We first examined students' time investment (number of accesses per student, the number of grids accessed per student and the number of different grid fields per student). The n = 215 students assigned to the intervention condition accessed between zero and all five of the grids. The number of accesses was by far highest on the day before the exam, and still considerable on the exam day itself. Higher achieving students, that is, those with higher study-specific prior grades and higher course performance at post-test, tended to engage more often with the learning activities. Moreover, students who perceived higher intrinsic value of learning educational psychology at pre-test, tended to access more grid fields, and undertook more accesses overall. The number of accesses was further related to gender with female students making more use of the learning activities, and to course-specific self-efficacy at pre-test, indicating that those students who were more confident in their course performance tended to work more often with the learning design. The described correlations between time-investment and student characteristics were small. We further found that 33.5 % of the students used the learning activities as part of a repeated self-assessment strategy. Furthermore, students' behavior when engaging with the learning design diverged substantially from the instructions they were given, and there was a large amount of heterogeneity in students' learning paths (e.g., navigating from high to low cognitive complexity).

5. Discussion

In a randomized field experiment, we investigated the effects of an individualized learning design on university students' motivation, on their performance, and because our sample consisted of teacher students, on their professional development with regard to inclusive education. We found that the learning design positively affected the self-concepts of effort avoidant students. Moreover, we found that students' attitudes and their self-efficacy towards inclusive education increased in the intervention condition while remaining unchanged in the control condition.

Concerning students' subject-specific motivation in educational psychology, we hypothesized that the self-concept, the self-efficacy towards the exam, and intrinsic and utility values would profit from the individualization of the learning design. We found a beneficial effect only for self-concept (hypothesis 1a), and it depended on students' effort avoidance: Effort avoidant students in the control condition lowered their self-concept from the beginning of the course until three months later when they had progressed with the course. It might be that these students had difficulties with the multitude of possible learning activities in this course, which consisted of face-to-face lectures, video lectures, and the assessment activities in pdf-documents. By contrast, if effort avoidant students were given more structure within the learning design, and by providing instant feedback on learning activity performance, their competence perceptions developed more positively. This covariate x treatment interaction had an intermediate effect (Cohen, 1988), and it aligns with findings showing that giving structure is an important prerequisite for learning (e.g., Alfieri et al., 2011; Kirschner et al., 2006), and especially so for students with low self-regulation skills (e.g., Jitendra, Kay Hoppes, & Xin, 2000). Unlike self-concept, students' self-efficacy towards the exam remained unaffected by the intervention and declined in all students. Rather, self-efficacy seemed to be associated with prior grades, in line with expectancy-value models of academic motivation and emotion (Eccles & Wigfield, 2020; Pekrun, 2018). Future efforts to increase self-efficacy towards the exam could include explaining students how retrieval practice can help them improve their performance and instructing them to use a strategy of repeated self-testing within the learning design (McDermott, 2021). This way, the connection between the learning activities and successful course performance could become more explicit.

Furthermore, in contrast to our expectations (hypothesis 1b), the intervention did not foster students' valuing of educational psychology. It could be speculated that the design of the learning activities in the intervention and control conditions did not differ much in the amount of autonomy they provided to the students. In both conditions, the students could flexibly decide when they wanted to watch a video lecture or to work on assessment activities. Surprisingly, however, despite this granting of autonomy, intrinsic value slightly declined across the semester in both conditions. This result is in contrast to earlier findings reporting mean stability of intrinsic value in another cohort taking the same class with the same teacher (Dietrich, Moeller, Guo, Viljaranta, & Kracke, 2019). Apart from possible sampling variation, this finding could be explained by the smaller amount of face-to-face situations in the present cohort compared to typical university lectures. This could have lowered the perceived satisfaction of students' need for relatedness (Deci & Ryan, 2000), which is a precondition for intrinsic motivation. The other value facet, utility value, was neither affected by the intervention. The cues concerning practical utility that students received through the learning design instructions might not have been sufficient to stipulate higher utility (Harackiewicz et al., 2014). Perhaps the relevance of the learning contents for students' future profession as teachers still need more explicit cues to be recognized (as for example in Gaspard, Dicke, Flunger, Brisson, et al., 2015).

Again, in contrast to our hypothesis (hypothesis 2), being assigned to the learning design intervention did not increase students' course performance. This finding might be related to the extent to which students actually used the learning activities, as our additional analysis showed. Like in previous studies (e.g., Jansen et al., 2020) and not surprising, compliance with the intervention is often critical for intervention success. With our study design, however, we cannot discern to what extent students' high achievement was the cause of both their intense engagement with the learning activities and their high course performance (Dvorak & Jia, 2016), and to what extent high engagement in working within the learning design might have uniquely impacted performance.

Overall, the absent intervention effect on performance is in contrast to prior studies on individualized online and blended learning (e.g., Zhang et al., 2020). In the study of Zhang and colleagues, for example, students received learning reports showing their own learning behavior in relation to the whole class, combined with face-to-face reminders for students with low online engagement. This intense intervention positively affected both students' use of online resources and their performance and is an example of a learning design strategy to support self-regulated learning, especially the monitoring of one's learning. The importance of supporting self-regulation strategies in online learning as means to improve performance is widely recognized (e.g., Sailer et al., this issue). Possible intervention strategies to be implemented in future versions of the learning design are, for example, individualized prompts that guide students in using adaptive cognitive and metacognitive strategies while working with the learning activities (Lehmann, Hähnlein, & Ifenthaler, 2014), or supports for students' time management (Liborius et al., 2019).

Regarding our third hypothesis (hypothesis 3), as intended, the learning design intervention positively affected teacher students' attitudes and their self-efficacy towards inclusive education in their future professional life. We can therefore conclude that the intervention strategy of modeling a professional approach to heterogeneity with our learning design as an example (Avramidis et al., 2000; Burke & Sutherland, 2004) successfully impacted both of these student outcomes. Interestingly, addressing the topic of inclusive education as content of the learning design was obviously not a necessary precondition for the intervention effects. In fact, students in both the intervention and the control condition learned about inclusive education in video and face-to-face lectures. The instruction method thus seems to be more important for attitude and belief change in this context than the learning contents per se. This is good news for teacher educators, especially because attitudes and beliefs about inclusive education have originally been described as stable dispositions (Wilkins & Nietfeld, 2004; Bosse et al., 2016), while our data show that they can be intervened upon.

Finally, learning analytics provided insights for further developing the learning design (Mangaroska & Giannakos, 2019). The foremost aim appears to be increasing the efforts to motivate all students to make use of the learning activities. As our data showed, students with lower initial motivation in educational psychology, and lower achieving students less frequently or never used the assessment activities. Apparently, these students need a different approach to comply with the goals of the learning design. A potential strategy might entail helping students recognize the potential of the learning design for their learning success (e.g., how retrieval practice can improve their knowledge acquisition). Moreover, given the high number of last-minute accesses to the learning activities, the learning design could provide better supports for self-regulated learning and time management (Liborius et al., 2019). Thus far, in our learning design students could only see which activities they already had completed. Analytics-based nudges and information to students might be a better scaffold for students' self-regulated monitoring of their activities (Blumenstein, 2020). In the present context, one component of this might be visualized feedback on students' individual learning paths (Blikstein et al., 2014; Pérez-Álvarez, Maldonado-Mahauad, & Pérez-Sanagustín, 2018, see also Appendix C). Learning analytics had revealed the heterogeneity therein and showed that students indeed made use of the possibility to select their individual learning path. Finally, analytics data showed that most students did not follow the given instructions how to engage with the learning design. It might be that the instructions require more salience.

Another promising option to further develop the learning design might be to incorporate collaborative learning activities. This yields the potential to stimulate higher modes of students' cognitive engagement (Chi & Wylie, 2014) and consequently positive impacts on knowledge acquisition (e.g., Mateescu et al., 2019). For such cognitive benefits to occur, learning activities need to include dialoguing with other, as for example in joint explaining, discussing, and reflecting (Chi & Wylie, 2014). We suggest that collaborative learning activities might thus be most suitable for high complexity levels. Furthermore, non-cognitive outcomes like feelings of enjoyment might be positively affected through collaborative learning (Mateescu et al., 2019). This would also address the risk of social isolation through individualized learning and/or online learning. This criticism of individualized learning is especially relevant during the COVID-19 pandemic.

5.1 Limitations and directions for future research

The present study has a number of limitations that open up avenues for future research. First, although we tried to measure students' self-regulation as one key factor of successful online learning, our measurement instrument had poor psychometric quality and could not be used in the analyses. It remains a pertinent question for future studies to investigate students' self-regulatory skills as a predictor of their learning behavior within learning designs, and as a possible outcome of the intervention.

Second, in the intervention condition, our results showed that students who engaged more frequently with the learning activities, were the ones with higher course performance. We however had no information about the learning behavior in the control condition. It would be interesting to compare students' learning behavior when making use of the grid-related learning activities to their interaction with the same activities in pdf format. This would allow for a more direct test of our assumption that our learning design, more so than offline learning tasks, encourage students to use practice testing and repeated self-assessment as a learning strategy.

Future research could also take a more comprehensive perspective on learning behavior (when, how, and how often students access the learning activities) in examining whether distinct types of learners exist, who of them actually approaches the learning design in whichever different ways, and to what extent these differences possibly predict motivation and performance. If systematic individual differences existed, more successful approaches to learning within our learning design could potentially be distinguished from less successful ones, and this kind of information could be used to improve the instructions given to students.

Third, we lacked information about the students' in-the-moment motivational experiences when they actually worked within the learning design. Were the learning tasks intrinsically motivating? Did students feel competent during test taking? Such repeated momentary, state-like motivational experiences can be the cause of mid- and long-term motivational development like assessed in this study (Dietrich et al., 2019). Therefore, an evaluation of the processes taking place during the intervention would be informative in exploring intra-individual mechanisms leading to change or stability in motivational outcomes. In fact, during our data collection we tried to assess state motivation and emotions via experience sampling questionnaires after each learning task (see Dietrich et al., 2017), but students had the option to skip these questionnaires, and most of them made use of this option. Therefore, an alternative assessment method needs to be developed. Like state motivation, the state performance in each learning task could be used to study the assumed mechanisms involving momentary success, failure, and expectancies (see Musher-Eizenman, Nesselroade, & Schmitz, 2002).

Finally, our study did not measure students' attitudes towards digital technology. In both their role as students, as their role as future teachers, these attitudes are crucial to the target group students of our intervention (Sailer et al., this issue). Given that digital differentiation grids were introduced as a type of learning design to address learner heterogeneity through digital technology, we hypothesize that teacher students' attitudes towards such technology improve through the intervention. This will be an important question to address in future studies.

5.2 Conclusion

This study showed how principles for an individualized learning design in higher education can be derived from psychological theory and evidence on motivational and cognitive learning processes (Bodily et al., 2019). Moreover, for the context of teacher education we showed how students can be professionalized to effectively use digital technology to address the challenge of heterogenous learner characteristics. We deem sound theoretical foundation to be important, because higher education teachers and especially teacher educators need to know how they can design individualized learning environments, and how they can support future teachers in developing their digital competence (Mishra & Koehler, 2006).

While main effects of the here-studied learning design were observed on teacher professional development, other effects like those on self-concept depended on learner characteristics, or on students' compliance with the intervention as in the case of course performance. This underscores that effective learning design requires not only careful instructional planning but also responding to individually differing needs of students. Achieving such ambitious goals was obviously challenging and sometimes hardly possible during the COVID-19 pandemic, where university and college teaching was suddenly shifted from offline to online mode (Hodges, Moore, Lockee, Trust, & Bond, 2020). In this crisis situation, it was an asset to build on the already developed learning design. This aligns with recent findings showing that digital teacher competence was vital in adapting to online teaching during the pandemic (König, Jäger-Biela, & Glutsch, 2020).

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